Analytical management model for data-driven companies

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ABSTRACT
This qualitative research proposes a management analytical model framework for data-driven companies. The framework was developed from the narrative review of the specialized literature on management models focused on data analysis to leverage the competitiveness of data-driven companies. An analytical management model is a set of logically interrelated management fundamentals, systemically integrated and coherent with an organizational philosophy based on data analysis for strategic decision-making, aiming to generate analytical advantage and, consequently, sustainable competitive advantage in business. The structure of the proposed framework has the following components: Analytical Competition and Analytical Advantage; Strategic Positioning and Analytical Focus; Transformative Leadership and Data-Driven Journey; Market Orientation and Trend Analysis; Domain of Data Science and Business Analytics; Data-Driven Decision Making; and Analytical Project Management. The main contribution of this research is of a theoretical-managerial nature and aims to identify determining factors for the ideation of a management model focused on data analysis. As future studies, the operationalization of the framework's components is suggested, enabling its implementation in knowledge-intensive companies to validate its adequacy to the context of analytical competition.

Keywords: Analytics Economy, Analytical Competition, Business Analytical Model, Management Analytical Model.

1 INTRODUCTION

Finding the ideal management model for a company requires a process of identifying key information, analyzing and evaluating this information, and making decisions about the available options for business success (FNQ, 2017). This key information is analyzed in order to arrive at an ideal management model that addresses the company's own characteristics, such as its business model, interaction with the external environment, understanding of the internal environment, and points in common between the management methods in use in the company with reference models (LIMA; REDAELLI, 2023). Still, it is important to consider the strategic objectives of the business, that is, what the company wants to achieve in the long term, and to know pertinent comparative references that give direction to the construction of an effective own management model (PAGLIUSO; CARDOSO; SPIEGEL, 2012).

A management model is a representation of reality that describes the relationships between different elements of a company's management. It is the way a company organizes itself in relation to the processes it uses to carry out its business model (FNQ, 2017). In this sense, Amitt and Zott (2020) state that there is no pre-established ideal management model that companies must consider specific aspects, such as the sector of operation, the type of economic activity developed, the philosophy and organizational culture, the strategies and objectives of the business. In this way, defining the most efficient and effective management model for the reality of a company leads to the improvement of the essential points of the business, enabling the creation of value for all stakeholders.

In the view of Bock and George (2018), Grover *et al*. (2018), Gao (2020) and Kotorov (2020), among the main benefits of a management model are:

(i) Pursuit of competitive differentiation in the market**:** differentiation is the act of developing a set of distinctive aspects of the company's offerings in relation to the competition's offerings, and having control of core competencies, which are sources of comparative advantage, and maintaining operational excellence are requirements for a company that wishes to stand out from the competition.

(ii) Standardization of processes: the systematization of management practices aims at the best method to perform a job. For this reason, processes must be monitored to ensure the quality of operations, seeking a standard of operational excellence to be followed for the execution of activities. Standardizing processes is also important to ensure a work model, stipulate a well-defined path for the execution of activities, and provide predictability to the process. Thus, the company improves its quality, reduces risks and increases productivity.

(iii) Communication between sectors**:** access to information is the basis of good interpersonal relationships. An effective management model standardizes the language and improves the dialogue between the various sectors. Management communication includes processes necessary to ensure that process data is generated, collected, distributed, stored, retrieved, and organized in a timely and appropriate manner.

(iv) Process mapping and monitoring: process mapping is a technique used to understand how the business is operating, identifying each process activity. Measuring and monitoring the results that a company is achieving is achieved with the use of *Key Performance Indicators* (KPIs) for a company to identify if its objectives and goals are being achieved.

(v) Risk management: it is possible to plan, organize, direct and control a company's human and material resources, in order to mitigate risks in a company's operation. With this information, important data can be obtained for the decisions made to be the most assertive. In addition, it is necessary to establish strategies to achieve the ideal balance between growth and return on investment goals, as well as to mitigate the associated risks.

In this sense, this article proposes a *framework* of an analytical management model, conceptualized here as a set of logically interrelated management fundamentals, integrated in a systemic way and coherent with an organizational philosophy based on data analysis for strategic decision-making, aiming to generate analytical advantage for companies to achieve sustainable competitive advantage.

In this article, we adopt the definition of 'analytical advantage' as the dynamic capacity gained by fact- and data-based management and the strategic use of quantitative data analysis, mathematical methods, and descriptive, predictive, and prescriptive statistical modeling algorithms to guide decisions and actions that enable companies to seek sustainable competitive advantage (REDAELLI; LIMA, 2023). In this context, 'competitive advantage' refers to the approach of Economics that evaluates the result of the management of a company that positions it, in terms of return on equity, above the average of its sector of operation (PORTER, 1989).

2 DEVELOPMENT

This qualitative research uses the method of narrative review of the specialized literature on the subject of 'management models' to build the proposed *framework*, as suggested by Rother (2007).

Framework is understood as a structured set of activities necessary to achieve the objectives expected in the essential definitions of a study construct, as well as the existing relationships between these activities, presented in a conceptual way. The literature on organizational modeling considers 'framework' differently from 'model': 'framework' is a theoretical construction involving concepts obtained from a reference theoretical framework and from critically analyzed empirical studies; the notion of 'model' presupposes the detailing of a framework operationalized steps to be put into practice, with the suggestion of methods, techniques, tools, training, and policies specific to each case in which it will be applied (RAVITCH; RIGGAN, 2016). Thus, the analysis of a *framework* offers an opportunity for theorizing for the construction of a frame of reference based on theories already consolidated in practice in the field of study in question. Thus, the use of a *framework* allows flexibility of modification and emphasis on the understanding of the object of study.

The main characteristics of a *framework* are: (i) it is not just a set of concepts, but a construct in which each concept plays a role that illustrates the key interrelated factors; (ii) does not provide a causal/analytical scenario of the diagnosed company, but an interpretative approach to the company's reality; (iii) it does not offer a theoretical explanation, as occurs in quantitative models; provides an understanding of the reality studied; (iv) it does not provide knowledge about the business reality, but about the interpretation and perceptions of those involved in these facts; (v) is indeterministic in nature and therefore does not allow predicting an outcome; (vi) can be developed through a process of qualitative analysis; and (vii) the data sources consist of many theories oriented to the discipline object *of the framework*, which become empirical data of the proposed analysis, based on the study of multidisciplinary theories of knowledge, metasynthesis, or a systematic synthesis of the results obtained by qualitative studies, seeking to generate new interpretations in a given field of study.

The methodology used to develop *the proposed framework is shown in Chart 1, following all the recommended actions, based on a multidisciplinary framework of specialized academic and commercial literature to describe a systemic diagnosis based on management excellence models established in* data-driven companies.

Chart 1 - Methodology for building the *framework*.

Phases	Actions Taken
Phase 1	Map references in the state of the art of specialized academic and commercial literature on data-driven management models, including the use of scientific articles and academic and business books.
Phase 2	Carry out extensive reading and categorization of the selected data in order to group them both by discipline and by a scale of importance and representative power within each discipline, in order to maximize the effectiveness of the research and ensure the effective representation of each discipline.
Phase 3	Identify and name concepts in order to analyze the selected data and discover new concepts that emerge from the literature review.
Phase 4	Deconstruct and categorize the concepts found to identify their main attributes, characteristics, assumptions and role, and, subsequently, organize and categorize the concepts according to their characteristics and ontological, epistemological and methodological role. The result of this phase includes the names of the concepts, a description of each of them, the categorization according to their ontological, epistemological or methodological role, and the presentation of references for each concept.
Phase 5	Integrate concepts to group those that have similarities, reducing the number of concepts and allowing them to be manipulated.
Phase 6	Synthesize the concepts in a theoretical framework that makes sense to researchers and future users of the framework.
Phase 7	Validate the proposed *framework* and its concepts to verify that it makes sense not only for researchers, but also for other scholars and practitioners of the subject. Validating a *framework* is a process that starts with researchers, who look to other experts for feedback.

Source: Adapted from Cecin *et al*. (2022).

The components of the proposed management analytical model *framework*, as well as the business analytical model on which it is based, are presented in Chart 2.

Chart 2 - Theoretical framework for the elaboration of the *proposed framework*.

Theoretical References	Key Issues and/or Perspectives
Amitt e Zott (2020)	The study is based on more than 20 years of rigorous collaborative and empirical theoretical research, with a pragmatic orientation. It is action-oriented and provides entrepreneurs and executives with a detailed guide to the design and implementation of innovative business models and scalable management models for companies.
Bock and George (2018)	They show which business models drive rapid growth and how to create, test, adapt and innovate successful business and management models for any type of company.
Davenport's Harris (2018)	They provide the roadmap for a company to become an analytical competitor, showing how to create new strategies based on analytics. The five-step model of analytical competition describes the typical behaviors, capabilities, and challenges of each step. They explain how to utilize a company's capabilities and how to guide it toward the highest levels of competition in the data-driven business world, emphasizing key resources: human and technological.
Evans (2019)	It introduces the fundamental concepts of modern business analytics and provides tools for understanding how data analytics works in companies. Examines business analytics from both descriptive and predictive perspectives.
Ghandi, Bathia e Dev (2021)	They explain decision-making data analysis with models and algorithms, theoretical concepts, applications, experiments in relevant domains or focused

	on specific issues. Explore the concepts of database technology, machine learning, knowledge-based systems, high-performance computing, information retrieval, discovering hidden patterns in large volumes of data, and data visualization. They feature pattern mining, clustering, classification, and data analysis capabilities.
Gordon (2023)	It takes a hands-on approach and covers key use cases for analytics in different business areas, including marketing, HR, operational, and financial analytics. It grounds the discussion on data, analysis and visualization, and on understanding the legal and ethical responsibilities that come with it.
Krantz (2023)	It presents a *framework* to ensure that there is alignment between what the business needs, what data teams can deliver, and the competencies that leaders should engage in. It describes a process for addressing the most common biases and psychological resistance to change, both at the individual and organizational cultural level, and examines the importance of interpersonal skills as well as technical capabilities. It advises how companies can better focus their data resources to ensure they support the most critical and value-added business activities.
Lima and Redaelli (2023)	The analysis arising from data-based decision-making allows, through the interpretation of sets of small and large volumes of data, the generation of insights for executives to define strategies to solve problems, improve processes, generate innovation and seek more competitiveness. Companies called data businesses adopt this stance as part of a strategy championed by leadership and pushed down to decision-makers at all levels, empowering their executives to recognize the strategic importance of data and to utilize better qualitative and quantitative tools to make better decisions. They present the concept of Analytical Competition and *Data-Driven* Journey, which describe the characteristics and management practices of companies that have evolved to a higher level in analytical maturity. The evolution of a company from the use of *Business Intelligence* to Analytical Competition requires the formulation of strategies to manage data, a significant investment in technology, training of executives in *expertise* in data management and the creation of a data-driven organizational culture *for decision-making*.
Lisinski (2013)	It presents a structure of management science methodology, synthesized in the determination and description of its basic components, covering three levels of analysis and making a detailed description of these levels: philosophy; methods; and management practices. It uses a structural analysis to identify and identify the characteristics of particular components of the management science methodology.
Skinny (2015)	It explores the logic of successful companies and how they are based on business models, management models, strategy and practices, aiming to explain management as the ability to transform complexity into performance.
Porter and Tanner (2015)	They present a *framework* for organizational excellence as a form of systematic comparative diagnosis of organizational excellence models. It introduces the process of self-assessment, explores the main approaches to self-assessment, and illustrates the practical benefits of self-assessment with case study examples.
Provost e Fawcett (2016)	They present data *science* principles and analytical thinking needed to extract useful knowledge and business value from data. These principles underpin the processes and strategies needed to solve business problems through data mining techniques.
Sahay (2018)	It discusses the main categories of data analytics: descriptive, predictive, and prescriptive, with their tools and applications in business. It focuses on descriptive analytics which involves the use of descriptive methods and data visualization, as well as data analysis tools, big data applications, and the use of dashboards to understand business performance.
Seebacher e Garritz (2021)	According to the authors, only 5% of all companies can be considered data-driven, which means that 95% of all companies do not use data in decision-making. This poses a huge risk to all stakeholders. In this context, many executives believe that simply buying an AI-IT solution will solve the problem. Executives must develop the concepts and competencies of data-driven management to apply these new technologies. Describes the path to data-driven management, and describes the steps required to implement data-driven management.

Sharda, Delen & Turban (2019)	The ever-evolving and increasingly complex business environment is shrinking the time for decision-making, while the global nature of decisions is expanding, requiring the development and use of computerized decision support systems. They present the theoretical and conceptual bases of decision support and the tools and techniques available.

Source: Prepared by the authors.

Based on these references*, the* proposed Management Analytical Model (MAG) framework represents a guideline that allows the connection of management processes, exploring the synergies of organizational conditions in dynamic business environments. This ideation logic offers a practical, integrative approach that helps manage the frustration of uncertainty and increases the level of readiness for strategic decision-making based on data analysis.

MAG is in the context of the *Analytics Economy*, which, according to Berndtsson (2018), Cao (2019) and Tang (2022), is the economic environment that uses data analysis as a guiding action for new business structures and logics to generate value from the strategic use of data. Designed especially for companies in knowledge-intensive economic sectors, it helps expand the dynamic capabilities required by contemporary business and supports the creation of a business value stream from data. This is possible through the integration of external and internal contexts, which is not just about adaptability or commitment, resulting in a sustainable future business. The model track is adaptive, integrating short-term, medium- and long-term challenges, and the strategic north creates a sense of urgency and dedication to a position of competitive advantage in the market. It connects the past and the present, through descriptive data analysis, with the future, through predictive and prescriptive data analysis. However, it does not predict the realities of tomorrow, as these depend on the decisions that entrepreneurs and executives make based on the analyses carried out, but its logic facilitates dealing with the unknown in a pragmatic way, harmonizing the desired and the possible, the present and the future. In this way, it represents an opportunity to develop a path on how to execute a strategy that serves the present and future of the company simultaneously.

Embedded in the context of the *Analytics Economy*, MAG is flexible, integrative, and avoidance of prescriptions, combining concepts from Mathematics, Statistics, Computer Science, and Management to enable companies to pursue growth by integration that benefits from the value options created by innovation, the exploration of trends and plausible new logics of the future, and the formulation and operationalization of deliberate competitive strategies. To adapt to such a variety of contexts, MAG's ideation logic is integrative and modular, connecting strategy with innovation, making the future more plausible and enhancing the adaptability and agility of strategy execution.

In this sense, the components of MAG are:

(i) Analytical Competition and Analytical Advantage: theoretical framework on which the drivers of the analytical management model are based.

(ii) Strategic Positioning and Analytical Focus: Assists in defining the strategic focus of business premises based on operational gains with efficiency management or market gains with innovation, facilitating the performance of market actions based on Analytical Competition.

(iii) Transformative Leadership and *Data-Driven* Journey: Establishes senior management's commitments to the evolution of the use of data for strategic decision-making and assesses the level of analytical maturity the company is at and how it plans to evolve to higher levels.

(iv) Market Orientation and Trend Analysis: business management philosophy that places customer needs and expectations at the center of business decisions. Specifically, in knowledge-intensive industries, it means deeply understanding customer needs, changing customer preferences, and the competitive environment. Trend analysis is related to market orientation, involving monitoring and interpreting long-term changes in the industry, technology, economy, and social patterns.

(v) Mastery of *Data Science* and *Business Analytics*: allows you to transform large volumes of data into useful information. This is vital for identifying opportunities, optimizing processes, and predicting trends. *Business Analytics* refers to the process of collecting, processing, and analyzing data to assist executives in making informed decisions by utilizing statistical analysis methods and techniques. The *Business Analytics* domain allows you to understand and interpret business performance to identify areas for improvement, based on quantitative analysis.

(vi) Data-Driven Decision Making: refers to the process of making strategic choices based on the analysis and interpretation of real data, rather than the use of intuition or casual observation.

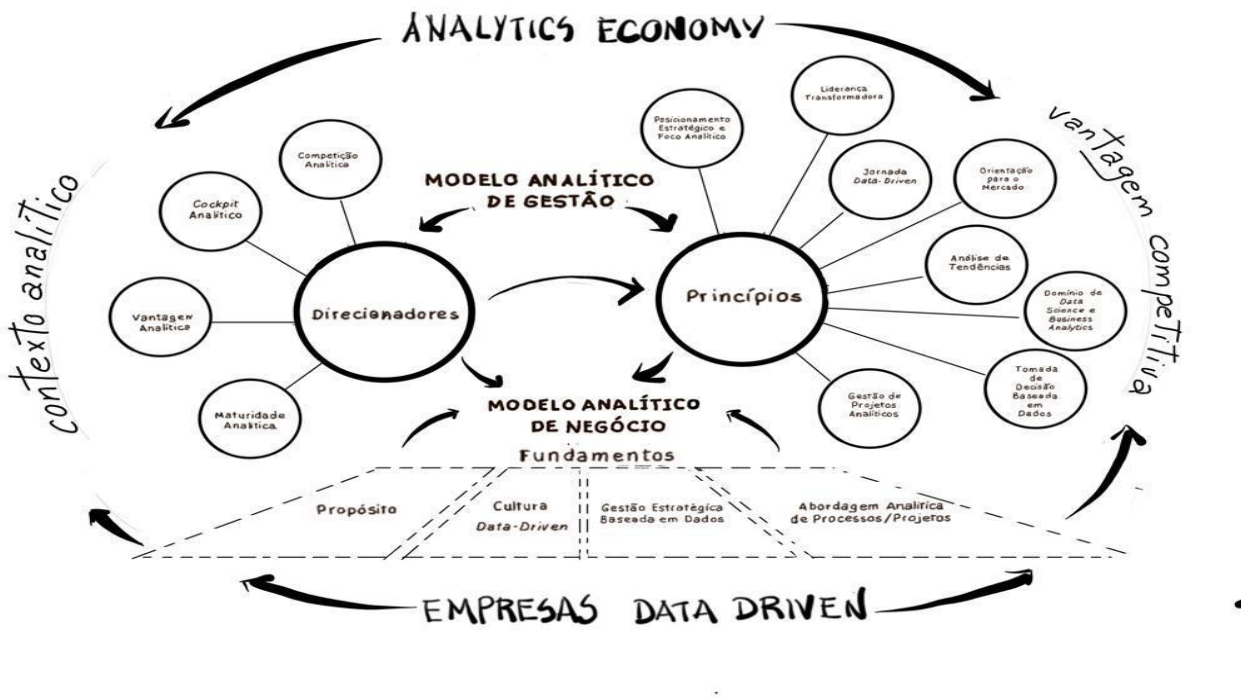
(vii) Analytical Project Management: This involves the planning, execution, monitoring, and completion of projects that focus on data analysis to generate insights.

In this sense, Figure 1 illustrates the integrative view of the Business Analytical Model and the proposed Management Analytical Model. Figure 2 shows the specific structure of the MAG. These figures synthesize the vision of strategic positioning and analytical focus.

An analytical business model is a set of logically interrelated management fundamentals, systemically integrated and coherent with an organizational philosophy based on data analysis for strategic decision-making, to generate analytical advantage for companies to achieve competitive advantage in business. The business analytical model that underpins MAG suggests a business management approach based on data analysis for strategic decision-making. The model is composed of the following components: (i) Analytical Purpose; (ii) *Data-Driven Culture*; (iii) Gare Strategic

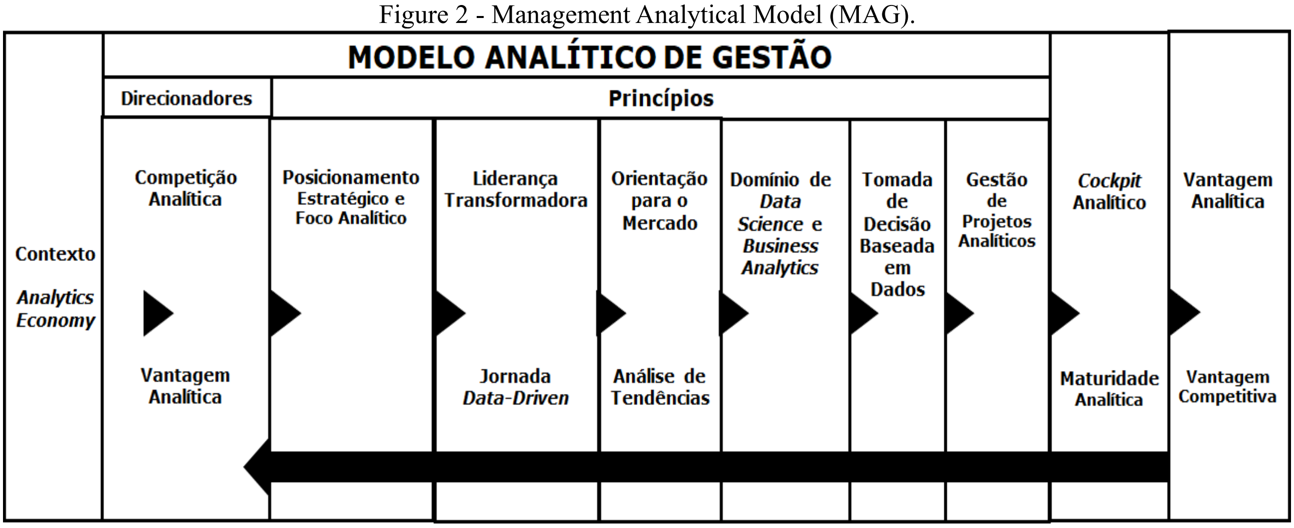
Data-Based; (iv) and Analytical Approach to Processes and Projects. The model aims to generate analytical advantage for companies to achieve competitive advantage in business. It also suggests the importance of an integrated business model and management model to achieve analytical advantage (REDAELLI; LIMA, 2023).

Figure 1 - Business Analytical Model and Management Analytical Model.



Source: Prepared by the authors.

Figure 2 - Management Analytical Model (MAG).



Source: Prepared by the authors.

Based on the definitions of Saulles (2020), Pentland, Lipton and Hardjono (2021), Yaseen (2022), Lima and Redaelli (2023) and Redaelli and Lima (2023), the components of MAG are:

2.1 STRATEGIC POSITIONING AND ANALYTICAL FOCUS

According to Seddon *et al*. (2017), Vidgen, Shaw and Grantt (2017), Marr (2021), Asplen-Taylor (2022) and Lima and Redaelli (2023), the definition of the strategic positioning of companies is almost always based on the practical knowledge of what entrepreneurs and executives believe really works, what does not work, and why. Practical knowledge that is generally available is essential, but because it is available to everyone, it rarely succeeds in being decisive.

The assumption that all important business knowledge is made available by *Enterprise Resource Planning* (ERP) or by subject matter experts often kills innovation, stifles change, and blocks improvement in companies that have come to believe that their way of doing things is the best. So, even as customers and markets change rapidly and frequently, the survival and growth of businesses requires a focus on today's core offerings and the revenues they generate. If companies have insufficient products and services that are already consolidated, but still viable, they will lose additional profits that can generate investments. Alerting entrepreneurs and executives to apply new technologies to old offerings, restarting their growth cycle, can guide a future direction, which is the main objective of data analysis.

According to Abbosh, Nunes and Downes (2021), 'pivot' is a term that translates the need for a company to change course in the face of new challenges or crises. It means completely changing the direction or purpose of a company so that its sustainability is achieved by improving its competitiveness.

2.2 TRANSFORMATIVE LEADERSHIP AND *DATA-DRIVEN JOURNEY*

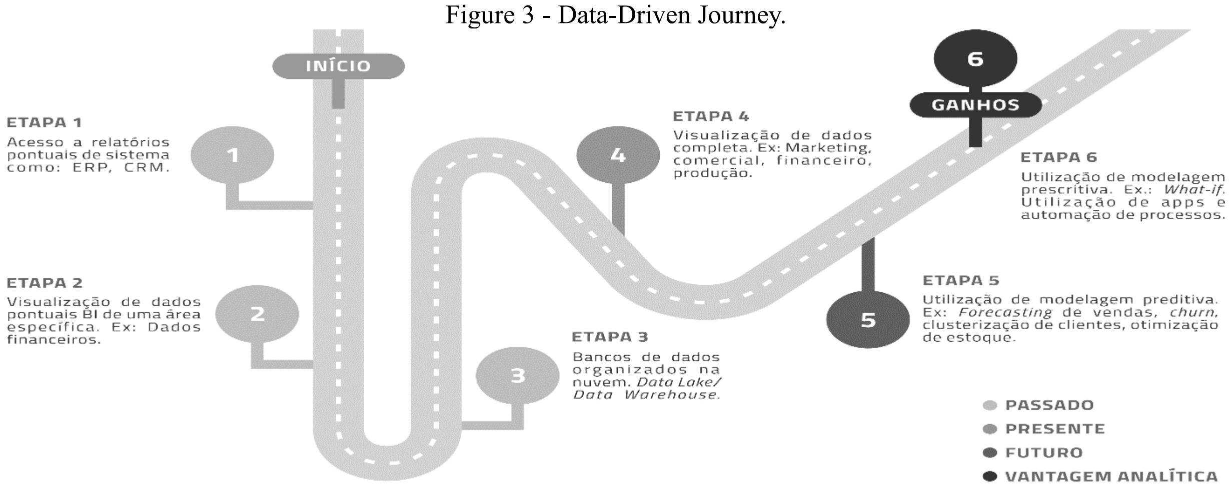
A company's *Data-Driven* Journey begins with raising executives' awareness of the use of reports extracted from ERP systems, which are the integrated business management systems used by companies to support their decision-making. In an initial phase, these systems use only internal data and analysis focused on descriptive statistics, which analyzes the past, advancing in the journey to obtain gains with the use of predictive and prescriptive statistical modeling.

Embracing the science behind data means deepening the analysis of internal issues by confronting them with issues of interaction with the external business environment. It's meant to inspire and remind you that a successful company doesn't settle, it's always learning, adapting, and growing, powered by data analytics. It is also necessary to consider that the same company **may be at different stages of analytical maturity** and thus, in the case of a company that was not born digital, it is likely that different areas are at different stages of the Data-Driven Journey.

It is a mistake to believe that the *Data-Driven* Journey has an end. In fact, the analytical advantage is born precisely when a company learns to apply data intelligence to test and validate products, adjust errors, experiment with prototypes and measure actions, in a practical, fast and real-time way. Therefore, being *Data-Driven* is a process based on interaction and analytical experimentation, with the use of metrics to measure the performance of new solutions, understand problems and improve competitiveness. In particular, in the context of Analytical Competition, it is to consider the customer's experience and perspective, monitor their level of satisfaction, and pivot whenever necessary. In this way, effectively conducting the *Data-Driven Journey* creates the right environment for decision-making based on data, rather than on intuition or experiences contaminated by noise and bias. Thus, the *Data-Driven Journey* creates the enabling context that allows companies to act in the Analytical Competition with a business analytical model and a management analytical model that use *Business Analytics* tools to define deliberate competitive strategies for innovation, value creation and the search for competitive advantage.

Figure 3 illustrates a *company's* Data-Driven Journey.

Figure 3 - Data-Driven Journey.



Source: Prepared by the authors.

2.3 MARKET ORIENTATION AND TREND ANALYSIS

Market orientation dealt with the business philosophy that puts the needs and expectations of customers at the center of all business decisions. In knowledge-intensive industries, this means deeply understanding customer needs, changing preferences, and the competitive environment. Companies with this philosophy use analytics techniques and tools to understand what their customers really need and want. This involves conducting customer research, data analysis, and working collaboratively with marketing and product development. The ability to respond quickly to changing market needs is critical and requires the agile development of new products and services, or the adaptation of existing ones to meet new identified demands. Understanding the market also means getting to know the competition in depth, analyzing how products and services compare to competitors, and ensuring that the company is positioned effectively in its market. This concerns market orientation and involves monitoring and interpreting long-term changes in the industry, technology, the economy, and social behaviors. Analytical competitor companies use methods, techniques, and tools to identify emerging trends by analyzing market data, observing competitors, and even academic research integrated into the business. According to Redaelli and Lima (2023), identifying trends is the first step in increasing the ability to interpret what trends mean for the business and how to respond appropriately to them. This can mean the need to invest in new technologies, change marketing strategies, redefine products and services. In knowledge-intensive industries, innovation is key, and analyzing trends helps stay ahead of the competition by adapting businesses to market changes and exploring new opportunities.

2.4 DATA SCIENCE *AND* BUSINESS ANALYTICS *MASTERY*

For Carillo *et al*. (2019), the great contribution of mastering analytical techniques and tools concerns advances in terms of critical thinking, that is, in the improvement of the mental processes of discernment, analysis, and evaluation, which includes all possible processes of reflection on intangible or non-intangible items to form a solid judgment that reconciles scientific evidence with common sense.

Data Science is the field of study that involves the use of scientific methods, business knowledge, algorithms, and systems to extract insights from data. Mastering *Data Science* allows you to transform large volumes of raw data into actionable information, which is vital for identifying opportunities, optimizing processes, and predicting trends. Utilizing *data science in areas such as marketing (for customer segmentation), operations (for supply chain optimization), and product development (for data-driven product creation) requires utilizing advanced technologies and tools, such as machine learning and Artificial Intelligence (AI), allowing for more in-depth analysis and insight generation.*

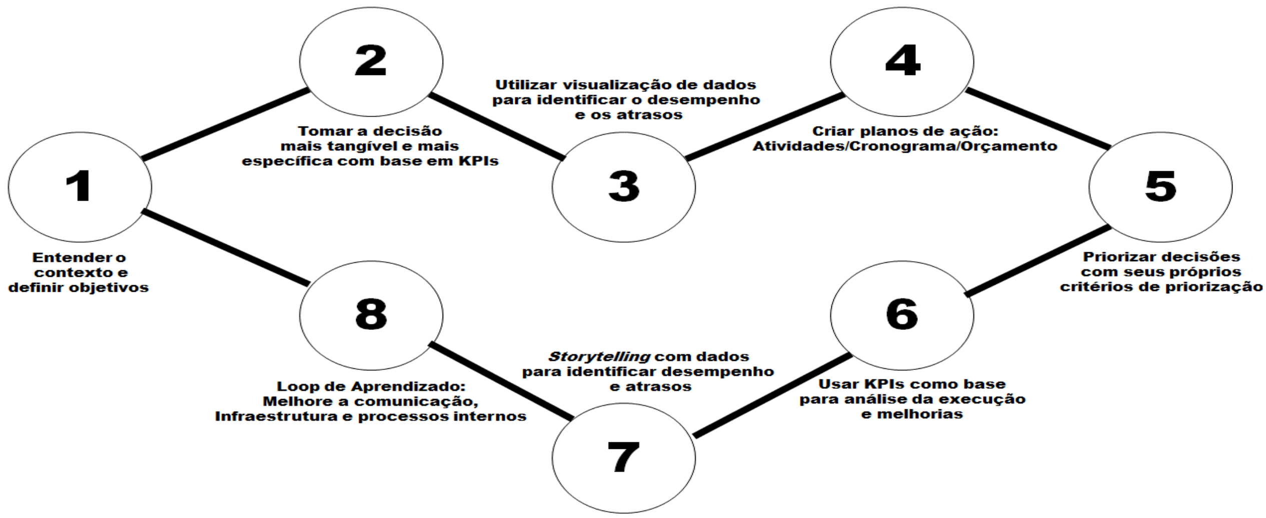
In this sense, *Business Analytics* refers to the process of collecting, processing, and analyzing data to assist executives in making informed decisions. It includes statistical and computational analysis methods and techniques. The domain of *Business Analytics* allows you to understand and interpret business performance, by identifying areas for improvement, seeking efficiencies and growth, based on quantitative analysis. Utilizing *business analytics* across the company can improve decision-making and optimization of marketing strategies, as well as efficient management of human and financial resources. Thus, *Data Science* and *Business Analytics* often work together. While *Data Science* may be more focused on prediction and advanced modeling, *Business Analytics* focuses on interpreting and applying insights to the business context (DAVENPORT; HARRIS, 2018; FILE; REDAELLI, 2023).

2.5 DATA-DRIVEN DECISION MAKING

Data-driven decision making, also known as *Data-Driven Decision Making* (DDDM) is a practice of collecting and analyzing data to support decisions. There is no consensus on a specific process to follow for this. Although many authors approach DDDM from the perspective of data, it is understood that it concerns the context of the strategic management of companies. For example, for Berndtsson (2018), Ghandi, Bathia and Dev (2021) and Kumar (2021), the main characteristics of a disciplined and data-driven approach to decision-making presuppose the use of KPIs aligned with strategies, guiding the logic of decision-making, thus allowing companies to learn from mistakes, analyze the results of bad and good decisions, generating improvement of *organizational learning* loops.

DDDM is based on empirical evidence, allowing executives to propose informed actions that result in positive business outcomes. The opposite of a data-driven process is decision-making based solely on intuition. For data-driven business owners and executives, listening to their gut may be part of their decision-making process, but they only take specific actions based on what the data reveals. On the contrary, in data-driven companies, business owners and executives understand the benefits of data-driven insights to make sensible business moves. As such, making data-driven decisions requires a multi-step process, ranging from analyzing the current situation to formulating an action plan. Figure 4 illustrates the step-by-step process of DDDM.

Figure 4 - Data-driven decision-making.



Source: Prepared by the authors.

Step 1: You need to understand the context of the decision and identify what goals the company hopes to achieve through DDDM, and then build a strategy around them. At this stage, it's okay if the strategy isn't completely defined, but the company needs to understand that big data will help it achieve its goals. Thus, articulating these objectives will shape data collection and analysis strategies from the start. Also at this stage, it is necessary to communicate to all those involved the need to commit to the continuity of the actions defined based on data-based decision-making. This is a value of what is called a '*data-driven* culture', and it is just as important as having the necessary infrastructure and analytical tools. By committing to using data in decision-making, the company recognizes the effectiveness of this approach and needs to do so in a way that builds trust with everyone. You need to determine whether your goals require using real data for analysis or experimental data for simulations or modeling. Real data is what is being collected and analyzed to try to figure out what is already happening in the business. Experimental data, on the other hand, is data collected from a controlled experimentation environment to discover which business practices work best.

Step 2: The company should focus on a few areas of the business and define questions to determine which areas need the most attention. Typically, the answer is related to marketing and sales, finance or operations, or a mix of the three. In those areas in which the company believes it will have the most benefits in terms of business growth with DDDM, priority should be given to those with the greatest impact. This requires identifying the specific business questions you plan to answer, in particular those related to the business objectives defined in the first step. Formulate this thought in the form of hypotheses that can be proven or disproved and that can be used as a starting point for research. You also need to identify the data sources you need and what data you can glean from them. When the company identifies in advance the specific data it needs to collect and how it will do so, it spends far less financial resources and time than if it simply collected everything and tried to figure out what to do with the data later. The definition and use of KPIs is essential so that the data collected factually supports the decision to be made, justifying it.

Step 3: The visualization of the KPIs is relevant so that you can examine the progress of the projects arising from the decisions made, and if they were really relevant to the business issue addressed. There are two broad categories of data, and since each of them can aid in decision-making, both are typically necessary. Qualitative data are non-numerical and subjective. They are observed, rather than measured. Quantitative data, on the other hand, is numerical, objective, and measured, not just observed. Not all data is suitable for use. The data should measure something meaningful, it should be accurate, formatted correctly, and not contain duplications and flaws. For these reasons, data collection methods are often tested in a pilot area before being deployed. If the company is working from existing data, it may have to 'clean' the data before performing the analyses, which entails verifying information, correcting errors, and removing redundancies and *outliers*. To have data quality, some key questions must be answered by visualizing it. Who collected the data, and is it reliable? Reliability requires verifying that all data have been collected using the same parameters, and that they do not contain false answers. How were the data samples collected? Is the data representative of reality? Does the data include *outliers* (unusually high or low measurements)? How does this affect the overall distribution of data? Are causal relationships truly causal or incidental? Or do the data from the collected variables give an inaccurate impression of causality? What are the assumptions underlying the data, and are they valid for analysis? And, most crucially, why was it decided to analyze the data in one way and not another? Even if you choose to delete some data, the company is likely to find that it has multiple internal data sources. Having multiple data sources means you can choose the best option for collecting data, based on what's fastest, cheapest, and most reliable.

Step 4: From the decision made, you need to create action plans to implement it. More complete action plans always have a schedule with all the activities necessary for the implementation of the decision, in addition to a budget that allocates the necessary resources for its operationalization.

Step 5: Create criteria for analyzing the progress of action plans avoids HiPPO behavior and drives monitoring analyses back into the DDDM cycle. This justifies the allocation of people to collect and analyze data on the execution of the action plans, and these people will be the first, and sometimes the only ones, to verify the veracity of the data. The most common mistake observed in implementing data-driven decisions is neglecting to validate the data before drawing conclusions. Especially in companies that previously didn't rely heavily on data to drive action, they may neglect to subject decisions to a quality control or governance process, and are likely to be incorrect in many cases.

Step 6: Analyzing the available data in the form of KPIs enables the discovery of insights. Even if you don't have the full capacity to do this analysis, it's still critical to know what kind of analytics are needed (such as diagnostics or forecasting), because analyzing different types of data requires different analytical skills. Dealing with quantitative data is relatively simple, but qualitative data, such as images, videos, speeches, and texts, require different conceptual knowledge and technical skills.

Step 7: Presenting the results of the analyses performed and telling meaningful stories from them is also a surprisingly difficult part of data analysis. Once someone has analyzed the data to come to conclusions, they must deliver those conclusions to the right people, at the right time, and in the right way, with stories that make sense. There's no shortage of interesting ways to present these data-driven stories and visualize them. Even complex ideas can be more easily communicated with a good presentation that contains graphs or *dashboards*. The purpose of this is to link the knowledge gained to actions that will benefit the business. Data *storytelling* needs to clearly portray both the rewards and risks of big data-driven decisions.

Step 8: The *knowledge loop* created by DDDM will allow the group involved in it to carry out learning moments, with lessons learned that are derived from the cycle carried out, which will indicate the need to improve communication, update the infrastructure and improve the data governance process.

In this way, DDDM is the practice of collecting data, analyzing it, and basing decisions on knowledge derived from the information generated by the analysis of these data. This process stands in stark contrast to making decisions based on intuitive feeling, tradition, or overly abstract theories. Data-driven decisions are typically more objective and can be easily evaluated based on their impact on the metric.

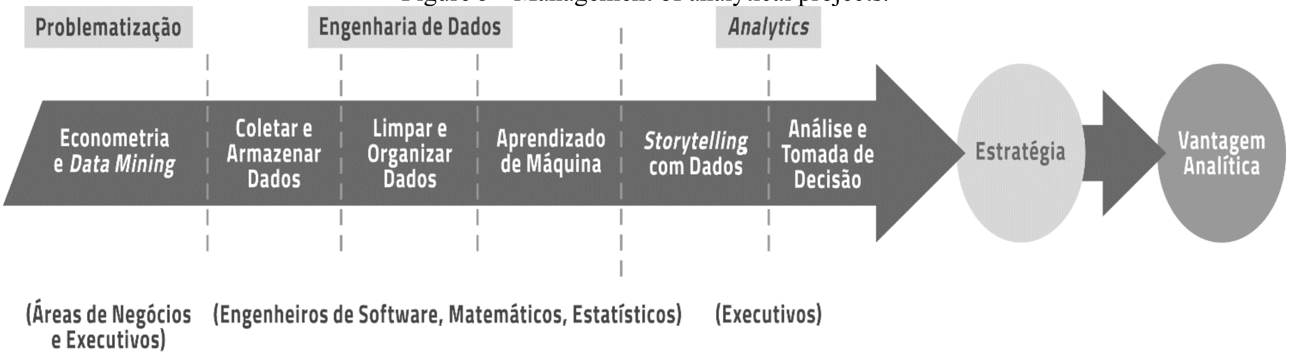
Underlying DDDM is the belief that better data leads to better decisions, which in turn lead to better outcomes. In fact, without data, people are at a much higher risk of being influenced by biases or acting on false assumptions. The success of DDDM depends on the quality of the data collected and the methods used for its analysis. DDDM is strongly quantitative, historically, its use has been limited due to the need for permanent collection of statistical data, but the spread of information systems to analyze large datasets has made DDDM much more accessible. Thus, it is not limited to large companies with vast computing resources. Companies of any size can use DDDM to transform their processes, becoming more agile by detecting new business opportunities and responding more quickly to market changes. With real-time data collection, executives can quickly measure the results achieved and create an agile *feedback* loop. These capabilities make data-driven businesses exceptionally customer-focused, and more competitive. They also lead to greater transparency and accountability, which can improve teamwork and people engagement.

DDDM's policies make it clear that inferences and fads are not driving the company, and the internal climate improves because people see that objective data supports management decisions. In companies that prioritize data-driven decision-making, goals are concrete and results are measured. Members of the management team often feel a greater sense of control because they can clearly see the results that are being achieved towards the set objectives. The tenor of interactions can become more positive because discussions are based on facts, rather than being driven by the individual ego and personality. Creating a data-driven culture thus requires a long-term commitment to educating the entire company and championing that effort from the top management. Even so, it is almost certain that the evolution to this new way of doing business will take time to take hold. The evolution to a data-driven culture generally follows five phases that show the levels of evolution of analytical maturity: (i) Data denial: the company starts with a distrust of data and does not use it; (ii) Data indifference: the company has no interest in the data being collected or used; (iii) Data awareness: the company collects data and uses it to monitor processes, but does not base its decisions on this data; (iv) Informed Data: executives selectively use data to support decision-making; and (v) Data-Driven: Data plays a central role in as many decisions as possible across the enterprise.

2.6 ANALYTICAL PROJECT MANAGEMENT

A project is a temporary effort undertaken to create a unique product, service, or outcome. An analytics project is similar to a software development project: in both cases, the goal is to gain economic benefits or create value for stakeholders. Figure 5 summarizes the logic of using *data science* in business and analytical project management.

Figure 5 - Management of analytical projects.



Source: Lima and Redaelli (2023).

For Singh (2015), an important initial issue to be considered in the management of analytical projects concerns the basic characteristic of the project that is planned to be carried out, in view of certain propositions about the problematization phase. Sometimes companies have a specific problem that emerges from the management analyses they conduct, but they don't have enough data on that specific problem. In this case, it is recommended that the company create a portfolio of projects with data *mining activities to* exploit large amounts of data, which are validated by applying the patterns detected in them to new data sets. In this sense, data *mining* is the analytical process designed to explore large amounts of data to find consistent and relevant patterns, or systematic relationships between variables, which are validated by applying the detected patterns to new data sets, with the work of data scientists. The basic assumption of data mining is active argumentation, that is, instead of the user defining the problem, selecting the data and choosing the tools to analyze such data, the data mining techniques automatically search the data for anomalies and possible relationships, thus identifying problems that have not yet been identified. On the other hand, sometimes companies don't have a specific problem, but they identify that they have a lot of data available from their ERP systems, and they can then use econometrics techniques to test hypotheses and predict economic phenomena that lead to the discovery of problems or the creation of significant comparative advantages. According to Gujarati (2019), Econometrics is the part of Mathematics applied to Economics to correlate data, and is often used in the definition of economic policies. It is a set of statistical tools used to understand the relationship between economic variables by applying mathematical models, and generally uses linear regression as a basic econometric model.

The next phase of the development of an analytical project is called Data Engineering, considered the *hard* phase of *Data Science* projects in business. In this phase, teams of data scientists with competencies in computer science and software engineering, applied mathematics and statistics, use data mining to organize data that will be used by administrators and executives for visualization, analysis, decision-making and proposition of deliberate strategies.

One of the most common approaches in this phase is the use *of data mining*, which formulates hypotheses about data quality, which must be accepted or rejected, based on the evaluation of these hypotheses, which goes through typical steps: (i) evaluation of the necessary data set; (ii) determination of success criteria and quality metrics; (iii) data preparation, modeling, and evaluation of results. Most of the time, the work can be cyclical, as some steps can be repeated multiple times. When the hypothesis evaluation is complete, a data model is created and put into operation. When the team of data scientists finishes these steps of the Data Engineering process, the generated database, called a data *lake*, a type of repository that stores large and varied sets of raw data in a native format, is then made available for queries by administrators and executives. With data *lakes*, you have an unrefined view of your data. This management strategy is increasingly used by companies that want a large, holistic repository to store data.

The first stage, data collection and storage, is preceded by the definition, by those involved in the problem to be solved, about the types and categories of data and what will be the sources of the data to be collected. Then follows the search, selection, collection, and storage of raw data. The data is said to be raw because it has not yet been processed for a specific purpose. Data in a *data lake* is defined only after it is queried. Data scientists can access the raw information when needed through predictive modeling or more advanced analytical tools. All data is retained when using a data *lake*: nothing is removed or filtered before storage. The data may be analyzed soon, in the future, or never. They can also be used multiple times for different purposes, unlike when data is refined for a specific purpose and repurposed more difficult. The term *data lake* is appropriate to describe this type of repository as a lake, because it stores a set of data in its natural state, such as water that has not been filtered. Data flows into the data lake from a variety of sources and is stored in its original format. In a data *lake*, data is transformed only when it is needed for analysis, through the application of benchmarking schemes. This process is called "schema to read" because the data is kept in a raw state until it is ready for use. Data *lakes* allow users to access and explore data the way they want, without having to move it to another system. Insight and reporting from a *data lake* is often *ad hoc*: users don't often need to pull analytical reports from another platform or repository type, but they can apply a schema and automate copying a report if needed.

The second stage, cleaning and organizing the data, is carried out by mathematicians and statisticians, who treat anomalies found, such as *missing* data or *outliers*. Here, too, it is necessary to define the treatments to be applied to these types of data by those involved in the problem to be solved. Then follows the cleaning and organization to generate a data *lake* with mined data. In other words, data *mining* tools analyze data, discover problems or opportunities hidden in the relationships of that data, and then diagnose business behavior, requiring minimal intervention from users, who can then focus solely on seeking knowledge to generate greater competitive advantage. It turns out, in practice, that when a *data lake* with mined data is finally made available, sometimes going through complex and time-consuming steps of collecting, storing, cleaning and organizing the data, they are already outdated and outdated, since the databases searched continued to be fed with data all the time. At this point, *machine learning* algorithms come into play to automate all the work conducted so far by the team of data scientists, increasingly improving the algorithms themselves and speeding up the process, so that the data *lakes* to be used are always as complete, mined and up-to-date as possible. Machine learning is an *analytics* method that automates the construction of analytical models derived from artificial intelligence and based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention. In summary, the use of artificial intelligence is the first step that analyzes the data and provides analytical results quickly to users. *Machine learning* is based on the application of artificial intelligence in a second step, which not only analyzes raw data but also looks for patterns in the data that can generate more insights.

From the end of the Data Engineering phase, the Analytics *phase begins*, which includes the stages of developing *storytelling* with data and business analysis and decision-making (, 2023). Then begins the *soft part* of *Data Science* focused on business, with the application of Business Intelligence concepts, methods, techniques and tools. In summary, *Data Science* deals with the collection of data from various sources, resulting from data mining, to analyze and support decision-making, predictively, in large amounts of data and generating insights. Strategic use of data *science* and effective interpretation of data can improve a company's operational efficiency and revenue growth in a variety of ways, creating analytical advantage that leads to increased competitiveness.

3 CONCLUSION

From the mapping of the specialized academic and commercial literature on business models and management models based on data analysis for strategic decision making, the categorization of relevant aspects for the structuring of a management *analytical model* framework was carried out.

Using an operational framework obtained from successful management models in *the Analytics Economy, information was selected that suggests* the appropriate actions for the successful execution of a data-driven business: (i) select a management model appropriate to the current economic scenario of *the Analytics Economy*, based on data the business model for *data-driven* companies ; (ii) collect data that minimizes analysis bias; (iii) analyze the data to reduce the likelihood of error; and (iv) derive a specific management analytical model framework for *data-driven companies*. The *proposed framework* suggests a business management approach based on data analysis for strategic decision-making.

The model is composed of interrelated management fundamentals, integrated in a systemic way and coherent with an organizational philosophy, and is formed by the following components: (i)

Analytical Competition and Analytical Advantage; (ii) Strategic Positioning and Analytical Focus; (iii) Transformative Leadership and *Data-Driven* Journey; (iv) Market Orientation and Trend Analysis; (v) Data *Science* and *Business Analytics* domain; (vi) Data-Based Decision Making; and (vii) Analytical Project Management.

In this sense, the main contribution of this research is of a theoretical-managerial nature and concerns the search for more scientific rigor in the process of structuring an analytical management model.

As suggestions for future studies, it is suggested to operationalize the components of the *framework* of the analytical management model, enabling its implementation in knowledge-intensive companies to validate its adequacy to the context of Analytical Competition.

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