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Introduction to Strategic Analytics

OBJECTIVES
1) To explain Strategic Analytics 2) To introduce the main pillars of the book: the fields of analytics, management science, information technology, statistics, artificial intelligence, and strategic management 3) To explain the fields of analytics, management science, information technology, artificial intelligence, and strategic management

LEARNING OUTCOMES AND MANAGERIAL CAPABILITIES DEVELOPED
1) Managers can learn to tackle complex problems in strategy through the integration of analytics and artificial intelligence within strategic management processes 2) Principles of Analytics: tools, support systems, and methods 3) Principles of Artificial intelligence: developments, types, and approaches 4) Identification of strategic problems

In today's environment, managers face turbulence and crisis. More information than ever is generated continuously: social media, financial performance management systems, customer relationship management systems, and internal and external reports. There are powerful trends: measuring and quantifying everything and skills in quantitative subjects are widely available. The problem for managers is not only to make sense of abundant quantitative information but also to engage with staff possessing analytical skills and exploit the Artificial Intelligence (AI) capabilities to support their work. Simultaneously managing multiple factors under pressure requires new managerial capabilities. Managers need to develop their strategies using clear strategy processes supported by the increasing availability of data. This situation calls for a different approach to

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strategy, such as integration with analytics, as the science of extracting value from data and structuring complex problems, and AI to increase the productivity of the team developing strategies.

Manager's decision processes can fall into a continuum which has on one hand pure analysis, which relies on established processes, and pure synthesis that involves identification of patterns and new ideas (Pidd, 2009). Strategic planning involves a mix between both extremes: analysis to identify problems and synthesis to observe trends and emerging situations before competitors. However, there is not a clear process when combining the two. Sometimes, emerging situations are discovered and then analysis is employed to confirm their impact while transforming them into new emergent strategies. In other circumstances, there is a careful planning process involving extensive data gathering and the construction of complex financial, operational, and other type models to validate the new strategies.

The idea behind "Strategic Analytics" is to answer a simple question: how can quantitative and qualitative information be used to make strategic decisions? Strategic Analytics does not imply turning managers into quantitative analysts or quantitative analysts into expert strategists. Organizations need interdisciplinary teams comprised by members who can talk to each other sharing a common language. Thus, Strategic Analytics works on the basis of providing a reasonable understanding of how a variety of quantitative methods, in conjunction with structured and unstructured data, can be used to help strategic decision-making in any organization. There is also the intent to show the real and practical benefit of Strategic Analytics. Strategic Analytics does not pretend to offer easy solutions to strategic problems but different ways of analyzing and solving strategic problems beyond the traditional qualitative approach to strategic management. Strategic Analytics is also an understanding of the context and processes in which analytics skills can be applied to support strategic management. Strategic Analytics also implies exploiting the AI capabilities to facilitate strategic decisions.

Future managers are taught a wide variety of concepts in strategy subjects but they are not taught how to apply them or even to connect them to related problems. Future managers need to develop capabilities to tackle problems that are not structured in a neat way like case studies are. In that sense, each chapter focuses on a case study with limited information that has to be solved applying a combination of theoretical concepts and analytical methods (quantitative and qualitative). The aim of this founding principle is to integrate strategic concepts with analytical tools in a unique set of capabilities (skills) to help future managers to tackle strategic problems using multiple sources of information. The main benefit is that quantitative methods, which are usually seen as a difficult experience for managers, are connected with a hands-on subject like strategy. Therefore, managers can learn capabilities to tackle complex problems in strategy through the integration of analytics (quantitative/qualitative methods to extract value from data) and AI within strategic management processes. Therefore, the book will provide a bridge to integrate quantitative methods with their application in strategy adding rigorous methods to solve real issues in strategy.

The rest of the chapter introduces the main pillars of the book: the fields of analytics, management science, information technology, statistics, AI, and strategic management.

1.1 What Is Analytics?

Organizations are competing using analytics because there is an increasing amount of data, people with capabilities to use data, and, in a highly competitive environment, it is more difficult to compete effectively. While organizations can use basic descriptive statistics from any of their existing data, organizations using analytics apply modeling to understand their environments, predict the behavior of key actors, e.g., customers and suppliers, and optimize operations. Organizations can obtain competitive advantage using multiples analytics applications but it requires a new type of organization and management (Davenport, 2006):

> A companywide embrace of analytics impels changes in culture, processes, behavior and skills for many employees. And so, like any major transition, it requires leadership from executives at the very top who have a passion for the quantitative approach … CEOs leading the analytics charge require both an appreciation of and a familiarity with the subject. A background in statistics isn't necessary, but those leaders must understand the theory behind various quantitative methods so that they recognize those methods' limitations-which factors are weighed and which ones aren't … Of course, not all decision should be grounded in analytics … For analytics-minded leaders, then, the challenge boils down to knowing when to run with the numbers and when to run with their guts (Davenport, 2006: pages 102–103).

An analytical perspective is important, when data has become a key strategic asset of organizations in recent years, and analytics creates value by delivering systematic decision support in a well-timed way (Laursen and Thorlund, 2010; Holsapple et al., 2014). Business Analytics (BA), one of the multiple branches in Analytics, comprises three key elements: Information Systems, Human Competencies, and Business Processes (Laursen and Thorlund, 2010). Business analytics reflects the convergence of three disciplines: statistics, information systems, and management science (Laursen and Thorlund, 2010). While the supporting disciplines are traditional, the innovation lies in their intersections. For example, data mining aims to understand characteristics and patterns among variables in large databases using a variety of statistical analysis, e.g., correlation and regression analysis. Information technology provides data and supports decision support systems, which are sustained by management science tools together with statistical analysis, for the development of analytics. BA is rooted in advances of information technology systems, which involve the acquisition, generation, assimilation, selection, and presentation of data, together with tools, statistics, and management science, to develop the data into knowledge to support decision-making. In a similar definition, Mortenson et al. (2015) suggest analytics is the intersection of basic disciplines: technologies (electrical engineering and computer science), decision-making (psychology and behavioral science), and quantitative methods (mathematics, statistics, and economics), and their applications: information systems, AI, and operational research. Figure 1.1 shows Mortenson et al.'s (2015) representation of the concept of analytics.

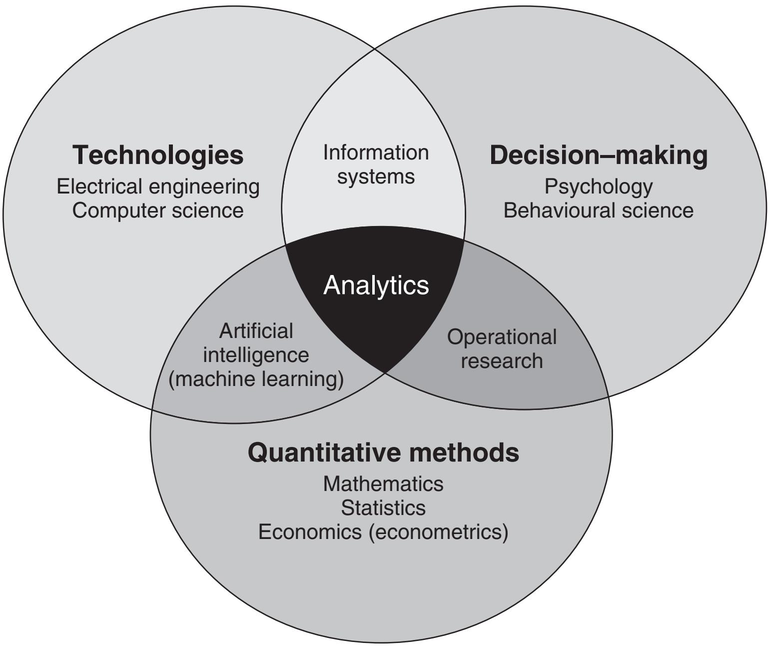

Figure 1.1 The analytics field. *Source:* Mortenson et al., 2015 / with permission of Elsevier.

In terms of types of analytics, Davenport proposes three types: descriptive, predictive, and prescriptive (Davenport, 2013), which are described below.

- **Descriptive analytics.** It employs traditional statistical skills to present data collected from internal organizational activities and external data. It is utilized to understand what happened during their past business activities in order to disclose whether the current business objectives have been obtained. Then the next step is to investigate the reasons behind the results by drilling down into more detailed data and explore scientifically, e.g., test and validate or reject hypotheses. It is characterized traditionally as data mining, business intelligence (BI), and dashboards. Building upon descriptive analytics, diagnostic analytics delves into data to uncover the reasons behind past events (Delen and Zolbanin, 2018). It uses methods like visualization, drill-down analysis, data discovery, and data mining to pinpoint the root causes of specific problems (Delen and Zolbanin, 2018).
- **Predictive analytics.** It involves statistical and mathematic techniques to predict future unknown events or behaviors based on historical data to support operations. Some of the popular techniques in this area cover decision tree, text analytics, neural networks, regression modeling, and time-series forecasting. Predictive analytics also relies on data mining and other machine learning (ML) algorithms to identify trends, patterns, or relationships as volume, variety, and velocity of data increases.
- **Prescriptive analytics.** It uses optimization and/or simulation to identify the best alternatives to improve performance. Prescriptive analytics is used in many areas of business, including operations, marketing, and finance. For example, finding the best pricing or portfolio of new product investments strategy to maximize revenue. Prescriptive analytics can address questions such as: How much should we produce to maximize profit? Should we change our plans if a natural disaster closes a supplier's factory and if so, by how much?

In terms of analytics, there is a wide variety of tools so an exhaustive list of tools will be beyond the scope of this book. Table 1.1 shows a list of the most common tools extracted from Gandomi and Haider (2015) and Chen et al. (2012).

From a process perspective, Liberatore and Luo (2010) suggest analytics follows a four-step process. First, data is collected from diverse systems. Then data extraction and manipulation are two tasks performed together with the objective to obtain and organize the data for analysis. The second step is data analysis comprising three activities: analysis, predictive modeling, and optimization. Analysis can involve presenting and analyzing data using interactive tables, charts, and dashboards. Predictive modeling is employed to estimate trends, classify data, and validate relationships. Optimization attempts to obtain the optimal solution. The

Table 1.1 A selection of analytics tools.

Method	Brief description	Suggested further reading
Text analytics	Text analytics is employed to extract information from textual data such as social network, blogs, online forums, survey responses, documents, news, and any logs from interactions with customers. The basic tools to perform the analysis are statistical analysis, computational linguistics, and machine learning. Some of the outcomes from their use are: ● Information extraction generates structured data from unstructured text. ● Text summarization provides summaries from multiple documents to present the key information existing in the original text considering location and frequency of text units. ● Sentiment analysis analyze text, which contains opinions, to infer positive or negative sentiment. The analysis can be performed at document, sentence, and aspect levels.	Aggarwal and Zhai (2012)
Data analytics	Data analytics comprises technologies based on data mining and statistical analysis. More specifically, data mining algorithms, such as statistical machine learning (Bayesian networks, Hidden Markov models), sequential and temporal mining, spatial mining, process mining, and network mining, are the key tools. Data mining algorithms perform classifications, clustering, regression, association analysis, and network analysis.	Berry and Linoff (1997) Hand et al. (2001)
Network analytics	It evolved from bibliometric analysis, citation networks and co-authorship networks tools. The current focus is on link mining, which is the prediction of links – social relationships, collaboration – between end users, customers, etc., and community detection, which involves representing networks as graphs and applying graph theory to identify communities. Another focus is on the dynamics of social networks using agent-based models, social influence, and information diffusion models.	Aggarwal (2011)
Visual analytics	The objective is to facilitate analytical reasoning through interactive visual interfaces that synthesize information from big, ambiguous, and dynamic data. It integrates information visualization with data management and data analysis together with human perception and cognition fields. Some applications are in: ● Spatial data such as geographic measurements, GPS data, and remote sensing. ● Temporal data such as patterns, trends, and correlations of data over time. ● Network data related to different real networks such as transportation, electric power grids, and communities.	Andrienko and Andrienko (2005) Dykes et al. (2005) Simoff et al. (2008)

methods employed in this stage are discussed in the next section. The third step is the interpretation of the analysis into insights. Data visualization offers insights into what happened in the past. The purpose of predictive modeling is to help to foresee future issues if the current trends continue. Optimization gives potential solutions under certain situations. The fourth step involves translating the insights into actions related to operational aspects, redefining processes or defining/adjusting strategies.

It is important to remember that big data and data science terms are different: big data refers to the data in large volume and data science to the methods to analyze this data. One of the recent fields emerging from the rise of big data and analytics is data science. Data science is an interdisciplinary field that combines statistics, data mining, and other tools to generate analytical insights and prediction models from structured and unstructured big data (George et al., 2016). Data science focuses on the systematic study of the organization, properties, and analysis of data and the process of inference together with confidence in the inference (Dhar, 2013). Big data, as the raw material for data science, has a set of characteristics: volume, variety, and velocity. Building on the notion of volume, "data scope" refers to the level of completeness of data describing events (George et al., 2016). Scope implies a wide range of variables, whole populations rather than samples, and numerous observations on each participant. A higher number of observations shifts the analysis from samples to populations (McAfee and Brynjolfsson, 2012). Variety relates to the extreme diversity in the type of data provided from internal and external sources from numeric to textual data. In terms of velocity, data is streaming in at unprecedented speed and must be dealt with in a timely manner. Another characteristic in addition to increasing velocity and variety of data is variability since data flows can be highly inconsistent with periodic peaks occurring in different units of time, e.g., minutes, days, months.

For the analysis of big data, there are a number of challenges because traditional statistical concepts apply to situations where a sample of the population is analyzed; however, big data can capture the entire population (George et al., 2016). First, there is a (very) large number of potential explanatory variables available. Second, the data is too large to be processed by conventional personal computers. Third, a model that shows a strong relationship between independent variables and the dependent variable together with strong predictive validity may not demonstrate a causal relationship between variables. Causality needs a field experiment in which an independent variable is manipulated for a random sample of the target population. Fourthly, statistical significance becomes less meaningful when working with big data. Variables that have a small effect on the dependent variable will be significant if the sample size is large enough and spurious correlations will appear when using a large number of variables (George et al., 2016).

Laursen and Thorlund (2010) offer a useful guide to connect questions, type of analysis, and competencies required to perform analytics, see Table 1.2.

Table 1.2 Approaches to analyze big data.

Type of question	Type of analysis	Competencies required
Is there any relation between an action and the results obtained?	The most basic analysis is to retrieve a set of data that provides evidence of the actions, e.g., price changes, and results, e.g., sales changes. Then, the data is presented in a certain format, e.g., a contingency table bar charts, etc., leaving the interpretation to the users. This is usually the realm of visual analytics (Simoff et al., 2008) or descriptive analytics.	Data manager or report developer to retrieve data and organize in a visual format. No knowledge of the business is required.
What is the behavior of a certain customer/performance?	Sometimes, there is no knowledge about the performance of a certain variable so the result of this analysis is simple descriptive statistics such as sums, average, range, and standard deviations. This is usually the realm of descriptive analytics (Keim et al., 2008).	Data manager or report developer to retrieve data and organize in a visual format. No knowledge of the business is required.
What is the correlation between a certain event and the results? Is the action causing any effect on the results?	Hypothesis-driven analytics employs statistical analysis and the intention is to validate the correlations between events and results. Interestingly, the use of traditional statistical tests to validate correlations, e.g., 95% confidence interval, may not be relevant in the context of big data since the data contains the whole population (so a comparison of the average between variables may be enough) (George et al., 2016). In terms of analysis, they can be cross-sectional, e.g., regression analysis, or longitudinal, e.g., time series analysis.	Analytics to execute appropriate statistical tests and business knowledge to ensure the quality of the selection of the variables, e.g., variables clearly describe the business.

What can be learnt from the events that occurred/actions taken?	Data-driven analytics, e.g., data mining and explorative analytics, attempts to create models for specific decision support. This is not theory-driven but data-driven. In other words, the algorithms will find the optimal model without restrictions. The quality of the findings depends on the performance in the data set not the theoretical significance. However, there are validation procedures such as testing the model in a different subset of data than the one employed to develop it (Lismont et al. 2017). Data-driven is best suited for complex tasks due to changes in data, large amounts of data and variables, and limited initial knowledge.	Computer science to develop algorithms – e.g., neural network, decision trees, binary regression, and machine learning – that search across the data and create models explaining the relationships in the data Business is also required to evaluate the reasonability of the model.
What is the best model to describe the factors driving the results with and without a clear variable in mind?	Data-driven analytics can also be performed with a specific variable in mind but no knowledge about the drivers of the variable. Then, the model is employed in predictive mode to find out future events (predictive analytics). In this case, data mining has a target variable and a lot of input variables without knowing their impact on the target variable. Another analysis is just simply looking for patterns in data. This is employed when there is a large set of variables that do not generate sufficient information so there is a need to reduce, or group, them into a smaller, and more meaningful set of variables. This is usually performed through cluster analysis (Kaufman and Rousseeuw, 2009), cross-sell or basket analysis models (Berry and Linoff, 1997), and up-sell models (Cohen, 2004).	Computer science to develop algorithms to search for variables to create a model.

1.2 What Is Management Science?

While analytics provide the context for the use of data for decision-making, management science, together with statistics, is one of the engines behind analytics. According to Mayer et al. (2004), the six purposes of management science in the area of supporting strategy making are:

- **Research and analyze.** Management science can generate knowledge in a specific domain, and specific issues, to develop deeper understanding of the impact of issues on the performance of organizations or society.
- **Design and recommend.** This activity focuses on translating available knowledge into new strategies by making recommendations or designing the strategies.
- **Provide strategic advice.** Its role is to provide advice to a client on a strategy for achieving certain goals given a certain context (e.g., environment, responses of other actors, etc.). It involves understanding the requirements of the decision-makers and the organization.
- **Clarify arguments and values.** In this role, management science practitioners analyze the values and argumentation systems that underpin the organizational debate. Given this purpose, analysts seek to improve the quality of the discussion detecting biases or limitations in the arguments
- **Democratize.** Analytics activities can have normative and ethical objectives related to the stakeholders. Powerful interests can be involved affecting the discussion so management science analysts can support views and opinions overlooked due to the lack of power. For example, simulation models may be useful to support claims over environmental impact.
- **Mediate.** In this role, management science designs the rules and procedures for the strategic making process and manages the interactions and progress of the process, especially facilitating meetings with different stakeholders and strategic decision-makers.

The top part of Figure 1.2 shows management science mostly oriented toward objects and focused on systems, strategies, and models, while the bottom part indicates its orientation to subjects, which comprises working with people (decision-makers, stakeholders, experts) and their interactions during the strategic management process. The arrows point to "styles" of analysis. When management science encompasses systems and strategies, the styles are rational, argumentative, and client-advisory as it provides reasons and arguments to support the decision-making process. When management science approaches the subjective part of strategic management processes, the styles will be participative, interactive, and process-oriented since their role is to generate forums for discussions where modes are "transitional objects" (Mayer et al., 2004).

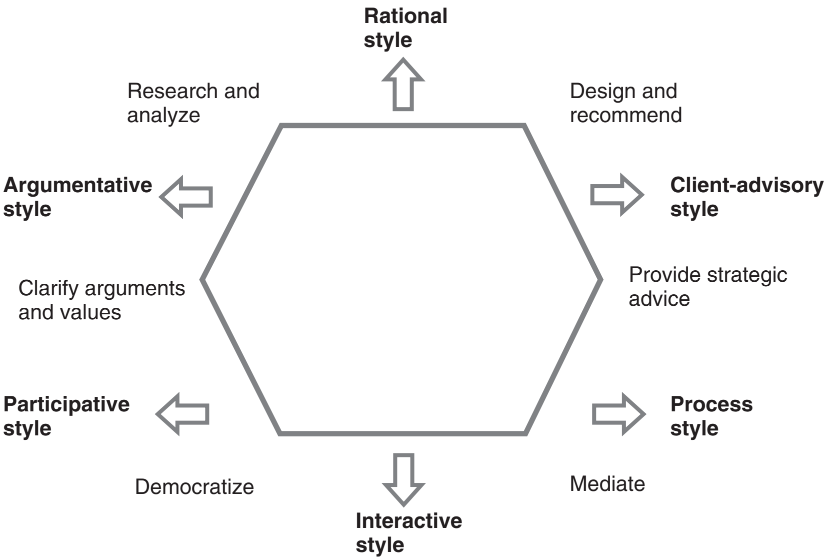

Figure 1.2 Management science styles. *Source:* Walker (2009) / with permission of Elsevier.

In practical terms, the translation of a strategic problem to the analytical world is accomplished through the process of finding meaning and structure to the strategic problem through the development of a model (Mayer et al., 2004). The model helps to visualize the data required together with precise definitions reducing ambiguity and confusion. The structure of the model can be validated to identify incoherent statements and spurious assumptions. The results of the model reflect the current and future behavior of the strategic problem given the assumptions about the problem. Finally, experiments on solutions and selection of strategic choices can illuminate a satisficing solution. The importance of each of the previous steps, translation, visualization, validation, simulation, and experimentation depends on the emphasis of the use of the model as indicated in Figure 1.2. A key aspect to highlight is that the model cannot be only one solution, but part of multiple models or methodologies to triangulate the strategic insights obtained. Figure 1.3 shows a categorization of modeling methods in management science reflecting the richness of the field.

From a management science perspective, **qualitative methods** are predominantly employed to structure problems that are ill-structured (not clearly visualized in the minds of the strategic decision-makers) or with parameters difficult to quantify (Williams, 2008). The methods cover multiple sets of issues. For example, one strategic problem may consist of understanding

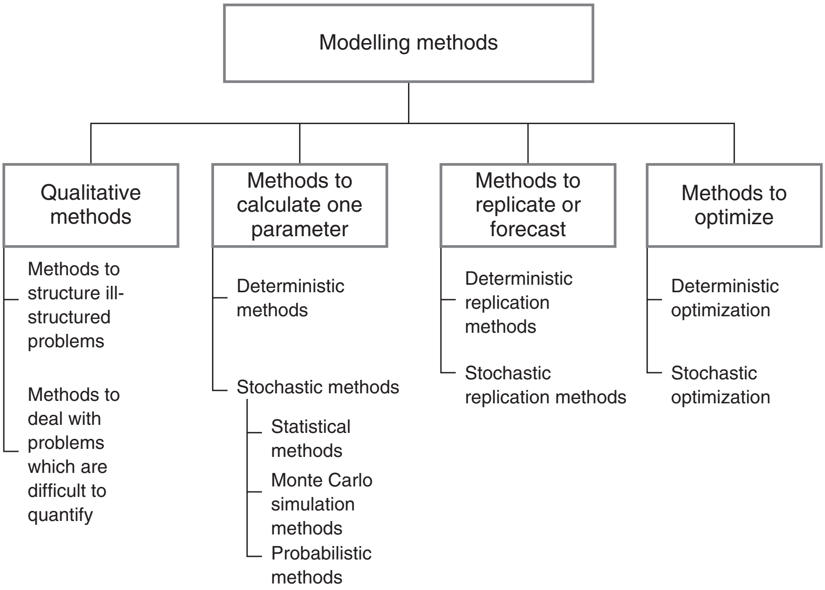

Figure 1.3 Basic categorization of modeling methods in management science.
Source: Adapted from Williams (2008).

interconnectedness inside the organization and across industry (see Soft Systems Methodology, Cognitive mapping and Causal loop diagrams in Table 1.3) or the need to manage interactions with other actors/stakeholders (see Drama theory in Table 1.3). Other strategic problems addressed are uncertain futures (see Scenario analysis in Table 1.3) or uncertainty in the strategic choices existing (see Robustness analysis in Table 1.3). Qualitative methods can also work in situations where parameters are difficult to quantify (Williams, 2008) so the aim of these methods is to support decision-makers to quantify parameters leading to an initial quantitative evaluation of the strategic problem. For example, decision trees can evaluate strategic actions considering subjective probabilities (see Decision trees in Table 1.3), and analytic hierarchy process and multi-criteria decision analysis (see Analytic hierarchy process and Multi-criteria decision analysis in Table 1.3) focus on the quantification of preferences in order to evaluate strategic options and choices.

Methods to calculate one parameter or a certain attribute of a system involve two types: deterministic and stochastic. Deterministic methods can include a simple profits statement analysis, where the attribute is profit, to the evaluation of the relative efficiency across multiple decision-making units, considering one dimension. Stochastic models assume that there is not one unique result of a certain

Table 1.3 Qualitative methods in management science.

Method	Brief description	Suggested further reading
Soft systems methodology	Approach used to understand and model human activity systems. The process involves appreciating the problem situation, uncovering different views from the key stakeholders, defining human activity systems, and identifying desirable and feasible changes to improve the problem situation.	Checkland and Scholes (1990)
Cognitive mapping	Group-based process to make sense of complex problems developing shared understanding using individual decision-makers' construction of reality (cognitive maps).	Eden and Ackermann (2013)
Causal loop diagrams	It is a method to represent the feedback structures responsible for the behavior of systems. It involves identifying causal relationships among concepts as well as the type of linkage (positive or negative). It can be a group- or individual-based method.	Sterman (2000)
Drama theory	A modeling method to understand activities between two or more competing or cooperating entities considering that humans, as decision-makers, may be irrational so employing drama can be a useful framework of analysis. It involves the use of role play.	Bryant (2003)

(*Continued*)

Table 1.3 (Continued)

Method	Brief description	Suggested further reading
Scenario analysis	It is a group process to help organizations to learn about future events by considering alternative possible outcomes and how the future will affect them through stories.	van der Heijden (2005)
Robustness analysis	It supports decision-making when there is radical uncertainty about the future, so it attempts to support rational decisions today given unknowable future conditions. It resolves the paradox by assessing decisions in terms of the attractive future options that they may keep open. It involves the use of decision trees to evaluate the diverse configurations to be faced at the end of the decision.	Rosenhead and Mingers (2001)
Decision trees	It basically consists of a simple diagram of decisions and consequences considering the uncertainty of their outcome through their probabilities. The decisions and outcomes are represented as branches and nodes, so the tree represents a sequential path of the set of decisions and their outcomes. Then decision-makers choose the optimal decision, which reflects the maximum expected values.	No specific reading is suggested since it is a fairly standard technique available in quantitative methods books.
Analytic hierarchy process	It implies selecting between different options considering the multiple goals a decision-maker has. The idea is to structure the criteria set hierarchically, with the overall goal of the decision at the top of the model, and then comparing between pairs of criteria while maintaining consistency using decision weights.	Saaty (1980)
Multi-criteria decision analysis	It is similar to the analytic hierarchy process but the main focus is on the use of diverse methods for evaluating the weights on the criteria and then applying the weights to the criteria scores for each individual option.	Belton and Stewart (2001)

attribute but a range of values. Depending on the purpose of the analysis, they can be evaluated as Statistical, Monte Carlo, or Probabilistic (Table 1.4).

Methods to replicate are utilized to understand how a system behaved in the past behaves currently or how it will behave in the future based on models reflecting the interactions between the different components of the systems. The aim of the methods is to achieve a representation of the system that is accepted by the users (validation) while simple enough to understand how it works (conceptualization). The methods can be classified as deterministic and stochastic. The main deterministic method is System Dynamics (Kunc, 2018; Kunc & Morecroft, 2007, Kunc & O'Brien, 2019), a methodology developed at MIT in the late 1950s (Table 1.5). Stochastic methods consider the existence of uncertainty in the system and its impact on the performance of the system. The uncertainty may be generated by randomness (discrete event simulation) or aggregation of multiple individual agents (agent-based simulation) (Table 1.5). Modeling can be very useful when the organization is facing up to complex issues as an interpretative approach to solve them. However, it is impossible to provide a comprehensive validation that a model is completely correct because of the interpretative approach to the complex problem. The key is the process of modeling, especially problem and model formulation (Robinson, 2004).

Simulation models can be used in different modes. The evaluation of their use is discussed in Pidd (2009) and it is based on Lane's folding star (Lane, 1995). For example, *ardent modeling* consists of the development of a formal mathematical model, which is able to run simulations, in order to develop a set of recommendations for changes in the real world. In *qualitative modeling*, the development of the model provides common language for managers or stakeholders to discuss their views of the system/problem under consideration. The model is mainly used to facilitate interpretation of the problem so there is no need to generate equations and gather data to run simulations. The main objective is to appreciate the situation. When the model use is *discursive modeling*, a formal mathematical model is developed with the objective to support training through experimentation. Its aim is to foster learning and appreciation of the complexity involved in certain situations.

The model acts as a practice or training ground for managers (Lane, 1995; Kunc & Morecroft, 2007). The model is generated to convey important theoretical elements, e.g., feedback processes, and includes guidelines to structure user's experience (Lane, 1995; Kunc & Morecroft, 2007). However, the interaction between the model and the users cannot be completely structured so interpretation of the situation will also arise. Finally, *theoretical modeling* implies the development of a formal mathematical model, which does not represent a specific problem or situation, to offer policy insights and communicate the conceptualization of a problem in general terms without specific users and with the intention to raise awareness.

Table 1.4 Quantitative methods to calculate one attribute in management science.

Method	Brief description	Suggested further reading
Data envelopment analysis	This method evaluates the relative efficiency of similar decision-making units in terms of inputs and outputs. The graphical nature of the tool allows the decision-maker to see the optimum units at the frontier and highlight the inefficient units.	Cooper et al. (2006)
Statistics	There is a large range of methods for analyzing data but the methods attempt to basically evaluate relationships between variables (correlation), independence between groups (factor analysis), differences between groups and treatments (analysis of variance), grouping items (clustering), and finding explanatory factors (regressions).	Cortinhas and Black (2012)
Monte Carlo	It is a broad class of computational algorithms that rely on repeated random sampling to obtain a range of possible outcomes and the probabilities they will occur for any choice of action. It allows considering risk in quantitative analysis and decision-making.	No specific reading is suggested since it is a standard technique available in quantitative methods books
Probabilistic	It involves the use of probabilities to evaluate the future result of a certain event based on judgmental, historical, or experimental information. There are many different methods among them Bayesian methods, Fuzzy methods, Stochastic/Markov processes, and Risk analysis.	Cortinhas and Black (2012)

Table 1.5 Quantitative methods to replicate in management science.

Method	Brief description	Suggested further reading
System dynamics	It represents organizations as a set of stocks and flows, which reflect accumulation processes, and feedback loops representing information flows and causal relations between the components of the organization. The representation of the behavior is mainly developed through time series of variables. Models are developed in either group- or individual-based processes.	Morecroft (2015)
Discrete event simulation	This method evaluates the impact of randomness in the behavior of people or materials as they move through business processes considering resources available. People or materials form queues until they are served in the case of scarce resources. The behavior is represented using rules and logical relationships between the components of the system. The main outcome of the analysis is a probability distribution of selected parameters.	Robinson (2004)
Agent-based simulation	This method focuses on the decision-making processes of individual entities and their emergent behavior over time. It usually involves evaluating the emerging behaviors resulting from the interaction of multiple individual entities. The focus is on understanding how individuals behaving in a certain manner and interacting with other individuals generate macro-level behavior.	Macal and North (2005)

Optimization methods develop models to find the "best" or "optimal" solution from a set of possible solutions. These models have generally two elements: the objective function, which represents the set of decision variables whose optimal value needs to be found, and a set of constraints, which limit the values that the decision variables can take. There are two major types of models: deterministic and stochastic (Table 1.6).

Given strategic management processes are complex and uncertain, it is important to explore the consequences of strategic decisions and plans before implementing them. Often the process of exploring the consequences is performed intuitively by highly experienced managers based on their long experience. While it is definitively important to have experience, as well as deep knowledge, in crafting strategy (Pidd, 2009), managers also have limited rationality and are subject to biases and heuristics. Biases and heuristics are useful in detecting patterns that resemble previous experience but strategies tend to be forward looking and uncertain, so previous experience may hinder rather than help managers.

Consequently, the role of external and explicit models, as the main outcome of management science processes (an integral discipline in Analytics), is to provide the platform to capture the critical aspect of the issues the decisions and plans are addressing. Management science models will not replace strategic decision-makers but they can be valuable tools to direct their thinking and articulate existing knowledge. Models can account for conditions where decision-makers are unsure about the result of a choice, so a formal model can provide optimized options for the set of choices under consideration (prescriptive analytics). In other circumstances, the model may help to understand the current situation to identify opportunities or threats using either existing big data or eliciting assumptions (descriptive analytics). Models are also able to present evidence of future issues when certain strategic decisions are implemented (predictive analytics). In other words, models facilitate "procedural rationality" (Pidd, 2009). Thus, models are concerned with the nature of strategy processes (search, design, and evaluation) rather than the outcome of the strategy process (e.g., differentiation or low costs, diversification or integration). In that way, models and modeling can be considered systematic procedures to support decision-making of bounded rational decision-makers (Pidd, 2009).

Strategy Analytics requires formal, illustrative, and metaphorical models as they are the most suitable for the issues faced during the strategy process. Realistic management science models involving more operational detail, big data, and process dimensions can become a competitive advantage. This is usually the realm of strategic operational research (Bell, 1998) and this is a useful description for many traditional big data analytics tools used currently in organizations. In other words, big data analytics is a source of "competitive advantage" but it does not directly support strategy design processes. Thus, Strategic Analytics differs from operational analytics.

Table 1.6 Quantitative methods to optimize in management science.

Method	Brief description	Suggested further reading
Deterministic optimization	There are different techniques under this method: linear programming (single objective function, linear combination of decision variables and the decision variables can have any value except non-negative); integer and mixed programming (the only difference with linear programming is that all or some of the decision variables can only have integer values); nonlinear programming (the objective function and the constraints are related nonlinearly); goal programming (there are multiple competing objectives but if the objectives can be weighted, then the problem will be presented as single-objective linear programming); and dynamic programming (the problem is divided into stages with a decision at each stage subject to the state to move in the next stage and the objective function has to satisfy a recursive requirement such as cost or distance).	Winston and Goldberg (2004)
Stochastic optimization	It is the process of maximizing or minimizing a mathematical or statistical function when one or more of the input parameters are subject to randomness. Stochastic processes always involve probability The objective is to maximize the function's output value in the face of numerous random input variables.	Heyman and Sobel (2003)

1.3 What Is Information Technology: New Challenges?

Currently, information technology needs to consider two key sources of data for decision-making: digital data streams flowing from a multitude of sources most of them without being controlled by the companies; and traditional data warehouses, which store the data generated mostly by transactional and internal systems. In any case, the key function of information technology is to deliver information to the strategy development process. One of the issues is the lack of a specific type of information that is going to be required and the timing for its use, especially to discuss emergent issues, e.g., high customer churn rate. Emergent issues can lead to the establishment of new strategies based on the knowledge generated from the analysis of the information, e.g., new pricing strategies to keep customers. In the case of designed strategies, they start defining objectives and performance measures, e.g., customer satisfaction, so the requirements for the type of information are clear and lead to purposeful creation of the data management processes, e.g., automatic capture of customer feedback. Some of the information acts as leads for future events so it helps to predict future results, e.g., level of customer satisfaction can predict the future churn rate. Other information reflects past behavior and supports monitoring processes related to the achievement of objectives and learning from the effectiveness of actions. The past information can be employed in optimization processes through learning the impact of actions to improve performance.

The revolution in the digital world is relentless and it is creating digital streams of structure and unstructured data which offer opportunities for existing and new firms to leverage decision-making (Pigni et al., 2016). One of the incredible paradoxes of this revolution is that organizations may be data rich but information poor due to the limited competencies for exploiting data and transforming it into information and knowledge (Pigni et al., 2016). Digital data streams promise to start an era beyond BI because BI exploits a large volume of data that has changed slowly, e.g., transactional data, and is created internally in the company. Digital data streams change fast, are generated by multiple sources (humans or machines), and there is a need to harvest from external environments or nontraditional sources so the challenges are different.

Pigni et al. (2016) suggest that digital data streams can provide multiple views on a transaction such as pre- and post-transaction details, as well as real time, and generate responses to events to create value for the organization. There are two activities that can extract value from digital data according to Pigni et al. (2016):

- **Process to actuate.** In this activity, the organization initiates action based on real-time processing of the digital data. For example, there is an event occurring that is being informed through digital data, and through the use of existing databases and other contextual data, the organization can provide suggestions on which to act.

- **Assimilate-to-analyze.** The organization merges multiple sets of data (real-time and static) to compose datasets that are used for insights later on. For example, a retailer uses existing correlations between external factors, customer profiles, and demand of certain products to determine sales forecasts and inventory replenishment decisions.

There are different factors affecting the extraction of value. First, the delay in processing data from the event until the decision can reduce value. A delay is generated by processes performed on the data such as data collection and preparation for analysis, analysis of the data to transform into information and transformation of the information into decision. Second, the set of skills are critical to exploit data streams. Skills depend on the knowledge base of the organization to convert data into improved decision-making. The conversion of data to knowledge starts with a decision-maker with enough understanding of the issues to request relevant information, followed by processing appropriate data to generate this information when it is available (Pigni et al., 2016). Third, the capacity to effectively identify and access real-time data streams that match organizational needs is necessary to create datasets to generate value (Pigni et al., 2016). Fourthly, an appropriate toolset (software and hardware) is required to access real-time data streams and harvest its content (Pigni et al., 2016). Finally, the organization needs to reach a level of readiness or maturity to exploit digital data and extract value. The level of readiness is associated with strategic, managerial, and cultural aspects of the organization as well as data skills. Both level of readiness, or "mindset" in Pigni et al.'s (2016) words, and toolset are key in order to create value from the flow of digital data.

Traditional data management involves a technical or business-oriented perspective in operating and maintaining the organization's information systems structure (Laursen and Thorlund, 2010). Data warehouses may be developed from a technical perspective rather than from the need for information which affects its usability in the BA process. If the data warehouse is owned by the technical area associated with information systems, then front-ends may not be user-friendly, not oriented toward the needs of the decision-makers or only dependent on internal data warehouses mostly originated from transactional systems (Laursen and Thorlund, 2010). Data acquisition is not thought of in terms of events; thus, data may not be recorded or recorded inadequately. However, data warehouses offer a common information platform ensuring consistent, integrated, and valid data since data is structured and cleansed from the different source systems (Laursen and Thorlund, 2010). Laursen and Thorlund (2010) suggest an architecture and processes for data warehouses:

1) **Source systems.** They consist of the systems that provide data for the warehouse and they can be internal sources such as Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM). External sources,

among other sources, can be originated from "web scraping," which is the automated extraction of large amounts of data from websites (George et al., 2016). Web scraping programs are relatively widespread and may come free of charge, such as plugins for Google Chrome (George et al., 2016). Some websites, such as Twitter, offer "application program interfaces" (APIs) to facilitate easy access to its content. Web scraping is used to extract numeric data, such as product prices, and extract textual, audio, and video data generated by firms and individuals, news articles, and product reviews (George et al., 2016). A final consideration of the data sources is their prioritization in terms of usability and availability. Interestingly, the relationship between both concepts is inverse: higher usability may imply lower availability, e.g., questionnaires, and higher availability may lead to lower usability, e.g., call center information.

2) **Extract, transform, and load.** These processes transform the data from the source into the data warehouse, merge with another sources, and load them to different locations. Some of the data can be negatively affected during the process of transformation while other data can improve it. In other circumstances, the combination of two lower quality data can lead to a set of data more available but perhaps less usable.
3) **Staging area.** This is an intermediate, temporal area between the source systems and the final location in the data warehouse. It is usually considered for processes related to the transformation of the data, e.g., to make compatible the different types of formats on databases existing from the source systems.
4) **Data quality process.** This process is performed by firewalls with profiling and cleansing tools. For example, incomplete data, duplicates, and inconsistent data can affect the performance of the warehouse so the firewall analyzes the data and rejects improper data. Profiling tools use statistical tools to search for anomalous data, e.g., missing gender or addresses.
5) **Data warehouse.** After the data is treated to have an adequate quality, the data is integrated and categorized in terms of dimensions and metadata for future analysis by the analytics teams. The data is organized using diverse methods such as dimensional modeling. Dimensional modeling adds to transactional data different dimensions to make the data more comprehensive such as adding to items information such as organization, time, and place. Metadata is the information related to documenting the data in terms of its origins, sources, size, composition, etc.
6) **Data mart area.** They are the foundation for relational data and cubes for users, as well as access for analytics. They are created based on reporting requirements from the analysts, so they involve organizing and selecting the data to answer users' specific questions.
7) **Analytics portal.** This area contains the reports for business users such as dashboards, scorecards, and retrospective reports. This is only the tip of the iceberg in terms of analytics processes.

1.4 What Is AI and How Can It Enhance Business Analytics?

AI, a field within computer science, aims to develop machines that can perform tasks requiring intelligence. These machines achieve this through functions like learning—either by autonomously identifying patterns in raw data (unsupervised) or by learning from human-labeled data (supervised), understanding, which relies on representing knowledge relevant to specific domains, reasoning, which can take forms such as deductive, inductive, temporal, probabilistic, and quantitative, and interacting, enabling collaboration with humans or other machines within tasks or environments. (Coveyduc and Anderson, 2020). Some models are:

1) **Natural language processing (NLP)**. These models are designed to give computers the ability to understand and create human language. This is a hard problem because people communicate using a lot of context and implied meanings that aren't said directly. Computers, which work best with clear instructions, struggle with this lack of clarity. One simpler type, called programmatic natural language processing (NLP), looks at words and uses a dictionary to do things if the words fit a certain pattern. However, because languages have so many variations, this method doesn't work well for most uses. Therefore, stochastic models are usually the best way to handle the complexities of language.
2) **Statistical NLP**. Existing parsing methods struggle with long conversations or extensive texts. A more sophisticated approach is required, one capable of learning new concepts and word meanings from context, mirroring human comprehension. While instantaneous AI-driven contextual understanding is not yet a reality, statistical analysis offers improvements over programmatic parsing. This typically involves tokenization and key identification, calculating term frequency–inverse document frequency (TF–IDF) to highlight significant words, determining word sequence probabilities, and ranking – steps that collectively enable a richer understanding of the text.
3) **Machine learning**. This is a broad classification for models that create insights from statistical generalization of data. Machine learning models learn by minimizing penalties or maximizing rewards, using functions, parameters, and weights. There are three main learning categories: supervised, unsupervised, and reinforcement. Supervised learning, the most common, trains models using labeled data (questions and answers), adjusting weights and parameters through backpropagation to improve accuracy. Weber (2023) indicated that supervised learning can employ algorithms and methods such as regression, decision tree, naïve Bayes, vector machines, and random forest. Unsupervised learning uses unlabeled data, aiming to find patterns and often simplifying data for supervised models. Some algorithms

and methods in this area are K-means, recommender system, and hierarchical clustering (Weber, 2023). Reinforcement learning assigns costs or rewards to actions, guiding the model toward desired outcomes. Algorithms in this area are Q-learning, temporal difference, and deep adversarial networks (Weber, 2023).

4) **Markov-related models**. There are two models in this category: Markov chains and Hidden Markov chains, which represent stochastic processes. If a stochastic variable has the Markov property (its current state fully determines its future state), it can be modeled as a Markov chain. Markov chains generate text by predicting the next word based on the highest probability derived from TF–IDF within a large training dataset. While statistically superior to grammar rule modeling and relatively fast, Markov chains require extensive training data and struggle to produce long, coherent texts on a single topic. Variations exist that improve accuracy through smoothing and increased data access. Hidden Markov models (HMMs) differ from regular Markov models by having hidden, nondeterministic states, allowing for more complexity and information derivation. While HMMs, especially when combined with word embedding technologies like Word2vec, offer improvements over traditional Markov models, they still share the limitation of requiring large datasets for optimal performance. Neural networks offer a potential advantage in achieving similar accuracy with smaller datasets.

5) **Neural networks**. They are comprised of interconnected nodes, or artificial neurons, organized in layers, where the first layer receiving the initial data is called input layer, then multiple layers of interconnected nodes (hidden layers) process further the data before passing to the output layer, which gives the result or prediction. Each node performs a simple mathematical operation on the input it receives and passes the result to the next layer. In more detail, when the node receives inputs from other nodes, each of these inputs is multiplied by a corresponding weight. These weighted inputs are then summed together, e.g., a weighted average. This is called Input Summation. Then a bias term, which is a constant value, is added to the sum. The value can shift the activation threshold of the node, e.g., an intercept in a linear equation. Finally, the sum (plus the bias) goes through an activation function, which introduces nonlinearity to learn complex patterns. Common activation functions are sigmoid, Tanh (hyperbolic tangent), Piecewise-Linear Functions (e.g., ReLU [Rectified Linear Unit]), and other functions such as softplus, elu and selu, and swish (Lederer, 2021; Sharma et al., 2017).

   The connections between nodes have weights that determine the strength of the signal. Neural networks learn by adjusting the weights of the connections between nodes. This is done through training with the data. This process is known as backpropagation.

- **Deep learning.** Neural networks with multiple hidden layers are called deep neural networks. Deep learning is at the core of AI.

  Chatbots and text generators are based on nonlinear programming–based neural networks. Speech recognition is another area where such neural networks are used. Amazon's Alexa uses long short-term memory.

Weber (2023) proposes a business analytics model for artificial intelligence (BAM. AI) based on the integration of three processes: knowledge discovery in a database (KDD), Cross-Industry Standard Process for Data Mining (CRISP-DM), and Analytics Solutions United Method for Data Mining/Predictive Analytics (ASUM-DM). It describes the model to implement BA and AI in two cycles: development, which is closely following CRISP-DM, and deployment, which involves aspects related to the implementation (use and exploitation) of the models/algorithms in real environments. Coveyduc and Anderson (2020) propose five steps to implement AI in an organization:

1) **Ideation**. This step involves understanding your motivation to implement AI, e.g., what problem is going to be addressed? with the objective to define a set of goals for the AI technology.
2) **Defining the project**. It entails identifying the improvements to be achieved with the AI technology through a clear plan of the project to implement it. You may use design thinking (Micheli et al., 2019) to support you in this step.
3) **Data curation and governance**. Data is the key component in any AI technology, as AI needs a lot of it to be trained. Data can come from multiple sources, so it needs to be curated and consolidated. Data quality has to be evaluated since its quality will determine the quality of the responses from AI.
4) **Prototyping**. It is suggested to start building an initial version of the AI system and improve iteratively through a set of use cases to validate how it works. The AI system will improve with more data and parameter adjustments over time. This improvement can be measured with specific metrics (Blagec et al., 2020; Naser and Alavi, 2023).
5) **Production**. After finalizing the prototype, the case for investing and fully implementing the AI technology is ready. It is useful to review the AI technology with respect to the motivations defined during the first step. There are some additional tasks to perform in this step. First, selecting the technologies appropriate for the full implementation, e.g., scaling up. Second, determining the user/security framework. Finally, testing frameworks must be built to ensure the quality of the programming code, especially when new code is added.

AI adoption is a gradual process, not an instant transformation, due to three key limitations. First, AI builds upon statistics and analytics knowledge, thus companies should use their existing analytical skills and resources as a base for AI adoption (Davenport, 2018). AI represents an evolution of analytics, a kind of "Analytics 4.0," emphasizing AI and cognitive technologies as the next step after previous phases of BI, big data, and embedded analytics (Davenport, 2018). Second, companies should incrementally expand their analytical applications into AI, focusing on areas like product/service enhancement and business process optimization, rather than directly replacing BA. AI can also be used to accelerate existing analytical capabilities such as programming or data analysis (Davenport, 2018). Third, a thorough assessment of company culture, data/technology infrastructure, and available talent is crucial before implementing AI (Davenport, 2018).

However, a critical aspect for AI is data. Data is crucial for modern AI solutions, driving ML's ability to create accurate models (Gil et al., 2020). Effective AI strategies start with data but require investment in data science to align AI models with business goals. Supervised learning, using labeled data, is particularly valuable for training AI models that can automate and improve business processes (e.g., insurance claims, customer churn). Even unlabeled data can be useful for tasks like document retrieval.

1.4.1 Integration of GenAI with BA

One of the limitations of BA adoption is the knowledge of the tools and methods underpinning the different tasks related to BA. On the other hand, it is dangerous to adopt AI without understanding the limitations and risks inherent in predictive models. Human-augmentation frameworks offer a potential solution by automating predictive analytics development, democratizing ML for nonexperts (Schmitt, 2023). Integrating BA with AI should allow an AI-augmented workforce to retain decision-making, rather than being complete replaced through automation. However, challenges persist in model conceptualization, data processing, and the shift from traditional "discriminative" predictive and prescriptive analytics (which classify data) to "generative" analytics (which model the data distribution to create new synthetic data) (Feuerriegel et al., 2024).

Generative AI (GenAI) and traditional, discriminative ML approach problem-solving differently (Salazar and Kunc, 2025). GenAI models aim to understand and replicate data distributions, generating new, statistically similar data, making them ideal for simulations like demand forecasting, financial stress testing, and creating synthetic datasets when real data is scarce or sensitive. Discriminative AI, conversely, focuses on predicting specific outcomes from given inputs, excelling at classification and regression tasks such as customer churn prediction and credit scoring.

AI offers several avenues for simplifying BA. Automatic machine learning (AutoML) frameworks automate predictive model development, addressing skill gaps by handling model selection and hyperparameter tuning (Schmitt, 2023). “Augmented analytics” (AA), as suggested by Alghamdi and Al-Baity (2022), uses ML, AI, NLP, and Natural Language Generation (NLG) to automate the entire analytics workflow, including conversational interfaces for voice queries, thereby accelerating data preparation, visualization, modeling, and insight generation. While AA streamlines the process, skilled analysts remain essential for determining the business relevance and value of insights. A third approach, “Human-AI ensembles” (Choudhary et al., 2023), involves combining human and AI decision-making to tackle problems where neither has a clear predictive advantage, such as candidate selection. In these ensembles, human and AI collaborate on the same task, with AI augmenting human decision-making or automating parts of the process. Table 1.7 provides a summary of the impact of AI on BA.

A key concern with AA compared to traditional BA, which relies on static rules and human-controlled stable models, is AI’s capacity for autonomous learning, adaptation, and action, potentially leading to stochastic outputs (Pathirannehelage et al., 2024). This shift introduces changes in autonomy, responsibility, and accountability within organizational decision-making. Furthermore, challenges persist in transitioning from ML-driven predictive analytics to prescriptive analytics, which depends on optimization and simulation models.

Several factors influence AI integration in BA. Poor data governance and quality can feed inaccurate data to AI, creating technology and security risks if analysts are excluded (Rana et al., 2022). Flawed AI decision-making can lead to operational inefficiencies, harming sales, morale, and competitiveness (Rana et al., 2022). Completely replacing analysts and modelers with AI can foster overreliance, impeding AI development and adaptation to changing business needs, and potentially creating dependence on external entities for critical functions. Just as ethics and governance are crucial for traditional BA (Vidgen et al., 2020), they become even more vital when AI enhances BA, particularly in automated decision-making. A well-governed BA environment is preferable to an uncontrolled AI-driven one.

Some additional challenges for applying generative AI and large language models (LLMs) to BA applications, as suggested in Salazar and Kunc (2025) are:

- Despite their broad general knowledge, LLMs often lack a deep understanding of specialized business and financial concepts. Their grasp of industry-specific terminology and their ability to apply this knowledge to intricate analytical reasoning is limited. While fine-tuning with relevant data can offer some improvement, it doesn’t completely overcome the difficulties posed by more complex analytical tasks.

Table 1.7 A comparison between business analytics – and artificial intelligence–enabled analytics.

Concept	Data understanding and preparation	Data exploration and visualization (descriptive analytics)	Modelling (predictive and prescriptive analytics)
Discriminative business analytics	Data preparation, including quality checks, relies heavily on manual effort with limited automation for data transformation.	Relationship and pattern exploration, along with visual dashboard creation, is also a manual process driven by analyst interpretation.	Model development and fine-tuning, including cross-validation through training and evaluation, are performed manually to achieve optimal model fit.
Generative augmented analytics	Data profiling is automated, with algorithms suggesting data enrichment, performing quality checks (identifying outliers and correlations), and highlighting key attributes for analysis.	AI recommends visualizations based on data profiles, and users can leverage conversational interfaces to request insights, which are then presented in narrative form, automating the storytelling process.	Variable selection and feature selection are automated based on contribution, followed by automated cross-validation.

Source: Adapted from Salazar and Kunc (2025).

- LLMs typically struggle with tasks involving numbers, including mathematical calculations, quantitative reasoning, and extracting meaningful, data-driven insights from unstructured information. Even after targeted training, their performance on complex numerical problems remains constrained.
- Real-world application of LLMs in BA necessitates their integration with existing data infrastructure, BI tools, and dashboards. This integration presents technical hurdles related to data management, the art of crafting effective prompts (prompt engineering), interpreting the output from LLMs, and incorporating human feedback into the process.
- LLMs can generate outputs that sound authoritative but may contain factual inaccuracies, posing a considerable risk, especially when informing critical business decisions. Consequently, rigorous fact-checking and consistent human oversight remain indispensable.
- Employing LLMs for sophisticated, in-depth analytical tasks requires substantial computational resources. Scaling these models to effectively process enterprise-level workloads while maintaining acceptable costs and response times presents a significant challenge.
- Given that BA models frequently handle sensitive information, utilizing external LLM APIs introduces security and privacy vulnerabilities. It is crucial to develop methods that allow leveraging the capabilities of LLMs without compromising confidential data.
- In sectors with strict regulations, AI-driven decisions must be transparent and explainable, with comprehensive audit trails. However, the inherent "black box" nature of LLMs makes it challenging to understand their reasoning processes, thereby hindering compliance with these explainability mandates.
- General-purpose LLMs require significant customization to align with the unique vocabulary, key performance indicators, metrics, and decision-making frameworks of individual businesses. Tailoring these models to meet specific organizational needs is a complex undertaking that demands considerable domain-specific expertise.

1.4.2 Implications of AI Adoption in Business Decision-making Processes

As explained previously, AI can be employed for automation and/or augmentation. While automation implies replacing human work, e.g., repetitive tasks such as data entry, report generation, and customer service responses, augmentation enhances decision-maker capabilities providing insights that can aid decision-making, e.g., analysis of large datasets to identify patterns and trends in data.

The adoption of GenAI in decision-making will be strongly determined by type of process, context, and enablers, e.g., existence of large datasets and structure, determining its use for automation and/or augmentation (Salazar and Kunc, 2025). Once AI is adopted and replaces human work, the inherent capabilities related to this type of work will be lost, which can be dangerous to evaluate the AI performance and generate overreliance on AI. Therefore, potential long-term impacts will be heterogeneous across business processes, professions, and companies, but more importantly there can be a potential decrease in resilience when specific long-term capabilities residing in humans are lost (Salazar and Kunc, 2025).

Keding (2021) found in a systematic review of the literature a set of impacts from AI on decision-making:

- **Managerial cognition.** AI can help to reduce data overload as the amount of information increases together with volatility, uncertainty, and complexity, as well as improve individual performance by providing adequate data relevant to decision-making. Additionally, AI can lead to consistency in decision-making and fairness, which may enhance legitimacy for decisions. However, AI has a set of limitations: the positive impacts are context specific; AI may not account for moral principles, organizational values, and ethical standards; and decisions may be influenced by biases existing in the data.
- **Complementary skills.** AI can facilitate the focus on decisions that are more judgmental and intuitive, e.g., creating the big picture of a strategic problem. AI can enhance significantly tasks such as predictions and other tasks that are objective and codifiable.
- **New decision-making governance mechanisms.** Since AI will facilitate the implementation of analytics-based decision-making, it may require a culture that accepts evidence-based decisions. Another possibility is the decentralization of strategic planning and strategic decision-making through the use of AI by managers outside the top management team. Therefore, there is a need to define accountabilities and responsibilities of managers in terms of fiduciary, legal, and ethical issues from automation of decisions.
- **Agility and participation in strategy development.** Given AI can integrate more organizational knowledge into the strategy development process, it may reduce political friction between participants in the process and increase organizational buy-in.
- **Predictive logic in business models.** The use of AI can influence the generation of data-driven businesses, or adaptation of existing business to the digital world, by understanding and predicting changes in customers and the environment.

1.5 What Is Strategic Management?

There is not a unique definition of strategic management but a series of propositions on the range of the process involved in developing strategies. For example, McGee et al. (2010) suggest strategy can be decomposed into four components: external logic (how a company positions relate to its environment); internal logic (the resources and competences to employ to implement the strategy); the performance over time (the achievement of long-term objectives and survival); and the managerial requirements (the role of general managers and the process of strategic management, which involves planning, managing, monitoring, and maintenance of strategies). McGee et al. (2010) also explain the nature of strategy: strategy deals with the future which is uncertain, so strategy involves risks that need to be considered in the plans and actions. However, the plans and actions for implementing the strategy are not simple since there are multiple interacting components (external, internal, and managerial), which require coordination. Another factor compounding the risk is that plans and actions are irreversible because once a strategy is implemented it changes many external and internal aspects that make it difficult to go back.

Designing and implementing strategy, the realm of strategic management, requires frameworks and tools to address the uncertainty, complexity, and risk underpinning it (Pfeffer and Sutton, 2006). Essentially, a strategy framework is a conceptual representation, or a model, that managers can use to design strategies with a clear description of the logic and sources used (Pfeffer and Sutton, 2006). In other words, there are strong indications (e.g., complexity, uncertainty, risk, future orientation, limited ability to process the problem, evidence requirements, and existence of models) that strategies can be designed and shaped using management science tools. Management science tools work best as part of strategic management frameworks.

In the framework proposed in this book, four components comprise the strategic management process (Figure 1.4). The process starts with a definition/understanding of the business in terms of mission and vision of the business followed by an understanding of the external forces affecting the firm today and in the future (macro factors: political, economic, social, technological, environmental; industry factors: industry structure dynamics and its evolution) as well as a review of the resources and capabilities of the firm in terms of its competitive positioning (products, services, value creation, business model). The results of the previous stage are the basis for designing the strategy in terms of positioning and the conceptualization of the resources and capabilities to sustain it. The design of the strategies involves a creative conceptualization of the resources and capabilities needed for the new strategies (Kunc and Morecroft, 2010). Strategies will be affected by not only the resources and capabilities available to managers but also

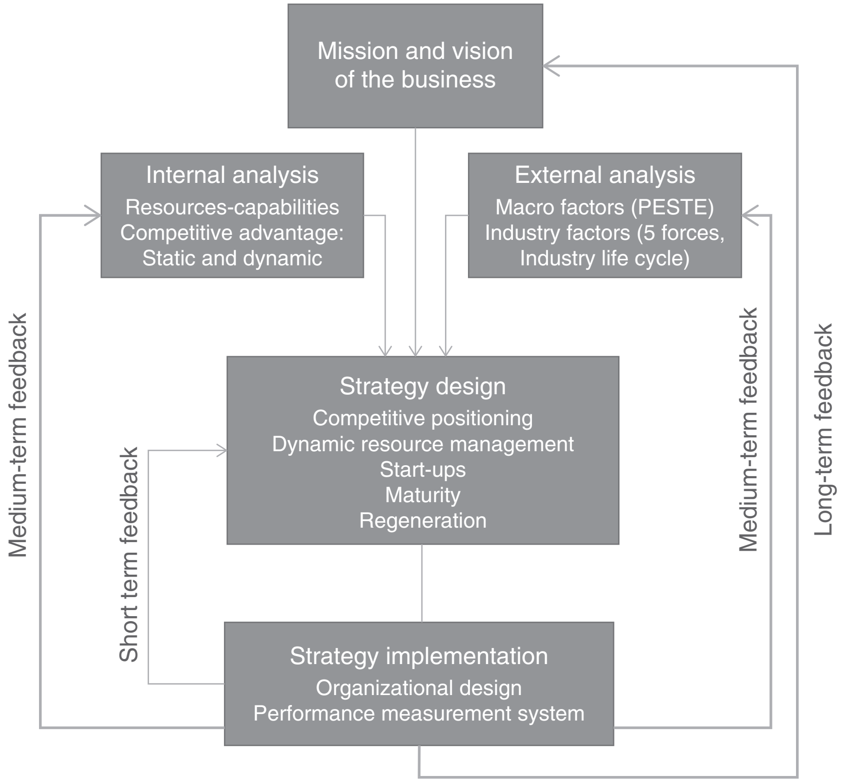

Figure 1.4 Strategic management process.

the life cycle of the organization. For example, some strategies cannot be performed at the beginning of the company, e.g., merger and acquisition, and other strategies, e.g., diversification, result from the need for growth occurring when the company reaches maturity. After reaching an agreement in the top management team about the future strategies, their implementation involves managing (reinforcing, building, acquiring, and reorganizing) resources and capabilities to adapt them to the new or updated competitive positioning. Resource management is an inherently complex task because resources and capabilities interact forming a complex dynamic system where feedback processes, delays, and external factors affect their dynamic (Kunc and Morecroft, 2009; Kunc & Morecroft, 2007). Consequently, any implementation plans need to consider the future implications in terms of business as usual (base case), potential different external environments (scenarios), and expected contingencies (situations that may eventually happen). Finally, the implementation over time is monitored using performance measurement systems (IT systems, big data, and dashboards), which foster organizational learning and adaptation of the organization to emergent situations (e.g., applying descriptive and predictive analytics). The feedback from strategy can be monitored in the short term leading to modifying the management of resources or correcting minor erroneous strategy designs, e.g., data from a customer satisfaction survey indicates that certain product features need to be modified or the product has to be delivered through new distribution channels. However, if the lessons learned involve discovering new external factors, they will need to be tracked over time to observe the relevant trends before making adjustments to the strategy design. Similarly, if lessons from strategy monitoring reflect a change in the qualitative aspects of resources/capabilities, e.g., loss of their uniqueness due to competitors' imitating them, then the strategy needs to be redesigned. Both processes take a longer time to develop than operational issues due to changes in the commitments from the organization. Finally, feedback from strategy monitoring can imply a more substantial change in the organization such as changing the mission, updating its vision and refocusing the business model. Table 1.8 presents a detailed account of the components of the strategic management framework.

1.5.1 What Are the Characteristics of Strategic Problems?

Strategic problems, which are at the core of the process of strategic management, have certain characteristics that make them more difficult to solve than *operational problems*. Operational problems are issues generated from daily routine decisions. For example, the development of a new brand will be considered a strategic problem but the definition of the advertising campaign to support the brand is usually an operational problem. The characteristics of problems are (Dyson et al., 2007):

- *Breadth of scope* suggests the existence of implications in and outside of the organization involving multiple stakeholders: owners (individual and institutional shareholders), external (customers, suppliers, local communities, governmental agencies, general society), and internal (employees and managers) with multiple, imprecise, and conflicting objectives.
- *Complexity and interrelatedness* of decision-making context where the interactions between many factors require important coordination in the present and future.
- *Enduring effects*, possibly of an irreversible nature with a *high level of risk* since it involves committing potentially inflexible resources against expected futures that might never materialize affecting the organization's prosperity and survival.
- *Significant time lag* before impact, with widening uncertainty over the timescale involved, which may generate agency problems such as making no decision or leaving the outcome to chance.

Table 1.8 Description of the strategic management process components.

Step	Brief description	Chapter
Mission and vision	The first task in the strategic management process is setting and visualizing the direction of the organization. Even small organizations, which are run by the owners, require a sense of direction that will reflect the intent of the owners. Where is the intent of the owners or top managers coming from? Paradigms, experiences, and facts define owners' mental models, which are personal explanations about how the real world works. Mental models are responsible for the interpretation of the key external factors affecting current and future performance of the organization and the key internal factors that are at the core of the performance of organization. On the one hand, the mission defines the core purpose of the organization defined by the perception of the key internal factors and the values shared in the organization. On the other hand, the future of the organization using its core purpose in the future is expressed in the vision.	Chapter 6 for competitive advantage: static analysis
External analysis	The external environment can affect the organization's actions as well as its performance. Consequently, it is fundamental to consider the external environment in the strategic management process. The external environment can be divided into three parts according to the closeness to the organization: rivalry with existing organizations (closest); industry dynamics defined by the suppliers, potential entrants, substitutes, and customers (mid-range); and the remote environment comprised by the political, economic, social, technological, and environmental factors that determine the two closest layers to the organization. Another important component of the external analysis is the industry life cycle. Industry life cycle can affect any organization, not only for-profit. The life cycle is driven by the usefulness of the industry, or group of similar organizations, for the consumers or users of their services. Industries proceed through four stages (introduction/birth, growth, maturity, and decline), which reflect the rate of growth of sales. The introduction stage is driven by the process of changing buyers' behaviors to adopt the new product/service. Sometimes, this stage takes decades. Growth occurs when a large number of buyers change their behavior and adopt the product/service massively surpassing the capacity of the existing organizations to serve them. This situation leads to the entrance of more organizations trying to capture part of this demand. Maturity corresponds to the saturation of the market and growth rate declines toward zero, i.e., when all potential buyers have adopted the product sales are driven by replacements or natural growth rate (ageing). Finally, a new product/service attracts the current buyers and sales will decline determining the disappearance of the industry in its current form. Organizations either regenerate or liquidate.	Chapter 3 for exogenous factors (PESTE) Chapter 4 for industry dynamics (5 forces) Chapter 5 for industry evolution (industry life cycle)

Internal analysis	Competitive advantage is at the heart of any organization's performance, from micro business to large corporations through nongovernmental organizations. Competitive advantage involves creating value for its buyers differently than competing organizations. Creating value depends on the strengths and weaknesses of the organization without following strategic recipes. Managers can use tools to analyze an organization's capacity to generate value for buyers before designing the strategy.	Chapter 6 for competitive advantage: static analysis
	Traditional concepts are complemented with management science tools, e.g., dynamic simulation, to support the process of competitive positioning over time. For example, business-level strategies like Porter's generic strategies are evaluated over time as part of a competitive environment.	Chapter 7 for dynamic resource management (dynamic resource-based view of the firm)
Strategy design	Starting a new business is performed by many people but managing a successful start-up is a formidable challenge, especially for those who lack prior business ownership, management skills, and experience. Thus, this chapter offers an introduction to the concepts of business model, business plan, and financial needs that play an important role in the beginning of a business.	Chapter 10 for start-ups
	The set of strategies that companies tend to adopt when they are reaching maturity are driven by, on the one hand, long-term objectives such as economic sustainability; productivity, sustaining competitive position, stance in the value system, product/service positioning, and social responsibility. On the other hand, markets are becoming saturated by competitors and running out of new customers. Thus, strategies to address competition, find new markets, and improve efficiency are fundamental for surviving.	Chapter 11 for maturity
	Two responses can develop when organizations face a decline in their markets. These responses are important because they can determine the fate of an organization – survival or death. First, innovate and change to offer different products/services. Second, they can respond rigidly and fall into organizational decline through a downward spiral. What conditions are needed for each situation to emerge? What signals develop to understand the decline process? Developing a strategic framework for regeneration depends on distinguishing between flexible and inflexible organizations.	Chapter 12 for regeneration
Strategy implementation	Strategy can be affected by the behavior of multiple stakeholders. Thus, strategy implementation is not only a top-down process originated from the top management team but it also occurs bottom-up when stakeholders and employees make decisions every day. The effectiveness of the implementation of strategies resides in the way that the organization is designed and organized. Organization design implies building the foundations of purpose and core values, policies and structures that determine business decisions and effective learning processes. Therefore, strategy implementation is how to design and improve business processes and organizational structure to achieve the goals and objectives.	Chapter 8 for organizational design
	The process of defining organizational performance together with the goals and control systems is fundamental to achieve the desired organizational performance. Defining organizational performance is key because managers measure what they value and what they measure affects their behavior significantly. Moreover, this is a key process that defines the data available for the organization that can be exploited through analytics to feed back to the top management.	Chapter 9 for performance measurement system

- *Disagreement* about the motivation for, and the direction and nature of the strategic problem since strategic problems have *no obvious right answers* because of the many uncertainties surrounding their future impacts.
- *Challenging the status quo* and creating a politicized setting where change is contested and the *coordination of a large number of people is complex* and difficult due to the significant scale and importance of the strategic decision to solve the problem.

Consequently, the approach to addressing strategic problems can be influenced by multiple aspects such as the organizational structure, culture, and actors involved. The next section presents a summary of the different approaches existing in strategic management.

1.5.2 Different Approaches to Strategic Management

Mintzberg et al.'s (2008) "Strategy Safari" offers a comprehensive overview of strategic management by categorizing it into 10 distinct schools. These schools broadly fall into prescriptive and descriptive approaches. The first three prescriptive schools focus on developing strategies through formal analysis and planning, progressing from unique designs to specific market positions. The subsequent six descriptive schools examine how strategies emerge. Within these, the initial three describe the role of individual strategists, ranging from visionary leaders to cognitive microanalysis of individual decision-makers. The next three explore external influences: culture, power dynamics, and the environment. The power school views strategy as a negotiation, while the cultural school highlights culture's impact. The Configuration School integrates these perspectives, considering process, content, structure, and context like organizational lifecycle stages.

Each aspect of strategy's process and content has potential advantages and disadvantages. For instance, while a defined strategic direction provides focus, it can also create blind spots to emerging opportunities or threats. Key strategic considerations include the interplay of internal (organization) and external (environment) factors; the inherent complexity arising from numerous possible combinations; its impact on the organization's future; its dual nature, encompassing both output (content) and creation (process); its potential to be deliberate or emergent; and its combination of conceptual and analytical activities.

Table 1.9 categorizes strategic management into 10 distinct schools, each with a unique perspective on how strategies are formed and what influences them. These schools can be understood by examining several key concepts: their core summary, the strategy development process they emphasize, and the key actors responsible for shaping the strategy.

The table highlights a spectrum of approaches. The Design, Planning, and Positioning Schools lean toward more deliberate and analytical processes. The Design School emphasizes achieving a fit between internal capabilities and external opportunities, with the CEO as the architect. The Planning School advocates for a structured, formal process driven by planning staff, resulting in incremental change through detailed plans. The Positioning School also takes an analytical stance, focusing on market analysis to define strategic positions, with analysts playing a key role in identifying these positions.

In contrast, the Entrepreneurial, Cognitive, and Learning Schools focus more on the mental and emergent aspects of strategy making. The Entrepreneurial School sees strategy as the visionary output of a dominant leader, leading to potentially revolutionary change. The Cognitive School emphasizes the mental models and interpretations of leaders, resulting in often emergent strategies. The Learning School views strategy as an evolving pattern of actions driven by collective learning and incremental adjustments throughout the organization.

The Power, Cultural, and Environmental Schools highlight the influence of external dynamics. The Power School frames strategy as a negotiation among various power players within the organization, leading to often messy and emergent outcomes. The Cultural School emphasizes the role of shared values and beliefs in shaping strategy, resulting in infrequent but potentially significant changes driven by collective ideology. The Environmental School posits that strategy is primarily a reactive adaptation to external pressures, with the degree of change depending on the dynamism of the environment.

In terms of the strategy development process, the table reveals a range from planned and deliberate (Design, Planning, Positioning) to more informal, emergent, and even messy processes (Entrepreneurial, Cognitive, Learning, Power). The outcomes of these processes also vary, from formal plans to patterns of behavior and shared perspectives. The key actors involved range from a dominant CEO or planning staff to analysts, entrepreneurial leaders, and even everyone within the organization in the case of the Learning School.

The underlying conceptualization of the organization and its environment also differs across the schools. More analytical approaches tend to favor stable and ordered organizations operating in understandable environments, while more emergent approaches acknowledge complexity and dynamism. The organizational lifecycle can also influence the relevance and applicability of different schools.

In essence, Table 1.9 illustrates the diverse and sometimes conflicting perspectives on how strategies are made, ranging from rational, top-down approaches to more organic, bottom-up, and externally influenced processes. Understanding these different schools provides a richer appreciation for the complexities of strategic management. Additionally, the 10 schools of strategic management have

Table 1.9 Summary of the strategy schools.

Concept	Design	Planning	Positioning	Entrepreneurial
Summary	Strategy is about aligning an organization's internal strengths and weaknesses with external opportunities and threats.	Strategy is a highly structured, formal process, often with a strong quantitative focus using budgets and numerical scenarios.	Strategy is an analytical process that examines competitive landscapes, leading to generic strategies and the development of strategic initiatives.	Strategy stems from the leader's vision and insights, driving bold actions.
Strategy development process	Strategy development follows a planned approach, seeking unique, informal, and straightforward strategies, with occasional adjustments.	Strategy development involves detailed plans, breaking down overall strategies into smaller sub-strategies and programs. It's a formal, deliberate process leading to gradual, incremental change.	Driven by economic analysis, this process aims for planned market positions supported by deliberate competitive actions. Strategies result in piecemeal, frequent adjustments.	This process centers on creating a unique, personal vision for a specific market niche. Strategies are typically visionary, intuitive, and emergent, with change being opportunistic and revolutionary.
Key actors responsible for the development of the strategy	The Chief Executive Officer (CEO) is the primary strategist, acting as the architect of the organization, taking a dominant and decisive role.	Corporate planning staff, the planners, are the key actors, developing procedures that managers follow to formulate strategies.	Analysts play the main role, generating the portfolio of market positions, with managers responding to their analysis.	The entrepreneurial leader is the sole actor, holding a dominant position and driven by intuition.

Source: Aadapted from Kunc (2024), Table 1.

	Cognitive	Learning	Power	Cultural	Environmental
	Strategy resides in the minds of leaders, shaped by their perceptions, interpretations, bounded rationality, and cognitive styles.	Strategy develops through learning, incremental adjustments, and emergent actions, combining sense-making, entrepreneurial spirit, and venturing.	Strategy is a process of negotiation, conflict, and competition, involving managing coalitions, stakeholders, and political dynamics.	Strategy is shaped by shared values, beliefs, myths, culture, ideology, and symbolism.	Strategy is a response to the external environment, ranging from coping and adapting to evolving or even disappearing if conditions are unfavorable.
	Strategy development focuses on the top management team's micro-behaviors and mental perspectives. The interaction of these perspectives generates mostly emergent strategies, with change being variable.	The process is informal, emergent, messy, and continuous. The main outcomes are strategies as patterns of unique actions. Change is mostly incremental.	Strategy development is a political process, leading to patterns of cooperative and/or competitive actions. Outcomes are often messy and emergent, resulting in frequent changes.	Strategy development involves collective, unique, and ideological perspectives. Resulting strategies are shaped by the collective ideology, with infrequent changes.	Strategy development involves identifying and adapting to specific market/industry positions. Strategies can range from no change to radical change, depending on the environment.
	Leaders, either individually or in teams, are the key actors, with their cognition playing the central role.	Everyone in the organization can contribute to strategy development as part of the learning process.	Anyone with power within the organization can be a key factor in strategy development.	While strategy development is a collective effort, symbolic leaders may guide the process.	There are no specific actors, but those involved in environmental analysis play the most significant roles.

important implications for the implementation and use of BA and AI to support strategic management processes, as described in Table 1.8. Consequently, you have to evaluate carefully the context of the strategic management processes before proceeding with the use of BA and AI.

1.6 Strategy Analytics: Integrating Management Science and AI with Strategic Management

The strategic problems can be exacerbated when there is not only dynamic complexity due to existence of feedback processes between the components of the system (organizational and external factors) but also complex behavior in the decision-makers, such as personal aspirations, mental models, and values (Roth and Senge, 1996). Large multi-business organizations are examples of high dynamic complexity. Under high dynamic complexity, causes of problems cannot readily be determined by direct experience, and actors in the system don't have a deep understanding of the causes of problems. Dynamic complexity requires high-level conceptual and systems thinking skills (Roth and Senge, 1996), which is the management science style described at the top level of the hexagon in Figure 1.2. High behavioral complexity exists under conditions of profound conflict in assumptions, beliefs, and perspectives. Consequently, it is difficult to get people to agree on what should be done because they see the world differently and because they have different preferences and goals (Roth and Senge, 1996). Behavioral complexity requires high levels of interpersonal and facilitative skills (Roth and Senge, 1996), which is the management science style described at the bottom level of the hexagon in Figure 1.2. Table 1.10 shows the results of the combination of both dimensions.

Table 1.11 shows a brief explanation of the impact of the issues in terms of formulation and solutions developed using management science tools. Williams (2008) suggests puzzles are fairly easy to tackle since there is no ambiguity in the

Table 1.10 Complexity facing strategy analytics practitioners.

Dynamic complexity			
		Low	**High**
Behavioral complexity	**Low**	Puzzles	Messes
	High	Wicked problems	Wicked messes

Source: Roth and Senge (1996)/Emerald Group Publishing Ltd.

Table 1.11 Relationship between the problems faced in the strategic management process and the management science modeling process.

		Puzzles	Problems	Messes
Management science modeling process	Formulation	No ambiguity on the formulation about what needs to be solved, issues and options are clear.	The definition of the problem is rather clear and agreed.	There is a lot of ambiguity, no agreement about the issues, concept relationships or what is the situation.
	Solutions	There is a correct answer which requires logical thought even though the answer may not be easy.	There is a variety of approaches to solve it, so the problem has no single answer that is known to be correct.	Unclear formulation implies lack of clarity in the approaches or even if there is a solution at all.
Strategic management process		External factor analysis.	Strategy implementation.	Strategy design.

formulation of the model (either qualitative or quantitative) and there is an expected answer in terms of the outputs. Problems can be defined but there are multiple models that can be employed and none of them are exclusive. Finally, messes involve the most difficult situations since there is no agreement about the issue (so there is no clear formulation) or the solution, as there can be many potential valid outputs.

There will always be important questions related to the effectiveness of management science practices, the role of IT functions, and how big data analytics is different from traditional analytical frameworks and methods employed in strategic management. Management science practices provide substantive rationality (Simon, 1976) because they force strategists to be methodical and precise in their strategies. Big data analytics offers a platform for organizational learning, which depends on ongoing sensemaking activities. A key question about the use of big data in strategic management is how to relate backward-looking sensemaking from big data that has been accumulated over time to the development of future sensemaking associated with strategic management. Calvard (2016: page 70) suggests "big data is often used in the traditional retrospective sensemaking mode to consolidate and enact a partially existing reality identified by the data." Consequently, there is a need to complement backward-looking analysis with forward-looking foresight. This need can only be satisfied with the use of management science tools such as qualitative methods to structure problems, simulation, or optimization, together with strategic management tools.

Considering the relationship BA can have with respect to strategic management, there are four possible situations suggested by Laursen and Thorlund (2010); these are illustrated in Table 1.12.

Applying the lessons learned from the previous section, this book suggests that the evolution of Strategy Analytics in the era of AI will imply fundamental changes in approaches to decision-making, role of managers, and organizational configurations such as:

- Analytics-enabled or -augmented by AI will become ubiquitous and it will be able to support and replace, depending on the context, human managerial decision-making.
- Strategic management will have a holistic perspective to manage dynamic and behavioral complexity supported by the use of analytics and AI developing human–AI ensembles.
- Organizational configurations can become fragmented and horizontal as decentralized decision-making empowers all levels in the organization.

The changes will depend on the contextual factors discussed in Table 1.9 with organizations employing more prescriptive processes or fully digital becoming early adopters.

Table 1.12 Four situations between strategy and business analytics and AI.

Relationship	Consequence	Explanation
Strategic management is dissociated from the use of analytics/AI.	Analytics (management science) and AI are used on an ad hoc basis.	Companies do not have a clear strategy related to data management and information systems, so data is not used for strategic decision-making. Analysis is driven by erratic users' requests of information and quantitative models and business analytics is assessed by the speed on answering the request. AI is employed to perform queries on general topics without specific methods. Most of the issues are perceived on extremes: messes (highly complex) or without complexity.
Strategic management defines the use of analytics/AI.	Analytics (management science) and AI support monitoring strategy performance.	Analytics is mostly employed for monitoring the achievement of strategic objectives but there is no feedback from analytics to strategic management. Analysis has a reactive purpose providing reports, or quantitative models, for functional areas or individual departments to support the achievement of strategic objectives. AI is implemented in limited areas of the organization to assess operational issues providing early warning information. Issues are considered as problems that can be tackled only in the implementation, especially related to dynamic complexity.
Strategic management maintains a dialogue with analytics/AI.	Analytics (management science) and AI support strategy innovation by offering insights from data as well as testing the robustness of strategic ideas.	Strategic management employs analytics to improve the learning process about the performance of the business. Analysis not only reports the achievement of the objectives but also uncovers the reasons for the current performance. Analytics practice is based on strong management science competencies and technological resources to support the dialogue. AI is managed by a competent team that addresses new requirements from involved and informed users, who embed AI into their processes as an additional team member, e.g., augmented analytics. Information is used to adapt and optimize strategy. Issues are puzzles and problems with relative complexity.
Strategic management has a holistic perspective.	Analytics (management science) and AI is used as a strategic resource.	Information and analysis are considered strategic resources. Analytics and AI are responsible for analyzing and identifying opportunities and threats in the market and issues in the firm. Strategic management uses information systematically to develop strategies. The strength of Analytics and AI resides in people's competencies related to strategic development processes. People have both skills and knowledge of strategy and analytics in all organizational levels. AI is employed to drive augmented analytics or human–AI ensembles. All types of issues are considered, especially in terms of complexity.

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