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Analyzing The Role of Data Analytics in Business Decision Making at Almajdouie Motors

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Table of Contents

Chapter 1: General Framework of the Study	3
1.1 Introduction	3
1.2 Research Problem	4
1.3 Research Significance	4
1.4 Research Questions	5
1.5 Research Objectives	5
1.6 Research Hypotheses	6
1.7 Research Model	6
1.8 Suggested Industry / Organization	7
1.9 Research Methodology	8
1.10 Suggested Project Structure	10
Chapter 2: Literature Review	11
2.1 Introduction	11
2.2 Data Analytics: Concepts, Typologies, and Dimensions	11
2.3 Business Decision Making: Theories, Models, and Frameworks	14
2.4 The Relationship Between Data Analytics and Decision Quality	16
2.5 Data Analytics in the Automotive Sector	18
2.6 Relevant Empirical Studies	20
2.7 Summary and Research Gap	22
Chapter 3: Research Methodology	23
3.1 Introduction	23
3.2 Operational Definitions for Research Variables	23
3.3 Research Design (Research Onion)	24
3.4 Research Population & Sampling Methods and Technique	24
3.5 Data Collection Method	25
3.6 Types of Data	25
3.7 Statistical Analysis Procedures	25
3.8 Conclusion	26
Chapter 4: Statistical Analysis & Findings Discussion	27
4.1 Introduction	27
4.2 Sample Profile	27
4.3 Validity and Reliability Tests	29
4.4 Descriptive Statistics for Research Variables	30
4.5 Testing Hypotheses and Findings Discussion	32
4.6 Conclusion	33
References	34
Appendix A: Research Questionnaire	36
Appendix B: Table of Research Instruments	39

Chapter 1

General Framework of the Study

1.1. Introduction

The automotive industry in the Kingdom of Saudi Arabia has witnessed remarkable growth in recent years, driven by accelerated economic development and increasing demand for vehicles across various segments. In this context, Almajdouie Motors emerges as one of the leading companies in the vehicle import and distribution sector within the Kingdom. The company provides a wide range of global automotive brands, focusing on meeting local market needs and delivering high-quality after-sales services.

With intensifying competition in the automotive sector, it has become essential for companies to rely on scientific and methodological approaches in their business decision-making. Decisions based solely on intuition and personal experience are no longer sufficient to achieve sustainable success in an environment characterized by rapid change and evolving customer expectations. This highlights the importance of data analytics as a strategic tool that helps management understand market trends, analyze customer behavior, improve operational efficiency, and make informed decisions based on accurate and reliable information.

Almajdouie Motors possesses an extensive database that includes information on daily sales, customer preferences, inventory levels, supplier performance, as well as maintenance service and spare parts data. However, the true value of this data lies not merely in its existence, but in the ability to analyze it and transform it into actionable insights. When this information is analyzed systematically, the company becomes capable of identifying purchasing patterns, forecasting future demand, and improving marketing and pricing strategies.

From a practical perspective, data analytics can contribute to improving various aspects of the company's operations. For example, historical sales data can be used to predict demand for specific car models, helping with inventory planning and avoiding vehicle shortages or surpluses. Customer interactions and feedback can be analyzed to enhance the purchasing experience and after-sales service. Additionally, data can be used to measure the effectiveness of marketing campaigns and identify the most influential channels for reaching the target audience.

This research aims to study and analyze the role of data analytics in improving business decision-making processes within Almajdouie Motors. The focus will be on understanding how data is used at various management levels, identifying challenges the company faces in

implementing effective data analysis, and exploring opportunities to enhance the utilization of these technologies.

1.2. Research Problem

Despite significant technological advancement and the availability of sophisticated analytical tools, many companies in the automotive sector in Saudi Arabia face fundamental challenges in effectively leveraging their available data. While these companies possess vast amounts of information about their daily operations, transforming this data into well-informed strategic decisions remains an obstacle for many organizations.

In the context of Almajdouie Motors, the primary problem lies in the gap between the volume of available data and the ability to extract valuable insights that contribute to improving business performance. The company collects diverse information daily about sales, customer preferences, inventory movement, and team performance. However, the process of analyzing this data may not be systematic or comprehensive enough to support strategic decision-making based on strong evidence.

Hence, there is a need for deeper understanding of the role that data analytics can play in improving the quality of managerial decisions. The research problem can be summarized in the following main question: To what extent does data analytics contribute to improving business decision-making processes at Almajdouie Motors?

1.3. Research Significance

1.3.1. Theoretical Significance

From a theoretical perspective, this research contributes to enriching Arabic literature related to data analytics and its applications in the automotive sector specifically. Despite numerous studies on big data and advanced analytics, studies focusing on the Saudi market and the automotive sector in particular remain limited. The research also provides a conceptual framework clarifying the relationship between analytical capabilities and business decision quality, which may open avenues for future studies in this direction.

1.3.2. Practical Significance

At the practical level, the research provides practical insights that Almajdouie Motors and similar companies in the sector can benefit from. By identifying effective practices in using data analytics, management can develop better strategies to improve operational performance, increase customer satisfaction, and enhance competitive advantage. The

research also helps highlight practical challenges facing the implementation of effective data analysis, enabling companies to take proactive measures to address them.

1.4. Research Questions

This research seeks to address the following key questions regarding the role of data analytics in business decision-making at Almajdouie Motors:

Main Research Question: To what extent does data analytics contribute to improving business decision-making processes at Almajdouie Motors?

Sub-Questions:

- RQ1: What types of data does Almajdouie Motors currently collect and analyze for decision-making purposes?
- RQ2: How is data analytics currently utilized across different management levels within the organization?
- RQ3: What are the main challenges and barriers to effective data analytics implementation at Almajdouie Motors?
- RQ4: What opportunities exist for enhancing data-driven decision-making capabilities within the company?

1.5. Research Objectives

Based on the research questions outlined above, this study aims to achieve the following objectives:

- To examine the current state of data collection and analysis practices at Almajdouie Motors.
- To investigate how data analytics influences decision-making processes across different organizational levels.
- To identify and analyze challenges that hinder effective implementation of data analytics within the company.
- To explore potential opportunities for improving data-driven decision-making capabilities.
- To provide practical recommendations for enhancing the utilization of data analytics in business operations.

1.6. Research Hypotheses

This research proposes the following hypotheses to be examined through empirical investigation:

- H1: There is a positive relationship between the extent of data analytics utilization and the quality of business decisions at Almajdouie Motors.
- H2: Companies that implement systematic data analysis processes experience improved operational efficiency compared to those relying primarily on intuition-based decisions.
- H3: Investment in data analytics capabilities positively correlates with customer satisfaction levels.
- H4: The presence of a data-driven organizational culture facilitates better strategic planning and execution.

1.7. Research Model

The conceptual framework for this research is based on examining the relationship between data analytics (independent variable) and business decision-making quality (dependent variable). The model includes:

Independent Variable	Dependent Variable
Data Analytics: • Data collection systems • Analytical tools and techniques • Data quality and accessibility • Analytical skills and expertise	Business Decision Quality: • Strategic planning effectiveness • Operational efficiency • Customer satisfaction • Market responsiveness

The model suggests that effective implementation of data analytics capabilities leads to improved business decision-making outcomes, mediated by factors such as organizational culture, technological infrastructure, and employee competencies.

Research Conceptual Model

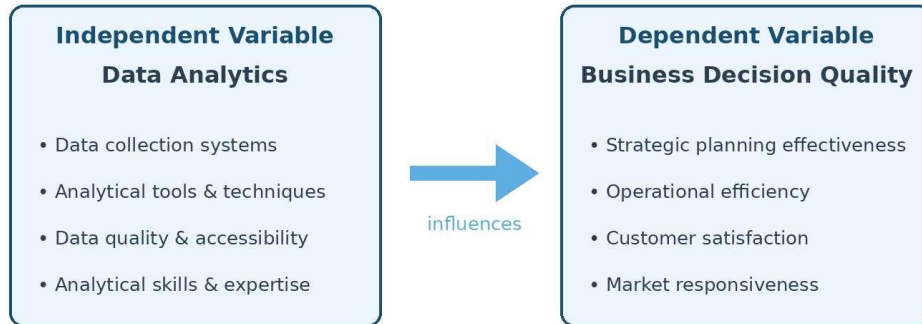


Figure 1: Research Conceptual Model

1.8. Suggested Industry / Organization for Empirical Study

Almajdouie Motors has been selected as the primary organization for this empirical study based on several strategic considerations:

Company Background: Founded in 1985 as a subsidiary of Almajdouie Group, Almajdouie Motors has established itself as a leading automotive distributor in Saudi Arabia. The company serves as the official dealer for multiple international brands including Hyundai, Genesis, Changan, Peugeot, and Citroën across various regions of the Kingdom.

Operational Scale:

- Seven service centers equipped with advanced technology
- Serves over 100,000 vehicles annually
- Twenty spare parts centers across Eastern and Northern regions
- Extensive dealer network throughout Saudi Arabia

Relevance to Study: The automotive sector generates substantial volumes of operational data, making Almajdouie Motors an ideal case for examining data analytics applications. The company's scale and market position provide access to diverse data sources including sales transactions, customer interactions, inventory management, and service operations.

Almajdouie Motors Overview



Figure 2: Almajdouie Motors Company Profile

1.9. Research Methodology

This study will employ a quantitative research methodology based on questionnaire data collected through Google Forms. The questionnaire will be distributed to employees and managers to examine the role of data analytics in improving business decision-making quality at Almajdouie Motors.

Research Design: A quantitative survey design will be used. This design is appropriate because it allows the researcher to collect measurable responses from the target sample and statistically analyze the relationship between data analytics and business decision-making quality.

Data Sources:

- Primary data collected through a structured questionnaire.
- Academic literature and previous studies related to data analytics and decision-making.
- Relevant company and industry information to support the research context.

Analytical Framework: The analysis will examine how data analytics capabilities influence business decision-making quality by using descriptive statistics, reliability testing, correlation analysis, and hypothesis testing.

Limitations: As this study relies on questionnaire responses, the findings may be limited by the sample size and the respondents' perceptions. However, the results will provide useful insights into the role of data analytics in business decision-making at Almajdouie Motors.

Research Methodology

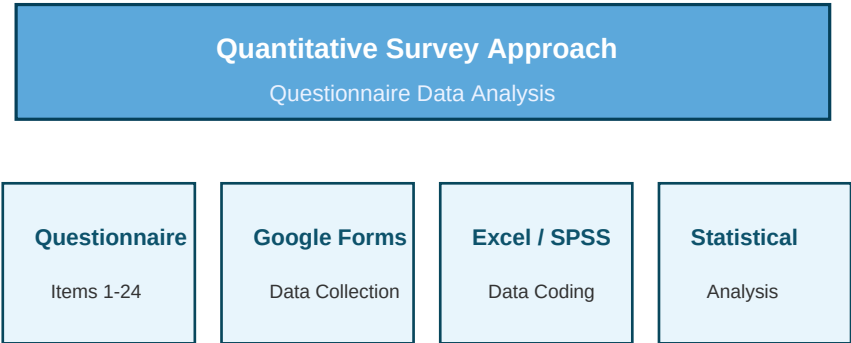


Figure 3: Research Methodology Framework

Data Analytics Process

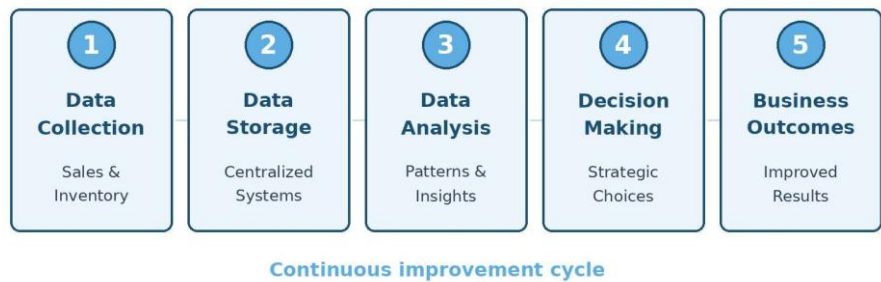


Figure 4: Data Analytics Process Flow

1.10. Suggested Project Structure

The complete research project will be organized according to the following structure:

Chapter	Content
Chapter 1: Introduction	Research background, problem statement, significance, questions, objectives, hypotheses, research model, scope, and project structure.
Chapter 2: Literature Review	Review of data analytics concepts, business decision-making theories, relationship between variables, and relevant empirical studies.
Chapter 3: Research Methodology	Operational definitions, research design, research population, sampling method and technique, data collection method, data types, and statistical analysis procedures.
Chapter 4: Statistical Analysis & Findings Discussion	Sample profile, validity and reliability tests, descriptive statistics for research variables, hypothesis testing, and findings discussion.
Chapter 5: Limitations, Recommendations & Conclusion	Research limitations, future research, practical recommendations, and conclusion.
References	Complete list of all sources cited in the research.
Appendices	Research questionnaire and table of research instruments.

Chapter 2

Literature Review

2.1. Introduction

This chapter provides a thorough and systematic review of the existing scholarly literature pertaining to the central themes of this research: data analytics and its role in enhancing business decision-making processes. The fundamental purpose of this literature review is threefold. First, it establishes the conceptual and theoretical foundations upon which the current empirical investigation is built. Second, it synthesizes the key findings of prior studies to identify areas of scholarly consensus and contention. Third, it delineates the specific gaps in the existing knowledge base that this research seeks to address, thereby clarifying its original contribution to the field.

The review is organized into six interconnected thematic sections. The first section examines the conceptual landscape of data analytics, including its definitions, typologies, and organizational dimensions. The second explores theoretical perspectives on business decision-making, tracing the evolution of thought from classical rational models to contemporary evidence-based frameworks. The third section investigates the empirically established relationship between data analytics capabilities and the quality of organizational decisions, including the key mediating and moderating variables. The fourth section addresses the specific application of data analytics within the automotive industry, both globally and in the context of the Saudi Arabian market. The fifth section reviews a selection of relevant empirical studies that directly inform the research questions and hypotheses of this study. The sixth and final section synthesizes the reviewed literature, highlights the identified research gaps, and positions the current study within the broader academic discourse.

The literature was sourced from peer-reviewed academic journals, scholarly books, industry reports, and credible institutional publications. Databases consulted include Scopus, Web of Science, Google Scholar, and the Saudi Digital Library. Search terms included combinations of “data analytics,” “business intelligence,” “decision-making,” “automotive industry,” “Saudi Arabia,” and “data-driven management,” among others. Priority was given to studies published between 2010 and 2025, although seminal earlier works were included where their theoretical contributions remain foundational and widely cited.

2.2. Data Analytics: Concepts, Typologies, and Dimensions

2.2.1. Defining Data Analytics

Data analytics is broadly defined as the systematic computational process of examining large and varied data sets to uncover hidden patterns, unknown correlations, market trends, customer preferences, and other useful business information (Chen, Chiang & Storey, 2012). At its core, the discipline combines elements of statistics, computer science, information systems, and domain-specific business knowledge to transform raw data into actionable intelligence that supports organizational decision-making.

Provost and Fawcett (2013) offer a particularly influential definition, characterizing data analytics as the science of extracting actionable knowledge from data. This definition emphasizes the practical, action-oriented purpose of analytics — the extraction of knowledge that can meaningfully improve decisions and outcomes, implying a rigorous methodological approach that distinguishes analytics from casual data inspection or simple reporting.

The academic literature also distinguishes data analytics from related concepts such as “business intelligence” (BI) and “big data.” Business intelligence traditionally refers to the tools, technologies, and processes used to collect, integrate, analyze, and present business information, with a historical emphasis on descriptive reporting and dashboarding (Negash, 2004). Big data, by contrast, emphasizes the volume, velocity, variety, veracity, and value of contemporary data environments — the so-called “5 Vs” framework (Gandomi & Haider, 2015). Data analytics represents the analytical core that bridges these domains, encompassing the full spectrum of methods from basic descriptive statistics to advanced machine learning and artificial intelligence.

For the purposes of this research, data analytics is understood as the comprehensive capability of an organization to collect, process, analyze, and apply data-derived insights to its decision-making processes at all organizational levels. This broad definition acknowledges both the technical dimensions of analytics (tools, algorithms, infrastructure) and the organizational dimensions (culture, skills, processes) that together determine an organization’s actual analytical capacity.

2.2.2. A Typology of Data Analytics

The literature consistently identifies four primary types or levels of data analytics, arranged in a hierarchical progression from retrospective description to prospective optimization. Understanding this typology is essential for evaluating the analytical maturity of organizations and identifying opportunities for capability development.

Type of Analytics	Core Question	Primary Method	Business Value
Descriptive	What happened?	Statistical summaries, dashboards, reports	Operational visibility and performance monitoring
Diagnostic	Why did it happen?	Drill-down analysis, correlation, root cause analysis	Understanding drivers of performance outcomes
Predictive	What will happen?	Regression, machine learning, time-series forecasting	Anticipating future conditions and proactive planning
Prescriptive	What should we do?	Optimization models, simulation, AI-driven recommendations	Automated and optimized decision support

Table 1: Typology of Data Analytics (Adapted from Davenport & Harris, 2017; Gandomi & Haider, 2015)

Descriptive analytics forms the foundation of organizational data use and is the most widely implemented across businesses of all sizes and sectors. By summarizing historical data through aggregation, visualization, and statistical description, it provides managers with a clear picture of past performance. Common tools include business intelligence dashboards, standard reports, and key performance indicator (KPI) scorecards (Chen et al., 2012).

Diagnostic analytics extends descriptive analysis by interrogating the causes underlying observed outcomes. Rather than simply reporting that sales declined in a given quarter, diagnostic analytics seeks to identify the specific factors — pricing changes, competitive actions, supply constraints, or shifts in customer preference — that drove the decline. Techniques include drill-down analysis, data segmentation, and correlation analysis.

Predictive analytics employs statistical models, machine learning algorithms, and historical data patterns to forecast future events or behaviors. Applications include demand forecasting, customer churn prediction, credit risk scoring, and predictive maintenance. The accuracy and business value of predictive models depend critically on the quality and representativeness of the historical data used to train them (Provost & Fawcett, 2013).

Prescriptive analytics represents the most sophisticated and value-generating tier of the analytics hierarchy. It not only forecasts future outcomes but recommends specific actions to achieve desired results or avoid adverse scenarios. Techniques include linear programming, stochastic optimization, simulation modeling, and reinforcement learning. While prescriptive analytics offers the greatest potential business value, it also demands the most advanced technological capabilities and analytical expertise.

2.2.3. Organizational Data Maturity Models

The concept of organizational data maturity has emerged as a critical framework for assessing an organization's capacity to derive value from its data assets. Gartner's widely referenced maturity model identifies five levels of analytical maturity: descriptive, diagnostic, predictive, prescriptive, and cognitive (automated) analytics (Laney, 2018). Organizations at lower maturity levels rely primarily on historical reports and spreadsheets, while those at higher levels integrate advanced analytics into their core decision-making processes and increasingly automate routine analytical tasks through artificial intelligence.

Research by McKinsey Global Institute (Manyika et al., 2011) found that organizations at the highest levels of data maturity were significantly more likely to outperform industry peers in profitability, productivity, and customer satisfaction. The study estimated that companies in the top quartile of data maturity achieved profit margins approximately sixty percent higher than industry medians. These findings underscore the strategic importance of systematically developing data maturity as a core organizational capability.

Data maturity is shaped by multiple organizational dimensions including technological infrastructure, data governance frameworks, workforce analytical skills, cross-functional data sharing culture, and executive leadership commitment to data-driven decision-making. Organizations seeking to advance their data maturity must address all of these dimensions in a coordinated manner; investments in technology alone, without corresponding investments in skills and culture, consistently yield disappointing results (Kiron et al., 2014).

2.3. Business Decision Making: Theories, Models, and Frameworks

2.3.1. Classical Rational Choice Theory

The study of business decision-making has deep roots in economics, psychology, operations research, and organizational theory. The classical rational choice model posits that decision-makers are fully rational agents who systematically evaluate all available alternatives, accurately assess the probabilities and utilities of their consequences, and consistently select the option that maximizes their expected utility (von Neumann & Morgenstern, 1944). This normative model provides a powerful theoretical benchmark but has been extensively critiqued for its unrealistic assumptions about human cognitive capacity, information availability, and motivational consistency.

The limitations of classical rationality were most prominently addressed by Herbert Simon (1955), whose concept of "bounded rationality" fundamentally reshaped the field. Simon argued that real-world decision-makers operate within significant cognitive and informational

and uncertain information; and they must make decisions in complex, dynamic environments. Rather than optimizing, Simon argued, decision-makers “satisfice” — they adopt decision procedures that are good enough rather than searching exhaustively for the theoretically optimal choice.

The concept of bounded rationality has profound implications for data analytics. If decision quality is constrained by information availability and cognitive processing capacity, then analytical tools that improve information quality, reduce cognitive load, and systematize the evaluation of alternatives can directly expand the effective rationality of decision-makers. From this perspective, data analytics can be understood as a set of technologies and methods that compensate for the inherent limitations of human cognition in complex business environments.

2.3.2. Evidence-Based Management

The evidence-based management (EBMgt) movement, pioneered by Pfeffer and Sutton (2006), advocates for the systematic use of the best available evidence in making managerial decisions. Drawing analogies with evidence-based medicine, EBMgt challenges managers to critically examine the empirical basis of their beliefs and practices, reject management fads lacking rigorous evidence, and prioritize decisions grounded in high-quality data and research.

Data-driven decision-making (DDDM) can be understood as the operationalization of evidence-based management principles within contemporary data-rich environments. A seminal empirical study by Brynjolfsson, Hitt, and Kim (2011), based on data from 179 large publicly traded U.S. companies, found that firms adopting DDDM practices were five to six percent more productive than their industry peers, even after statistically controlling for other determinants of performance including IT investments, capital intensity, and workforce characteristics.

McAfee and Brynjolfsson (2012) further argued that data is becoming a critical strategic asset, and organizations that fail to develop data-driven capabilities risk losing competitive ground. Their research emphasized that the value of data lies not in its collection but in its analytical application to organizational decisions, making the quality of analytical processes and institutional capacity for using data the key sources of competitive differentiation.

2.3.3. Decision Making Across Organizational Levels

Organizational decision-making is not a monolithic phenomenon but occurs across multiple hierarchical levels, each characterized by distinct time horizons, information requirements, and performance criteria. Anthony's (1965) classical framework distinguishes three levels: strategic, management (tactical), and operational. This framework remains foundational and

Decision Level	Characteristics	Time Horizon	Analytics Application
Strategic	Long-term planning, resource allocation, market positioning	3–10+ years	Market trend analysis, competitive intelligence, scenario planning
Tactical	Performance management, resource optimization, departmental planning	6 months – 3 years	Operational dashboards, variance analysis, demand forecasting
Operational	Day-to-day execution, process management, immediate problem-solving	Hours – weeks	Real-time monitoring, exception reporting, automated alerts

Table 2: Decision-Making Levels and Analytics Applications (Adapted from Anthony, 1965; Davenport & Harris, 2017)

At the strategic level, senior executives rely on analytics to assess market opportunities and threats, evaluate long-term investment alternatives, and develop competitive strategies. At the tactical level, middle managers use analytics to monitor departmental performance against targets, identify root causes of performance variances, and optimize resource allocation decisions. At the operational level, frontline managers and staff use analytics embedded in operational systems to make immediate decisions about inventory replenishment, customer service, quality control, and logistics.

For an organization of Almajdouie Motors' complexity, effective analytics must operate simultaneously across all three levels. Strategic analytics informs decisions about which vehicle brands to represent and which markets to enter. Tactical analytics guides inventory levels across service centers and allocation of marketing budgets. Operational analytics supports daily decisions about parts ordering, service appointment scheduling, and customer communication.

2.4. The Relationship Between Data Analytics and Business Decision Quality

2.4.1. Empirical Evidence of the Analytics–Decision Quality Link

A substantial and growing body of empirical research provides strong support for a positive relationship between data analytics capabilities and the quality of organizational decisions. Davenport and Harris (2017) conducted one of the most comprehensive cross-industry studies of analytics adoption and performance, examining over fifty companies across multiple sectors. Their research identified “analytical competitors” — organizations that had made

analytics central to their competitive strategy — and found that these companies consistently outperformed industry peers on key financial and operational performance metrics.

The landmark study by Brynjolfsson, Hitt, and Kim (2011) established a robust quantitative link between data-driven decision-making and firm productivity. Subsequent research has extended and refined this finding across diverse contexts. The MIT Sloan Management Review survey (Kiron et al., 2014), involving approximately 2,700 executives across 122 countries, found that organizations in the top analytically mature tier were twice as likely to have top-quartile financial performance, and three times more likely to achieve best-in-class customer satisfaction metrics.

In the specific domain of supply chain management — highly relevant to automotive distribution — Wamba et al. (2017) conducted an empirical study of 297 firms and found that big data analytics capability had a significant direct positive effect on firm performance, partially mediated by supply chain agility. The implication for Almajdouie Motors is significant: data analytics investments are likely to yield performance benefits not only through direct decision improvement but also through enhanced organizational agility and responsiveness to market changes.

2.4.2. Mediating and Moderating Variables

While the positive relationship between data analytics and decision quality is well-established, researchers have identified a range of mediating and moderating variables that significantly influence the strength and nature of this relationship. Organizational culture has consistently emerged as one of the most important moderators: organizations with cultures emphasizing transparency, experimentation, and evidence-based reasoning derive significantly greater performance benefits from their analytics investments than organizations with more intuition-driven or hierarchical cultures (Kiron et al., 2014).

Leadership orientation toward data-driven decision-making operates through the behaviors and priorities of senior executives. Davenport (2013) emphasized that when CEOs consistently model data-driven behaviors — asking for evidence to support recommendations and rewarding evidence-based thinking — the adoption of analytics cascades throughout the organization. Technological infrastructure, including data integration architectures and data quality management systems, plays a crucial mediating role in determining whether analytics investments translate into improved decision quality (Wamba et al., 2017).

The availability of analytically skilled personnel is another critical enabling factor. The most sophisticated analytical tools cannot generate value without the human expertise to design and execute meaningful analyses, interpret their results in business context, and translate

insights into actionable recommendations. The global demand for data analytics talent significantly exceeds supply, creating a talent scarcity that represents one of the most important constraints on analytics adoption across industries (Manyika et al., 2011).

2.4.3. Barriers to Effective Data Analytics Implementation

Despite the documented performance benefits of data analytics, many organizations struggle to realize these benefits in practice. Data quality is frequently cited as the primary technical barrier. Incomplete, inconsistent, duplicated, or inaccurate data fundamentally undermines the reliability of analytical outputs and erodes trust in analytics-derived insights. A study by IBM Global Business Services estimated that poor data quality costs U.S. businesses alone approximately 3.1 trillion dollars annually in reduced productivity and suboptimal decision-making (IBM, 2016).

Organizational resistance to change represents a pervasive human barrier. Managers who have developed expertise in intuition-based decision-making may perceive data-driven approaches as a threat to their professional judgment and status. Overcoming this resistance requires sustained change management efforts, compelling demonstrations of analytics value, and transparent communication about the complementary role of analytics relative to human expertise.

Skill gaps and a shortage of data-literate personnel constitute another major barrier, particularly in emerging markets such as Saudi Arabia. Al-Ghamdi and Badawi (2020) found that the lack of qualified data analytics professionals was the most frequently cited barrier to analytics adoption among Saudi Arabian organizations, cited by over seventy percent of surveyed executives. Privacy, security, and regulatory compliance concerns — including Saudi Arabia's Personal Data Protection Law (PDPL) enacted in 2021 — add further complexity to customer data utilization strategies.

2.5. Data Analytics in the Automotive Sector

2.5.1. The Data-Rich Nature of the Automotive Industry

The automotive industry is among the most data-intensive sectors in the global economy. Modern automotive value chains generate enormous and diverse volumes of data across every stage of the product and service lifecycle: from manufacturing line sensor data and supply chain logistics information, to showroom transaction records, customer service interactions, telematics data from connected vehicles, and digital marketing engagement metrics.

The strategic management of this data has become a defining competitive differentiator in the automotive distribution sector. Deloitte's 2020 study of automotive retail in the GCC region found that leading dealerships were using analytics for inventory optimization, customer lifetime value prediction, dynamic pricing, and personalized marketing. Analytics-driven dealerships in the GCC achieved average inventory turnover rates approximately twenty-three percent higher than non-analytics-driven peers.

2.5.2. Key Application Areas in Automotive Distribution

Sales forecasting and demand planning represent one of the highest-value applications of data analytics for automotive distributors. Accurate demand forecasts enable distributors to align vehicle orders with anticipated market demand, reducing the costly risks of both inventory shortfalls — which result in lost sales and customer dissatisfaction — and inventory surpluses — which increase financing costs, depreciation risks, and operational complexity. Advanced distributors now incorporate external data including economic indicators, competitor pricing, and consumer sentiment into their forecasting models.

Customer analytics has emerged as a particularly strategic application area as automotive distributors compete increasingly on the quality of the customer experience. By analyzing customer purchase histories, service records, demographic data, and digital interaction patterns, distributors can develop detailed customer profiles enabling personalized marketing communications, targeted service recommendations, and proactive outreach at key lifecycle stages.

Inventory management analytics enables distributors to optimize the composition, quantity, and distribution of vehicle and spare parts inventories across multiple locations. For Almajdouie Motors, which manages twenty spare parts centers across the Eastern and Northern regions of Saudi Arabia, the potential efficiency gains from inventory analytics are particularly significant. After-sales service analytics — including predictive maintenance, service capacity planning, and customer satisfaction analysis — is increasingly recognized as a critical value driver, given that after-sales operations typically generate higher profit margins than new vehicle sales.

2.5.3. The Saudi Arabian Automotive Market Context

Saudi Arabia represents the largest automotive market in the Middle East and North Africa region, with annual new vehicle sales consistently exceeding 500,000 units in recent years (Saudi Vision 2030 Report, 2023). The market is characterized by strong consumer demand for SUVs and pickup trucks, a young and rapidly growing population, increasing urbanization, and the emergence of new mobility options including electric vehicles. The market has also

witnessed significant shifts in brand preferences, with Chinese automotive brands gaining substantial market share.

The Kingdom's Vision 2030 initiative has created a powerful macro-level impetus for digital transformation across all sectors of the Saudi economy. The initiative's emphasis on economic diversification, private sector development, and technology adoption has accelerated investments in digital infrastructure and data-driven business practices. Despite these favorable conditions, the specific academic literature on data analytics adoption and impact in the Saudi automotive sector remains sparse, representing the key gap this research seeks to address.

2.6. Relevant Empirical Studies

2.6.1. Global and Cross-Industry Studies

Davenport and Harris (2017) examined the analytics practices of more than fifty companies across multiple industries and documented the specific organizational practices and investments that enabled companies to advance through stages of analytics evolution. Companies at the highest stages demonstrated sustained superior performance on financial metrics, customer satisfaction, and market share.

The MIT Sloan Management Review's analytics survey (Kiron et al., 2014), involving approximately 2,700 executives across 122 countries and 30 industries, found that sixty-seven percent of respondents reported that their organizations use analytics to create competitive advantage. However, only twenty-six percent reported sufficient analytics maturity to consistently make data-driven decisions — a gap particularly pronounced in emerging markets.

A meta-analysis by Brynjolfsson and McElheran (2016) examining 179,000 U.S. establishments over fifteen years found that adoption of data-driven decision-making was associated with five to eight percent productivity gains, with the largest gains occurring in environments characterized by high product complexity and market uncertainty — conditions closely paralleling those facing automotive distributors in dynamic markets like Saudi Arabia.

2.6.2. Automotive and Distribution Sector Studies

Verhoef et al. (2021) examined digital transformation including analytics adoption in automotive retail across twelve European countries. The study found that dealerships integrating customer analytics into their sales processes achieved customer satisfaction scores fifteen to twenty percent above industry benchmarks, with the competitive advantage

most durable when analytics capabilities were embedded in customer-facing processes rather than confined to back-office reporting.

Deloitte's GCC Automotive Retail Study (2020) found that while most distributors in the region had invested in basic business intelligence and reporting capabilities, only a minority had advanced to predictive or prescriptive analytics. Primary barriers identified were shortage of analytical talent, fragmented data architectures resulting from siloed IT systems, and cultural resistance among experienced sales and service managers.

A study by Lee, Kwon, and Shin (2019) examining data analytics adoption among automotive parts distributors in Asia found that companies with higher supply chain analytics maturity achieved significantly lower inventory holding costs and higher order fulfillment rates. The study's findings suggested that predictive analytics applied to spare parts demand forecasting could reduce stockout rates by up to thirty-five percent while simultaneously reducing total inventory investment by fifteen to twenty percent.

2.6.3. Studies in the Saudi Arabian Context

Al-Ghamdi and Badawi (2020) conducted a comprehensive survey of data analytics adoption among 150 Saudi Arabian companies across multiple sectors. Their findings revealed that while executive awareness of analytics' strategic potential was high, actual implementation remained predominantly at the descriptive analytics level. Three primary barriers were identified: a critical shortage of locally trained analytics professionals, a cultural tendency to prioritize relationship-based decision-making over data-driven approaches, and the absence of robust data governance frameworks.

Almutairi (2019) investigated business intelligence adoption specifically among Saudi manufacturing and distribution companies, finding that distribution sector firms lagged manufacturing peers in analytics maturity. The study suggested this gap reflected the historically relationship-intensive nature of distribution businesses in the Saudi market, where personal networks and experience-based judgment had traditionally been more culturally valued than systematic data analysis.

A study by the Saudi Authority for Data and Artificial Intelligence (SDAIA, 2022) examining data governance and analytics across Saudi organizations found that the automotive and transportation sector ranked sixth out of twelve sectors studied in terms of data readiness, emphasizing the need for automotive companies to invest in master data management, data quality improvement, and analytical workforce development.

2.7. Summary and Research Gap

The body of literature reviewed in this chapter collectively establishes several important conclusions. First, data analytics represents a powerful and empirically validated driver of organizational decision quality and performance, with documented impacts across multiple industries, geographic contexts, and organizational levels. The positive relationship between analytics capabilities and business outcomes is robust, having been confirmed by large-scale empirical studies involving thousands of organizations across dozens of countries.

Second, the value of data analytics is not automatic but depends critically on enabling organizational conditions including data-supportive culture, committed executive leadership, high-quality technological infrastructure, effective data governance, and an adequate supply of analytically skilled personnel. Organizations that invest in analytics technology without simultaneously developing these enabling conditions consistently fail to realize anticipated performance benefits.

Third, the automotive distribution sector represents a particularly high-potential application domain for data analytics, given the complexity and data-richness of automotive operations and the intensity of competitive pressures facing distributors in rapidly evolving markets. Specific applications including demand forecasting, inventory optimization, customer analytics, and after-sales service optimization offer documented performance improvement potential directly relevant to Almajdouie Motors.

Fourth, and most significantly, the academic literature on data analytics adoption and impact in the Saudi Arabian automotive sector is sparse and fragmented. There is a clear and significant gap in empirical research focused specifically on data analytics practices, challenges, and outcomes within Saudi automotive distribution companies. This research directly addresses this gap by conducting an in-depth examination of data analytics' role in business decision-making at Almajdouie Motors, contributing original empirical insights to both the academic literature and the practical knowledge base available to Saudi automotive distribution executives.

Chapter 3: Research Methodology

3.1 Introduction

This chapter presents the research methodology used to investigate the role of data analytics in improving business decision-making at Almajdouie Motors. It explains the operational definitions of the research variables, the research design, the research population, the sampling method, the data collection method, the types of data, and the statistical analysis procedures that will be applied in the study.

The methodology is designed to ensure that the research objectives and hypotheses are examined in a systematic and measurable way. Since the study aims to measure the relationship between data analytics and business decision-making quality, a quantitative approach based on a structured questionnaire is considered suitable for this research. The questionnaire will be distributed using Google Forms, and the collected responses will be analyzed using statistical techniques.

3.2 Operational Definitions for Research Variables

Operational definitions clarify how each research variable will be measured in the study. The current research includes one independent variable, Data Analytics, and one dependent variable, Business Decision-Making Quality. Each variable is divided into measurable dimensions that are represented by questionnaire items.

Variable Type	Variable	Operational Definition	Dimensions	Measurement
Independent Variable	Data Analytics	The organization's ability to collect, process, analyze, and use data to support decisions.	Data collection systems; analytical tools and techniques; data quality and accessibility; analytical skills and expertise.	Measured through 12 questionnaire items using a five-point Likert scale.
Dependent Variable	Business Decision-Making Quality	The extent to which managerial decisions are accurate, timely, evidence-based, and useful for achieving business objectives.	Strategic planning effectiveness; operational efficiency; customer satisfaction; market responsiveness.	Measured through 12 questionnaire items using a five-point Likert scale.

The independent variable, Data Analytics, focuses on how data is collected, accessed, analyzed, and interpreted within the organization. The dependent variable, Business Decision-Making Quality, focuses on the outcomes of using data in decisions, including strategic planning, operational efficiency, customer satisfaction, and responsiveness to market changes.

3.3 Research Design (Research Onion)

The research design follows the logic of the research onion, which organizes the methodological choices from broad philosophical assumptions to specific data collection and analysis techniques. The design of this study is summarized below.

Research Onion Layer	Selected Approach	Application in This Study
Research philosophy	Positivism	The study measures relationships between variables using numerical data.
Research approach	Deductive approach	The study begins with hypotheses and tests them using questionnaire data.
Methodological choice	Quantitative method	The study uses a structured questionnaire and statistical analysis.
Research strategy	Survey strategy	Data will be collected from participants through Google Forms.
Time horizon	Cross-sectional	Data will be collected once during the project period.
Data collection technique	Online questionnaire	A five-point Likert scale will be used to measure participants' responses.

This study adopts a quantitative, deductive, cross-sectional survey design. The quantitative design is suitable because the research hypotheses require measurable data and statistical testing. The deductive approach is appropriate because the study has already developed hypotheses based on the literature review and will test them using responses collected from the questionnaire.

3.4 Research Population & Sampling Methods and Technique

The research population refers to the group of individuals from whom the researcher aims to collect information. In this study, the population includes employees, supervisors, managers, and other individuals who have knowledge of business processes, data usage, reporting, customer service, operations, or decision-making practices related to Almajdouie Motors.

The target respondents may include staff from departments such as sales, customer service, operations, inventory, service centers, spare parts, information technology, and management. These participants are considered relevant because they are more likely to understand how data is collected, analyzed, and used in business decisions.

The study will use a non-probability convenience sampling technique. This method is selected because the questionnaire will be distributed to available and accessible participants through online channels. Convenience sampling is practical for academic projects where time and access to a full organizational sampling frame may be limited.

The expected sample size is at least 30 valid responses. However, collecting 50 or more responses is preferred because a larger sample can improve the reliability of descriptive statistics and hypothesis testing.

3.5 Data Collection Method

The primary data for this study will be collected using a structured online questionnaire created through Google Forms. The questionnaire includes demographic questions and research-variable questions. The demographic questions collect general information such as gender, age group, educational level, years of experience, and job level. The research-variable questions measure Data Analytics and Business Decision-Making Quality.

The questionnaire uses a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. This scale allows participants to express the degree to which they agree or disagree with each statement. The questionnaire items were developed based on the research model and the literature reviewed in Chapter 2.

The Google Forms link will be shared with participants through appropriate communication channels such as WhatsApp or email. Participants will be informed that their participation is voluntary and that their responses will be used for academic research purposes only. No personal names will be required, and responses will be analyzed collectively to maintain confidentiality.

3.6 Types of Data

This study will use both primary and secondary data. The combination of these two data types strengthens the research by linking empirical questionnaire findings with academic and industry literature.

Type of Data	Source	Purpose in the Study
Primary data	Questionnaire responses collected through Google Forms.	To measure participants' perceptions of data analytics and business decision-making quality.
Secondary data	Academic books, journal articles, previous studies, industry reports, and official company or public sources.	To support the literature review, research model, hypotheses, and discussion of findings.

Primary data will provide direct evidence from respondents, while secondary data will provide theoretical and contextual support for the study. The use of both data types will help produce more balanced and academically supported findings.

3.7 Statistical Analysis Procedures

After collecting the questionnaire responses, the data will be exported from Google Forms to Google Sheets and then to Microsoft Excel or SPSS for analysis. The statistical analysis procedures will be used to describe the sample, assess the reliability of the questionnaire, answer the research questions, and test the hypotheses.

Statistical Procedure	Purpose	Expected Output
Frequencies and percentages	To describe the demographic profile of respondents.	Tables showing gender, age group, education, experience, and job level.
Mean and standard deviation	To describe the level of agreement for each variable and dimension.	Descriptive statistics for Data Analytics and Business Decision-Making Quality.
Cronbach's Alpha	To test the reliability and internal consistency of the questionnaire items.	Reliability coefficient for each variable and for the overall instrument.
Correlation analysis	To examine the strength and direction of the relationship between variables.	Correlation coefficient between Data Analytics and Business Decision-Making Quality.
Regression analysis or hypothesis testing	To test whether Data Analytics significantly influences business decision-making quality.	Decision on accepting or rejecting the research hypotheses.

The results will be presented in tables and interpreted in relation to the research questions and hypotheses. The findings will also be linked to the literature review to determine whether they support or differ from previous studies on data analytics and decision-making.

3.8 Conclusion

This chapter explained the methodology that will be used to conduct the study. The research will adopt a quantitative survey design using a structured online questionnaire distributed through Google Forms. The target population includes employees and managers who are familiar with data usage and decision-making practices. The study will use primary data from questionnaire responses and secondary data from academic and industry sources. The collected data will be analyzed using descriptive statistics, reliability testing, correlation analysis, and hypothesis testing. This methodology provides a clear and systematic basis for the statistical analysis and findings discussion in Chapter 4.

References

- Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.
- Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). Pearson.
- Sekaran, U., & Bougie, R. (2016). *Research Methods for Business: A Skill-Building Approach* (7th ed.). Wiley.
- Davenport, T. H., & Harris, J. G. (2017). *Competing on Analytics: The New Science of Winning*. Harvard Business Review Press.
- Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36(4), 1165-1188.

Chapter 4: Statistical Analysis & Findings Discussion

4.1 Introduction

This chapter presents the statistical analysis and discussion of the questionnaire results collected for the study titled "Analyzing the Role of Data Analytics in Business Decision Making at Almajdouie Motors." The chapter describes the research sample, examines validity and reliability, presents descriptive statistics, tests the research hypotheses, and connects the findings with the reviewed literature.

The data were collected through online questionnaires using Google Forms. Two equivalent questionnaire versions were distributed: English and Arabic. After cleaning and coding the responses, the final dataset included 26 valid responses. The questionnaire items were measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Arabic responses were coded using the same scale to allow combined statistical analysis.

4.2 Sample Profile

This section presents descriptive statistics for the respondents who participated in the survey. The sample profile includes gender, age group, educational level, years of experience, job level, and questionnaire language.

Gender

Category	Frequency	Percentage
Male	26	100.0%

Age Group

Category	Frequency	Percentage
Less than 25 years	1	3.8%
25-34 years	6	23.1%
35-44 years	12	46.2%
45 years and above	7	26.9%

Educational Level

Category	Frequency	Percentage
Diploma	7	26.9%
Bachelor's Degree	11	42.3%
Master's Degree or above	8	30.8%

Years of Experience

Category	Frequency	Percentage
Less than 3 years	3	11.5%
3-5 years	2	7.7%
6-10 years	4	15.4%
More than 10 years	17	65.4%

Job Level

Category	Frequency	Percentage
Employee	10	38.5%
Supervisor	11	42.3%
Manager	3	11.5%
Senior Management	2	7.7%

Questionnaire Language

Category	Frequency	Percentage
English	16	61.5%
Arabic	10	38.5%

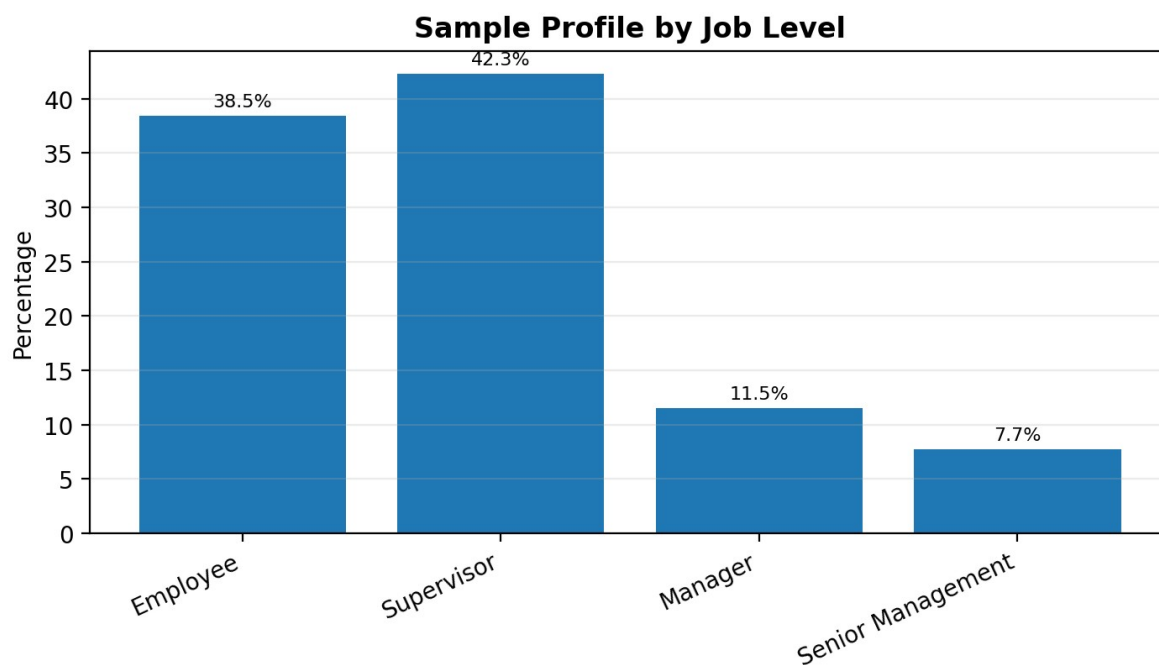


Figure 4.1: Distribution of Respondents by Job Level

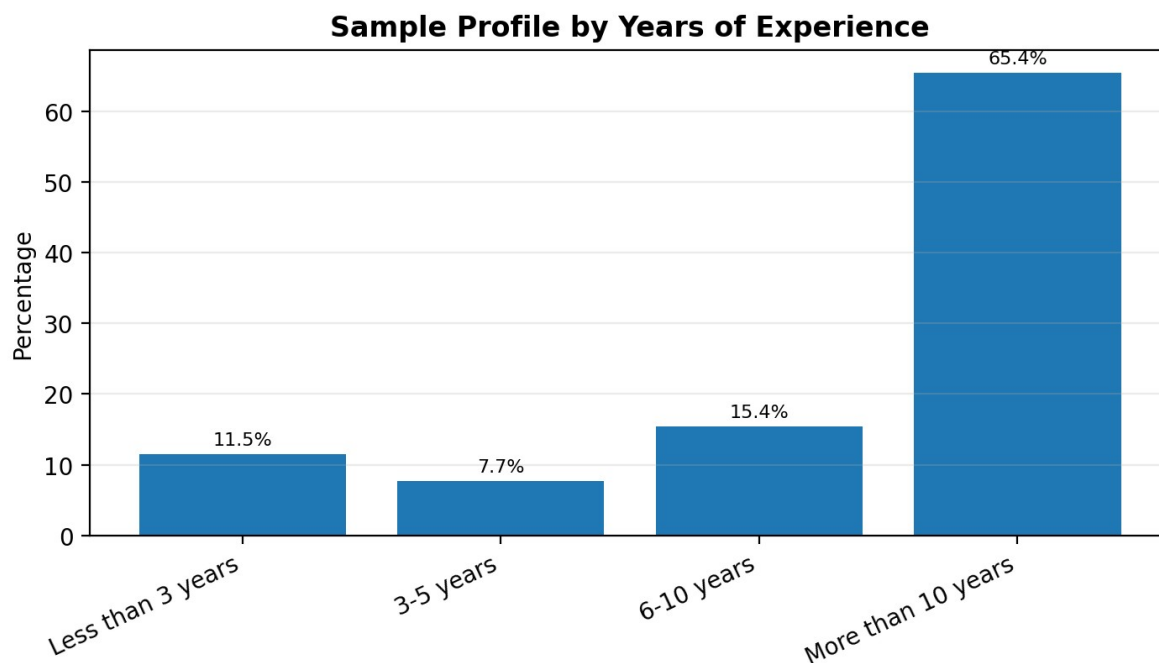


Figure 4.2: Distribution of Respondents by Years of Experience

The sample consisted of 26 valid responses. All respondents were male. The largest age group was 35-44 years, representing 46.2% of the sample, followed by respondents aged 45 years and above at 26.9%. In terms of education, 42.3% held a bachelor's degree, while 30.8% held a master's degree or above. The sample also showed strong practical experience, as 65.4% of respondents had more than 10 years of experience. Most respondents were supervisors (42.3%) or employees (38.5%), which indicates that the survey captured perceptions from operational and supervisory levels.

4.3 Validity and Reliability Tests for the Questionnaire

Reliability was assessed using Cronbach's Alpha. In social science research, Cronbach's Alpha values above 0.70 are generally considered acceptable, values above 0.80 are considered good, and values above 0.90 indicate very high internal consistency. The results show that the questionnaire has strong reliability across the major variables and dimensions.

Construct / Dimension	Items	Cronbach's Alpha	Interpretation
Data Collection Systems	3	0.769	Acceptable
Analytical Tools and Techniques	3	0.853	Acceptable
Data Quality and Accessibility	3	0.757	Acceptable
Analytical Skills and Expertise	3	0.817	Acceptable
Data Analytics (Overall)	12	0.923	Acceptable
Strategic Planning Effectiveness	3	0.855	Acceptable
Operational Efficiency	3	0.825	Acceptable
Customer Satisfaction	3	0.877	Acceptable
Market Responsiveness	3	0.835	Acceptable
Business Decision-Making Quality (Overall)	12	0.954	Acceptable

The overall reliability for Data Analytics was 0.923, and the overall reliability for Business Decision-Making Quality was 0.954. These values indicate high internal consistency and support the use of the questionnaire for further statistical analysis.

Validity was supported through content validity and construct consistency. Content validity was ensured by designing the questionnaire items based on the research model and the dimensions identified in the literature review. Construct consistency was examined through the positive relationships between each dimension and its related overall variable.

Variable	Data Analytics	Business Decision-Making Quality	Strategic Planning Effectiveness	Operational Efficiency	Customer Satisfaction	Market Responsiveness
Data Analytics	1.000	0.862	0.808	0.818	0.804	0.806
Business Decision-Making Quality	0.862	1.000	0.925	0.947	0.950	0.931
Strategic Planning Effectiveness	0.808	0.925	1.000	0.860	0.839	0.787
Operational Efficiency	0.818	0.947	0.860	1.000	0.886	0.832
Customer Satisfaction	0.804	0.950	0.839	0.886	1.000	0.840
Market Responsiveness	0.806	0.931	0.787	0.832	0.840	1.000

4.4 Descriptive Statistics for Research Variables

Descriptive statistics were used to identify the general level of each research variable and dimension. The interpretation scale used in this analysis is: 1.00-1.80 = Very Low, 1.81-2.60 = Low, 2.61-3.40 = Moderate, 3.41-4.20 = High, and 4.21-5.00 = Very High.

Variable / Dimension	Mean	Std. Deviation	Level
Data Collection Systems	4.256	0.744	Very High
Analytical Tools and Techniques	4.385	0.776	Very High
Data Quality and Accessibility	4.090	0.825	High
Analytical Skills and Expertise	3.885	0.859	High
Data Analytics (Overall)	4.154	0.698	High
Strategic Planning Effectiveness	4.321	0.792	Very High
Operational Efficiency	4.397	0.686	Very High
Customer Satisfaction	4.308	0.843	Very High
Market Responsiveness	4.179	0.967	High
Business Decision-Making Quality (Overall)	4.301	0.771	Very High

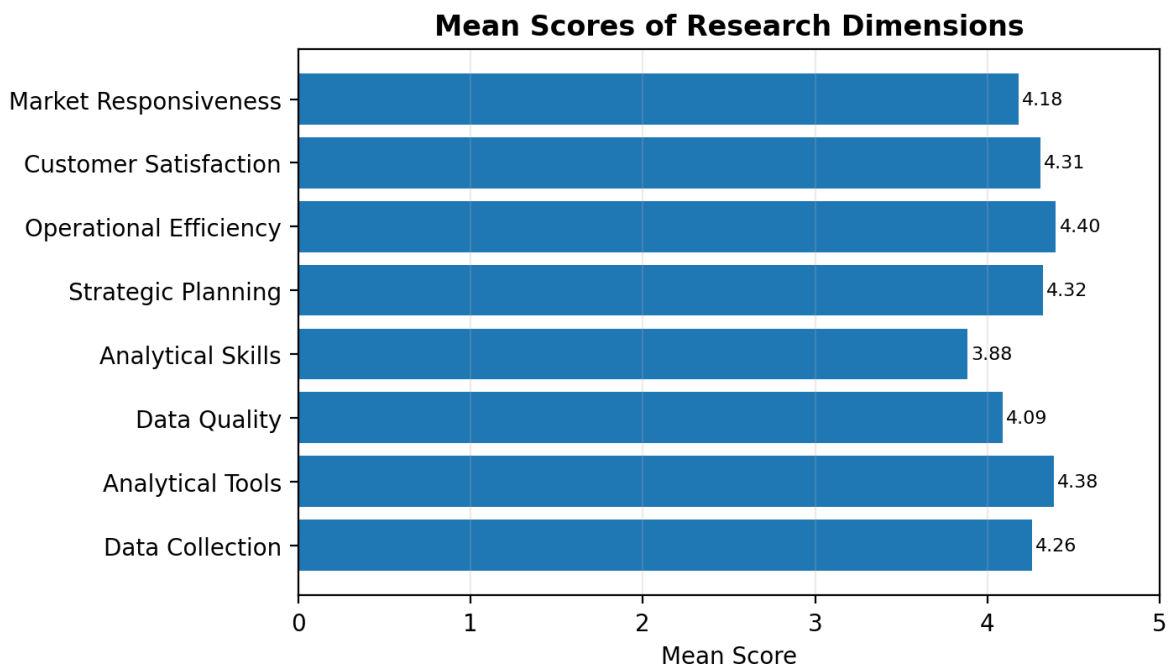


Figure 4.3: Mean Scores of Research Variables and Dimensions

The descriptive results show that respondents generally perceived the role of data analytics positively. The overall mean for Data Analytics was 4.154, which indicates a high level of data analytics utilization. Among its dimensions, Analytical Tools and Techniques achieved the highest mean (4.385), while Analytical Skills and Expertise recorded the lowest mean (3.885). This suggests that analytical tools are available and used, but employee training and analytical capability development remain areas for improvement.

The overall mean for Business Decision-Making Quality was 4.301, which indicates a very high level. Operational Efficiency achieved the highest mean among the dependent variable dimensions (4.397), followed by Strategic

Planning Effectiveness (4.321) and Customer Satisfaction (4.308). These findings suggest that data analytics contributes strongly to improving operational and managerial decision-making outcomes.

Research Question	Statistical Answer / Finding
RQ1: What types of data does Almajdouie Motors currently collect and analyze?	The results indicate high agreement on data collection systems (Mean = 4.256), suggesting that the organization collects data related to sales, customers, inventory, and services.
RQ2: How is data analytics currently utilized across management levels?	The high overall Data Analytics mean (4.154) and high Analytical Tools mean (4.385) indicate that analytics reports, dashboards, and digital systems are used to support decisions.
RQ3: What are the main challenges and barriers?	The lowest mean was for Analytical Skills and Expertise (Mean = 3.885), suggesting that training and analytical skills require further development.
RQ4: What opportunities exist for enhancement?	The very high decision-quality score (Mean = 4.301) indicates strong opportunities to expand predictive analytics, dashboards, training, and data-driven planning.

4.5 Testing Hypotheses and Findings Discussion

Pearson correlation analysis was used to test the research hypotheses because the study examines relationships between data analytics variables and business decision-making outcomes. A significance level of 0.05 was adopted. The results are shown in the following table and visualized in Figure 4.4.

Hypothesis	Tested Relationship	Pearson r	p-value	Result
H1	Data Analytics -> Business Decision-Making Quality	0.862	< .001	Supported
H2	Analytical Tools and Techniques -> Operational Efficiency	0.820	< .001	Supported
H3	Analytical Skills and Expertise -> Customer Satisfaction	0.733	< .001	Supported
H4	Data Analytics -> Strategic Planning Effectiveness	0.808	< .001	Supported

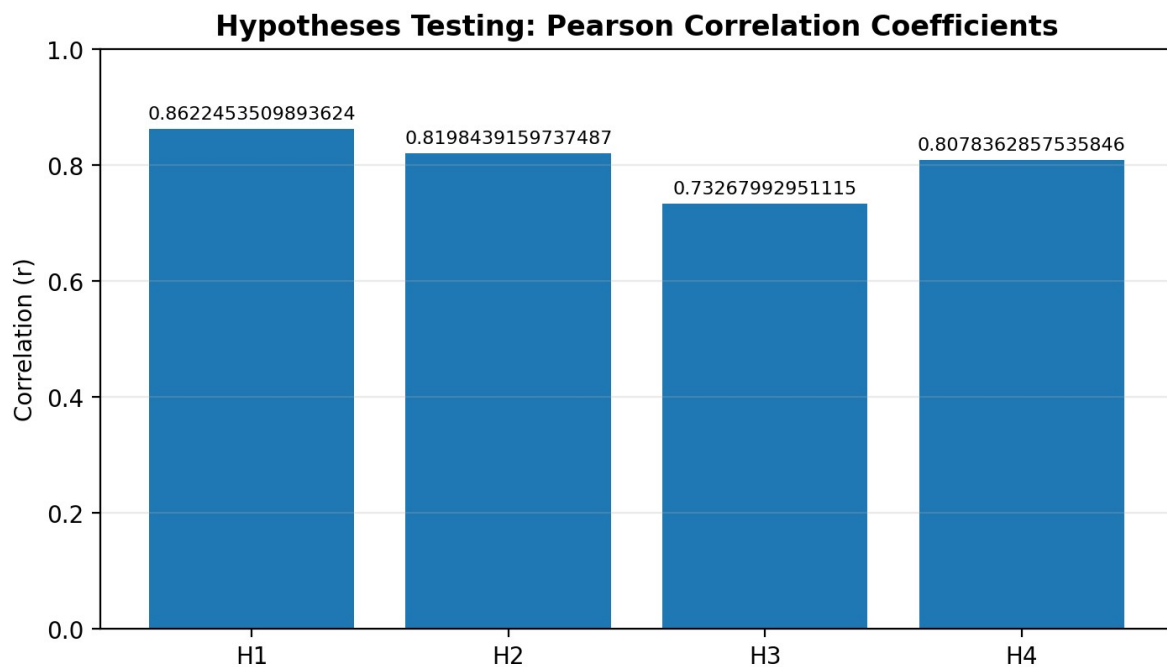


Figure 4.4: Pearson Correlation Results for Research Hypotheses

The results support all four hypotheses. H1 was supported because there was a strong positive relationship between Data Analytics and Business Decision-Making Quality ($r = 0.862$, $p < .001$). This means that greater use of data analytics is associated with higher quality business decisions. This finding is consistent with the literature, which emphasizes that data-driven decision-making improves decision quality and organizational performance.

H2 was supported, as Analytical Tools and Techniques were strongly related to Operational Efficiency ($r = 0.820$, $p < .001$). This suggests that dashboards, reports, Excel, Power BI, and similar analytical tools help improve daily operational performance, reduce errors, and improve resource utilization.

H3 was supported because Analytical Skills and Expertise showed a positive relationship with Customer Satisfaction ($r = 0.733$, $p < .001$). This indicates that when employees and managers can understand and apply data reports, the organization becomes better able to understand customers and improve service quality.

H4 was supported because Data Analytics had a strong positive relationship with Strategic Planning Effectiveness ($r = 0.808$, $p < .001$). This finding indicates that a data-driven approach helps management improve strategic decisions, long-term planning, and identification of future business opportunities.

Overall, the findings align with prior literature discussed in Chapter 2. Studies such as Davenport and Harris (2017), Brynjolfsson, Hitt, and Kim (2011), and Wamba et al. (2017) support the argument that data analytics improves decision-making, productivity, supply chain agility, and firm performance. The findings of the current study also support the practical relevance of data analytics in the automotive distribution sector, especially in areas such as sales forecasting, inventory planning, customer analytics, and operational efficiency.

4.6 Conclusion

This chapter analyzed the questionnaire responses collected from 26 participants. The descriptive results showed that data analytics is perceived as highly important in supporting business decision-making at Almajdouie Motors. The reliability results confirmed that the questionnaire has strong internal consistency, with Cronbach's Alpha values exceeding the acceptable threshold. The hypothesis testing results supported all proposed hypotheses, indicating strong positive relationships between data analytics and business decision-making quality, operational efficiency, customer satisfaction, and strategic planning effectiveness.

The results confirm that data analytics plays a significant role in improving managerial decisions. However, the findings also indicate that analytical skills and training represent a key area for improvement. Therefore, Almajdouie Motors can further strengthen data-driven decision-making by investing in employee training, integrated dashboards, data quality improvement, and advanced predictive analytics tools.

Updated References

- Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance? SSRN Working Paper.
- Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36(4), 1165-1188.
- Davenport, T. H., & Harris, J. G. (2017). *Competing on Analytics: The New Science of Winning*. Harvard Business Review Press.
- Gandomi, A., & Haider, M. (2015). Beyond the Hype: Big Data Concepts, Methods, and Analytics. *International Journal of Information Management*, 35(2), 137-144.
- Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). The Analytics Mandate. *MIT Sloan Management Review*, 55(4), 1-25.
- Kumar, V., & Reinartz, W. (2018). *Customer Relationship Management (3rd Edition)*. Springer.
- Provost, F., & Fawcett, T. (2013). *Data Science for Business*. O'Reilly Media.
- Sekaran, U. (2006). *Research Methods for Business: A Skill Building Approach (4th Edition)*. Wiley.
- Wamba, S. F., et al. (2017). Big Data Analytics and Firm Performance. *Journal of Business Research*, 70, 356-365.

References

1. Sekaran, U. (2006). *Research Methods for Business: A Skill Building Approach* (4th Edition). Wiley.
2. Davenport, T. H., & Harris, J. G. (2017). *Competing on Analytics: The New Science of Winning*. Harvard Business Review Press.
3. Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36(4), 1165–1188.
4. McAfee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution. *Harvard Business Review*, 90(10), 60–68.
5. Gandomi, A., & Haider, M. (2015). Beyond the Hype: Big Data Concepts, Methods, and Analytics. *International Journal of Information Management*, 35(2), 137–144.
6. Provost, F., & Fawcett, T. (2013). *Data Science for Business*. O'Reilly Media.
7. Almajdouie Motors. (2025). About the Company. Retrieved from: <https://almajdouie.com/overview>
8. Hyundai Almajdouie. (2025). Official Website. Retrieved from: <https://www.hyundai.com/almajdouie/ar>
9. Changan Almajdouie. (2025). Official Website. Retrieved from: <https://changan-ksa.com>
10. Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, 69(1), 99–118.
11. Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance? SSRN Working Paper.
12. Pfeffer, J., & Sutton, R. I. (2006). *Hard Facts, Dangerous Half-Truths, and Total Nonsense*. Harvard Business School Press.
13. Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). The Analytics Mandate. *MIT Sloan Management Review*, 55(4), 1–25.
14. Wamba, S. F., et al. (2017). Big Data Analytics and Firm Performance. *Journal of Business Research*, 70, 356–365.
15. Kumar, V., & Reinartz, W. (2018). *Customer Relationship Management* (3rd Edition). Springer.
16. Davenport, T. H. (2013). Keep Up with Your Quants. *Harvard Business Review*, 91(7–8), 120–123.
17. Manyika, J., et al. (2011). *Big Data: The Next Frontier for Innovation*. McKinsey Global Institute.
18. Laney, D. (2018). Infonomics. Bibliomotion.
19. Verhoef, P. C., et al. (2021). Digital Transformation: A Multidisciplinary Reflection and Research Agenda. *Journal of Business Research*, 122, 889–901.
20. Al-Ghamdi, A., & Badawi, N. (2020). Data Analytics Adoption in Saudi Arabian Organizations. *International Journal of Business Information Systems*, 34(2), 215–235.
21. Deloitte. (2020). *The Future of Automotive Retail in the GCC*. Deloitte Insights.

22. Almutairi, M. (2019). Business Intelligence Adoption in Saudi Manufacturing and Distribution Companies. *Journal of Emerging Markets*, 12(1), 44–61.
23. Saudi Vision 2030 Report. (2023). Annual Progress Report. Retrieved from: <https://www.vision2030.gov.sa>
24. Negash, S. (2004). Business Intelligence. *Communications of the Association for Information Systems*, 13, 177–195.
25. Rousseau, D. M., & McCarthy, S. (2007). Educating Managers from an Evidence-Based Perspective. *Academy of Management Learning & Education*, 6(1), 84–96.
26. Anthony, R. N. (1965). *Planning and Control Systems: A Framework for Analysis*. Harvard Business School Press.
27. Dean, J. W., & Sharfman, M. P. (1996). Does Decision Process Matter? *Academy of Management Journal*, 39(2), 368–396.
28. Brynjolfsson, E., & McElheran, K. (2016). The Rapid Adoption of Data-Driven Decision-Making. *American Economic Review*, 106(5), 133–139.
29. Lee, J., Kwon, O., & Shin, B. (2019). Impact of Analytics on Supply Chain Performance in Automotive Parts Distribution. *International Journal of Production Economics*, 211, 152–163.
30. IBM Global Business Services. (2016). *The Data Differentiator: How Improving Data Quality Improves Business Performance*. IBM Institute for Business Value.
31. SDAIA. (2022). *National Data Governance Report*. SDAIA Publications.
32. von Neumann, J., & Morgenstern, O. (1944). *Theory of Games and Economic Behavior*. Princeton University Press.

Appendix A: Research Questionnaire

Analyzing the Role of Data Analytics in Business Decision Making at Almajdouie Motors

Introduction

Dear Participant,

This questionnaire is designed to collect data for an academic graduation project titled "Analyzing the Role of Data Analytics in Business Decision Making at Almajdouie Motors." The purpose of this study is to examine how data analytics contributes to improving business decision-making quality, operational efficiency, customer satisfaction, and market responsiveness.

Your participation is voluntary, and your responses will be used only for academic research purposes. All information will be treated confidentially and analyzed collectively without identifying individual respondents.

Response Scale

Please select the answer that best reflects your opinion.

Scale	Response
1	Strongly Disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly Agree

Section A: Demographic Information

1. Gender

- Male
- Female

2. Age Group

- Less than 25 years
- 25-34 years
- 35-44 years
- 45 years and above

3. Educational Level

- Diploma
- Bachelor's Degree
- Master's Degree or above

4. Years of Experience

- Less than 3 years
- 3-5 years
- 6-10 years
- More than 10 years

5. Job Level

- Employee
- Supervisor

- Senior Management

Section B: Independent Variable - Data Analytics

Section C: Dependent Variable - Business Decision-Making Quality

Items 1-12 measure the independent variable (Data Analytics). Items 13-24 measure the dependent variable (Business Decision-Making Quality).

No.	Variable	Dimension	Statement
1	Data Analytics	Data Collection Systems	The organization collects accurate data related to sales, customers, inventory, and services.
2	Data Analytics	Data Collection Systems	Data is collected regularly from different departments to support business decisions.
3	Data Analytics	Data Collection Systems	The organization uses digital systems to store and manage business data.
4	Data Analytics	Analytical Tools and Techniques	The organization uses analytical tools such as dashboards, Excel, Power BI, or similar systems to analyze data.
5	Data Analytics	Analytical Tools and Techniques	Data analysis reports are available to support managers in making decisions.
6	Data Analytics	Analytical Tools and Techniques	Analytical tools help identify trends, patterns, and business opportunities.
7	Data Analytics	Data Quality and Accessibility	The available data is reliable and useful for decision-making.
8	Data Analytics	Data Quality and Accessibility	Employees and managers can access the data they need in a timely manner.
9	Data Analytics	Data Quality and Accessibility	The organization ensures that data is updated and free from major errors.
10	Data Analytics	Analytical Skills and Expertise	Employees have sufficient skills to understand and use data reports.
11	Data Analytics	Analytical Skills and Expertise	Managers are able to interpret data analysis results before making decisions.
12	Data Analytics	Analytical Skills and Expertise	The organization provides training to improve employees' data analysis skills.
13	Business Decision-Making Quality	Strategic Planning Effectiveness	Data analytics helps management make better strategic decisions.
14	Business Decision-Making Quality	Strategic Planning Effectiveness	Data analysis supports long-term planning in the organization.
15	Business Decision-Making Quality	Strategic Planning Effectiveness	Management uses data insights to identify future business opportunities.
16	Business Decision-Making Quality	Operational Efficiency	Data analytics contributes to improving daily operational performance.
17	Business Decision-Making Quality	Operational Efficiency	Data analysis helps reduce errors and improve work processes.
18	Business Decision-Making Quality	Operational Efficiency	Data-driven decisions improve resource utilization within the organization.

19	Business Decision-Making Quality	Customer Satisfaction	Data analytics helps the organization better understand customer needs.
20	Business Decision-Making Quality	Customer Satisfaction	Customer data analysis contributes to improving customer service.
21	Business Decision-Making Quality	Customer Satisfaction	Data-driven decisions help increase customer satisfaction.
22	Business Decision-Making Quality	Market Responsiveness	Data analytics helps the organization respond quickly to market changes.
23	Business Decision-Making Quality	Market Responsiveness	Data analysis supports better forecasting of customer demand.
24	Business Decision-Making Quality	Market Responsiveness	Data-driven decisions help the organization maintain competitive advantage.

Thank you for your valuable participation. Your responses will contribute to the success of this academic research.

Appendix B: Table of Research Instruments

Research Variable	Dimension	Number of Items	Item Numbers	Main References
Data Analytics	Data Collection Systems	3	1-3	Chen, Chiang & Storey, 2012; Gandomi & Haider, 2015
Data Analytics	Analytical Tools and Techniques	3	4-6	Davenport & Harris, 2017; Provost & Fawcett, 2013
Data Analytics	Data Quality and Accessibility	3	7-9	Wamba et al., 2017; Manyika et al., 2011
Data Analytics	Analytical Skills and Expertise	3	10-12	Davenport, 2013; Kiron, Prentice & Ferguson, 2014
Business Decision-Making Quality	Strategic Planning Effectiveness	3	13-15	Simon, 1955; McAfee & Brynjolfsson, 2012
Business Decision-Making Quality	Operational Efficiency	3	16-18	Brynjolfsson, Hitt & Kim, 2011; Davenport & Harris, 2017
Business Decision-Making Quality	Customer Satisfaction	3	19-21	Kumar & Reinartz, 2018; Verhoef et al., 2021
Business Decision-Making Quality	Market Responsiveness	3	22-24	Wamba et al., 2017; Deloitte, 2020

Total Number of Questionnaire Items

The questionnaire consists of 24 main items distributed across two main research variables:

- Independent Variable: Data Analytics - 12 items
- Dependent Variable: Business Decision-Making Quality - 12 items

In addition, the questionnaire includes 5 demographic questions related to gender, age, educational level, years of experience, and job level.