# CHROMA Model for the Information-Driven Decision-Making Process

Xileidys Parra

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# CHROMA MODEL FOR THE INFORMATION-DRIVEN DECISION-MAKING PROCESS

by

**Xileidys Parra**

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Director: **Prof. Dr. Xavier Tort-Martorell**

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*A mis padres, mis pilares... Por su amor, esfuerzo, ejemplo y orientación, que me enseñaron a siempre luchar por alcanzar mis sueños. Muy especialmente a la memoria de mi papito lindo Cristo Antonio Parra, porque desde donde te encuentres sé que estarás inmensamente feliz de verme alcanzar esta meta, te amo y siempre te amaré, gracias por todo y por tanto.*

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*Xileidys Parra*
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# ABSTRACT

The strong, progressive interaction between decision-making processes (DMP) and information technologies has led to breakthroughs in how business is conducted. These developments represent the advent of significant trends for data-driven DMP in terms of increased competitive advantages and business opportunities. However, there is still a gap between technological capabilities and organizational needs due to the fact that the adoption of technology solutions in many companies is faster than their capacity to adapt at the managerial level. Balancing this situation implies a process of self-recognition in which aspects that need to be addressed for the application of better analytical practices must be highlighted. Such evaluation is necessary to embrace more rigorously the use of data and analytics insights within organizations attempting to become information-driven companies. This thesis presents an evaluation methodology that is based on the foundations of maturity models and provides a framework for assessing and ranking the level of organizations' proficiency regarding their information-driven DMP. In this vein, the "Circumplex Hierarchical Representation of Organization Maturity Assessment" (CHROMA) model and its variant, "Simplified Holistic Approach to DMP Evaluation" (SHADE), which is applied to small and medium-sized enterprises (SMEs), provide a novel and holistic approach that embraces the most relevant aspects at the technological and management level to make more objective and better supported decisions. In this respect, the key factors that influence making better-informed decisions are grouped into 5 dimensions: data availability, data quality, data analysis & insights, information use, and decision-making. Both the CHROMA model with its $5 \times 5 \times 5$ structure (5 dimensions subdivided into 5 attributes, each classifiable into 5 proficiency levels) and its SHADE variant with a $5 \times 3 \times 5$ structure, were conceived to be applied in an organized and systematic way in accordance with this structure in order to characterize the organization's use of information in DMPs from an uninitiated stage to a completely embedded one. In this sense, its application consists of a methodology that involves interviewing key company personnel plus a brief web questionnaire, and the subsequent evaluation of the dimensions and attributes of the model. Both models were tested in a field study campaign in six family-run SMEs, which were deployed in two blocks. In the first block, three SMEs were analyzed through the application of the CHROMA model. In the second block, the SHADE version of the CHROMA model was applied to the other three SMEs that collaborated with the study. This field study campaign was very significant in terms of reaching a deeper understanding of the extent to which organizations are supporting their decisions with information obtained from data analysis and their willingness to improve accordingly. The findings indicate that, overall, data quality problems are the biggest challenge facing organizations. Moreover, data analysis remains limited, reactive and timid, is mainly focused on senior management and middle managers, and is very scarce at operational levels. Despite this, the findings in the "decision-making" dimension demonstrate that these organizations have, to some extent, been able to leverage their available data to support their decisions. These results confirm that both models are useful for collecting relevant and firsthand information through a close and personalized treatment to consequently identify strengths and weaknesses of specific aspects, thus providing a broader view that leads companies to prioritize improvement actions that could have a meaningful impact on the success and growth of the organization.

# RESUMEN

La fuerte y progresiva interacción existente entre el proceso de toma de decisiones (DMP) y las tecnologías de información (IT) ha conllevado a un gran avance que ha repercutido en la forma en que los negocios son conducidos. Estos avances han representado el advenimiento de tendencias significativas para el DMP impulsado por datos en términos de mayores ventajas competitivas y oportunidades de negocio. Sin embargo, existe aún una brecha entre las capacidades tecnológicas y las necesidades de la organización debido a que la adopción de soluciones tecnológicas conducidas por datos en muchas compañías es más rápida que su capacidad de adaptarse a nivel gerencial. Equilibrar este desbalance implica un proceso de auto-reconocimiento donde sean resaltados los aspectos que requieren ser atendidos para la aplicación de mejores prácticas analíticas. Tal evaluación es necesaria dentro de las organizaciones que intentan dar un uso más riguroso a sus datos y conocimientos analíticos para convertirse en compañías impulsadas por información. Esta tesis presenta una metodología de evaluación que basada en los fundamentos de los modelos de madurez proporciona un marco para evaluar y categorizar el nivel de competencia de las organizaciones en el DMP impulsado por información. En tal sentido, el modelo "Circumplex Hierarchical Representation of Organization Maturity Assessment" (CHROMA) y su variante "Simplified Holistic Approach to DMP Evaluation" (SHADE) para pequeñas y medianas empresas, ofrecen un enfoque novedoso y holístico que abarca los aspectos más relevantes a nivel tecnológico y de gestión para tomar decisiones más objetivas y mejor soportadas, en orden de hacer frente a esta situación. Al respecto, estos factores que influyen en la toma de decisiones mejor informada son agrupados en 5 dimensiones: disponibilidad de datos, calidad de datos, análisis de datos e insights, uso de la información y toma de decisiones. Tanto el modelo CHROMA con su estructura $5 \times 5 \times 5$ (5 dimensiones subdivididas en 5 atributos clasificables en 5 niveles de aptitud) como su variante SHADE de estructura $5 \times 3 \times 5$, fueron concebidos para ser aplicados de una forma estructurada y sistemática en concordancia con dicha estructura, en orden de caracterizar el uso de la información en el DMP de la organización desde una etapa no iniciada a una completamente embebida. En este orden de ideas, su aplicación consiste de una metodología que involucra realizar entrevistas a personal clave de la compañía más un breve cuestionario web, y la posterior evaluación de las dimensiones y atributos del modelo. Ambos modelos fueron probados en una campaña de estudios de campo en seis empresas familiares pymes, los cuales fueron desplegados en dos bloques. En el primer bloque, fueron analizadas tres pymes a través de la aplicación del modelo CHROMA. En el segundo bloque, se procedió a aplicar el modelo SHADE de CHROMA a las otras tres pymes que colaboraron con el estudio. Esta campaña de estudios de campo resultó muy significativa en términos de alcanzar una comprensión más profunda del grado en el cual las organizaciones están tomando decisiones impulsadas en la información resultante del análisis de datos y su disposición a mejorar en consecuencia. Los hallazgos señalan que, en términos generales, los problemas de calidad de datos constituyen el mayor desafío al que se enfrentan las organizaciones. Asimismo, el análisis de datos continúa siendo limitado, reactivo y poco audaz, principalmente concentrado en la alta gerencia y mandos intermedios, siendo muy escaso a niveles operativos. A pesar de esto, los hallazgos en la dimensión "toma de decisiones" demuestran que estas organizaciones, en cierta medida, han logrado aprovechar sus datos disponibles para soportar sus decisiones. Los resultados confirman que ambos modelos son útiles para recolectar información relevante y de primera mano a través de un trato cercano y personalizado para consecuentemente identificar fortalezas y debilidades de aspectos específicos, proporcionando así una visión más amplia que conduzca a las compañías a priorizar acciones de mejora, que podrían significar el éxito y crecimiento de la organización.

# CONTENTS

# List of Figures

# 1

# INTRODUCTION

The decision-making process (DMP) can be defined as the set of activities successively carried out in a dynamic, articulated and scheduled way for choosing the best alternative within a set of possibilities under uncertain and risky conditions. In business, the DMP identifies actionable solutions to solve problems as well as plan, improve and redirect the company's performance and strategy.

The DMP combines different disciplines to achieve a practical approach to make good decisions and thus, to achieve better results for the organizations. The DMP has gradually emerged as a discipline in its own right. It has evolved as result of multiple contributions from and research by the academic and professional community. The results have provided a better understanding of how to use data and of individual and group behavior when making decisions. This understanding has led to the creation of models used for both improving the way companies make decisions and also to help further research by addressing the analysis of alternatives that lead to decision-making [1–6].

Accordingly, a proper DMP is necessary to ensure an organization's operability, profitability, and efficiency and is, therefore, a fundamental aspect of its managerial system. It is clear that an effective DMP has to be based on objective and reliable evidence. This evidence may come from internal or external sources. It can take many different forms and can be available as raw data or information depending on its degree of processing, depuration, and analysis [2, 3, 7].

In this sense, the omnipresence of information technologies allows organizations the possibility of processing enormous amounts of data of many types and generated at ever higher speed. Obviously this data, when properly used, can help managers make better decisions [8, 9] and has generated interest in management research and practice towards the paradigm of objective evidence, data science and information exploitation [10, 11]. Indeed, more recently, it has been shown that providing individuals with the correct information limits susceptibility to irrelevant anchors [12].

## 1.1. THE TRUTH BEHIND THE EMBRACEMENT OF BUSINESS ANALYTICS

The exploitation of data through analytics tools for descriptive, predictive and prescriptive applications related to decision-making is an increasingly successful practice that has led to a significant improvement in the performance of many companies worldwide [13, 14]. Such technologies have proven to be useful in marketing, the development of new products and services, the optimization of supply chains, fraud detection, and even in recruitment [5, 15], and the number of fields of application is increasing [16, 17]. In a recent survey conducted by Accenture and General Electric (GE), more than eight out of ten enterprises believe data analytics will change the competitive landscape of their industries [18, 19]. For instance, GE is deeply involved in the development of the application of analytics to industrial processes based on the Internet of Things [9, 20].

Despite this, many organizations claim they do not know what the key information is, where to find it and/or how to process their data to support the different types of decisions and processes involved.

This is especially critical in situations involving non-routine decisions, as they present a greater challenge for organizations who may not have the appropriate technology platforms and/or experience required to support decisions made under unusual conditions [2, 3, 21].

In line with the above, it is still often the case that organizations find themselves unable to fully understand how to use analytics to take advantage of their data [14, 22]. The experience of managers struggling with enormous amounts of data and sophisticated analytics is a frequent issue. In the same manner, the effort required to understand the data available and generate good quality data (accurate, timely, complete, accessible, reliable, consistent, relevant, and detailed) while improving data usefulness for decision-making is an unsolved challenge [8].

This problem has been addressed in previous research that identified different problems and barriers that hinder the effective use of an organization's data [4–6, 14, 22–26]. These studies agree that the main difficulty lies in addressing the situation holistically considering the inherent complexity of the problem.

However, a recent study has found a growing trend in the use of data and analytical insights for organizations' strategic purposes such as to innovate business functions or entire business models [27]. Companies at the forefront of those trends have been successful in the use of their analytical capabilities to address business problems with a broader mindset. In this regard, improving the organization's information-driven DMP has contributed to the expansion of their capabilities to innovate, identify business opportunities, improve performance and achieve greater competitive differentiation. Moreover, data and analytics insights can help in harnessing the organization's streamline internal processes and in creating novel experimentation mechanisms for continuous learning and feedback [16].

Nonetheless, it is important to remember that large companies are the ones predominantly reporting such success stories. This, to a certain extent, is because these corporations have specialist data scientists and the technology required for addressing the challenges in the improvement of their information-driven DMP.

Conversely, for SMEs and especially small, family-run companies, such resources might be inaccessible, making it unfeasible for them to embrace commercially available business analytics solutions. In 2012, the adoption rate of business and big data analytics among UK SMEs was only 0.2 per cent, compared to 25 per cent for businesses with over 1,000 employees [28]. During the next five years, the rate of growth of analytics technology adoption in SMEs is expected to be less than 50% [29], which considerably higher compared to large companies.

## 1.2. Analytical Challenges in Family-Owned SMEs

Under this landscape, in the particular case of family-run small/medium-sized enterprises (SMEs), it is more common to find that such companies are lagging behind in the adoption of tools and analytical applications to take advantage of the available data in order to make better decisions and be more competitive [28–30].

In this order of ideas, family businesses can be defined as those in which ownership of their social capital belongs wholly or partially to a family, allowing them to exercise significant control over decision-making, and in which the members belonging to successive generations participate actively in the management of different parts of the company in positions of direction or not, making it evident the desire to keep the continuity of company's control within the succession line [31]. These companies cover a wide range of sizes from very small to large global companies [32].

Family businesses are a cornerstone of prosperity and stability in both the global economy and society. Many large, well-known companies are family-owned and proud of it. These companies create jobs, invest in their communities and contribute greatly to society. The characteristics and practices of long-lived family businesses are a great example to be followed by other family businesses as well as by all companies that aspire to maintain an entrepreneurial spirit, innovate and grow consistently [30, 32–37].

In this sense, the impact that family companies have on the global economy is unquestionable. They represent more than two-thirds of all businesses around the world, representing between 70 and 95% of all business entities and 50%-80% of employment in most countries. Moreover, these companies are responsible for generating more than 70% of global GDP annually [32–34].

Particularly in Spain, they represent at least "*90% of corporations and limited liability companies*" and "*account for 60% of gross value added and 70% of the employment generated in the country by the entire private sector*" [38]. Naturally, these rates agree and are largely consistent with those published in a recent research for the region of Catalonia, where this research will be focused, which confirmed that family businesses represent approximately "*90% of Catalan companies*", contribute to "*around 70% of the gross value added (GVA) generated by the anonymous society and limited liability companies established in Catalonia*" and also generate "*about 76% of private sector employment*" [39]. This confirms the importance of family businesses in the social and economic structure of Spain.

In line with the above, small and medium-sized enterprises are independent business entities that present characteristics that differentiate them from large companies in a number of key aspects ranging from the number of employees, revenue volume and equity value to aspects such as resource and knowledge constraints, lack of money, dependence on a small number of customers and the need for multi-skilled employees. It is of great importance to highlight that these companies are considered as catalysts for the future of the economy, constituting the predominant and most frequent figure in the economic structure of many countries in the world [40–42].

For these reasons, it is of great interest to support and foster the accelerated growth of family-run SMEs so that they are able to cope with dynamic changes and new challenges that begin to revolutionize the market and that are determinant in ensuring continuity and sustainability of the company. Indeed, some initiatives in the adoption of these technologies have been reported [8, 27–29]. However, even in those cases of family-owned SMEs that are applying good analytical practices in their DMP, their benefits will not be noticeable until they have reached sufficient maturity with regards to this particular issue.

The aforementioned particularities of family-run SMEs imposes additional challenges to promote and drive their growth. However, taking into account that family businesses are more efficient in their innovation processes [35], it can represent the impetus they need in order to determine specifically the aspects that must be addressed in order to help them become information-driven companies. Taking into account all the above, it is important to start and cast the spotlight on the family business model, which will allow a global vision to be obtained in order to improve the competitive position in general businesses.

This complex problem is of great interest and relevance for the academic and practitioner's community in the managerial field and has been tackled from different approaches in order to diagnose how companies use information for decision-making, identifying ways to provide them with the vision to improve and the way forward to achieve it. One of these approaches is represented by maturity models as described in the following section.

## 1.3. Maturity Models of Data-Driven Technologies in Businesses

From a managerial perspective, maturity is understood as the degree of completeness, perfection or preparation achieved by organizations in a particular characteristic or in a given field of knowledge [43]. In this sense, maturity models are useful business tools for assessing organizations, or their processes, through a standard reference model which comprises the idea of "predictable evolution and change patterns" [44].

Maturity models are deployed in a sequence of steps or discrete levels (scales) representing an organization's maturity in a given area. The scale of the maturity model can be used to assess an organization's current position and to define a roadmap for improvement. This organizational position spans from an early stage for organizations that have limited capabilities to the highest stage, representing complete maturity [45]. Thus, the basic principle of maturity models is the construction of a set of criteria and features that need to be fulfilled to understand and determine the current status of the organization [45]. Consequently, the organization's strengths and weaknesses can be identified and prioritized in order to plan improvement actions in the application domain under study [44].

Several authors [45–49] coincide in that maturity models can be descriptive, prescriptive or comparative depending on the application purpose. Descriptive ones are used to evaluate and understand in depth an organization's current situation or application domain. Prescriptive ones go beyond a description, providing recommendations, guidelines, best practices and roadmaps in order to reach higher levels of maturity. Finally, comparative models are useful in making comparisons across different organizations. Nonetheless, the application purpose of a maturity model can evolve successively from a descriptive one to a prescriptive and then to a comparative one.

Accordingly, several maturity models have been developed with the common objective of achieving a greater understanding of the application domain under analysis while describing the common challenges that organizations must overcome in their path to improvement. Maturity models provide a framework for highlighting areas or processes within an organization that needs specific attention [50]. In the following subsections, six different maturity models related to data-based technologies in businesses are summarized.

### 1.3.1. IBM DATA GOVERNANCE COUNCIL MATURITY MODEL

This is a descriptive model intended to assess the awareness and effectiveness of organizational data governance and is mainly addressed at identifying data governance gaps. The model defines a framework of five maturity levels: Initial, Managed, Defined, Quantitatively Managed, and Optimizing [51].

### 1.3.2. SME-SPECIFIED MATURITY MODEL FOR KNOWLEDGE-INTENSIVE BUSINESS PROCESSES

This maturity model seeks to evaluate the quality of business processes in SMEs under a self-assessment approach. Based on the EFQM model, this model defines indicators as success factors in seven key process areas: leadership, policy and strategy, partnerships and resources, process design, knowledge transfer and design, employees, information systems, and two specific process areas (innovation impulses and customers). The model also consists of five levels: Initial, Repeatable, Defined, Managed and Optimized, with an evaluation mechanism consisting of a questionnaire that validates the acceptance level that will result in improvement actions for the development of skills leading to knowledge management and the design of quality-oriented processes [52].

### 1.3.3. INFORMATION GOVERNANCE MATURITY MODEL

This maturity model proposes a high-level framework on the basis of standards, best practices and legal requirements aimed at companies of all types and sizes. It presents a set of key attributes of information governance based on eight essential principles: accountability, transparency, integrity, protection, compliance, availability, retention and disposition. The model establishes the following levels of maturity, completeness and effectiveness, describing distinctive features for each of the principles: Sub-standard, In Development, Essential, Proactive and Transformational. It also offers concrete guidance on how to use the model through a self-assessment scheme [53].

### 1.3.4. MATURITY MODEL FOR BUSINESS INTELLIGENCE SYSTEM PROJECTS IN SMES

This model establishes a framework for assessing the maturity level of business intelligence (BI) system projects in SMEs based on critical success factors. It also supports SMEs in the development of a roadmap for improving their BI systems. The model structure has three dimensions of maturity (Initial, Defined and Managed) for the stages of the BI implementation project life cycle [40].

### 1.3.5. TDWI ANALYTICS MATURITY MODEL GUIDE

This model proposes that analytical maturity involves a conjugation of technologies, data management, analytics, governance and organizational components. Accordingly, it establishes five basic dimensions of analytical maturity: Organization, Infrastructure, Data management, Analytics, and Governance. The evaluation mechanism of the model is based on the application of a benchmark survey of 35 questions related to 5 categories that make up the model dimensions based on a pre-established scoring system and defining the appropriate level of maturity (Emerging, Pre-adoption, Early adoption, Corporate adoption and Mature/Visionary) for each dimension, as well as an overall score [54].

### 1.3.6. THE "*Three Levels of Analytical Maturity*" MODEL

This model, developed by MIT for comparative purposes, establishes three levels of analytical maturity: Analytically Challenged, Analytical Practitioners, and Analytical Innovators. The principle to define and classify the maturity of an organization is based on the ability of the organization to use analytical tools to gain competitive advantage and to innovate. This model basically establishes a set of characteristic features that define each of the levels established and the evaluation mechanism is performed through a survey performed on multiple organizations [8].

Many maturity models of data-driven technologies in businesses have been introduced by corporations, consulting firms and researchers. However, none so far (to the best of our knowledge) has been developed that target decision-making. The above-mentioned maturity models place technology as the core issue, focusing only on one part or domain application (data governance, information governance, analytics, knowledge management, etc.) while neglecting the actual complexities associated with making better-informed decisions.

Therefore, this thesis presents our contribution to this topic, which is a maturity model that embraces the wholeness of such complex situations that are characterized by the convergence of technological and managerial aspects associated with information-driven DMP. This entails evaluating the organization's ability to take advantage of the available data in order to transform it into useful and relevant information, and how this information is used to make better decisions, identify business opportunities, innovate and gain competitive advantage.

## 1.4. THESIS OBJECTIVES

The main goal of this thesis is to propose a comprehensive methodology to consistently evaluate how organizations use data and information to make decisions, as well as to position them in a maturity reference model to help them improve. The method will take into account the most important technological and managerial factors involved in the information-driven DMP. Special emphasis is made on family-owned SMEs; however, without detriment, it is scalable to larger companies. This means developing the methodology through which the organization will be evaluated under an approach that seeks to provide useful insights into the organization's self-knowledge. Thus, by improving decision-making processes through the appropriate use of information, organizations can evolve to higher maturity levels.

Accordingly, the following specific objectives are proposed, which translate into the different stages required to achieve the main goal of this thesis:

- To study the evolution of the information-driven DMP and the antecedent models for the evaluation of the maturity in the organizations. This study will cover a timeframe ranging from the 50s to 2015 in order to consolidate the theoretical bases needed to develop the proposed methodology.

- To develop an assessment tool for the evaluation of information-driven DMPs in the organizations under a pragmatic, simple, objective and quick approach to allow systematizing the collection of information while minimizing disruptions and time spent (maximum of two hours per interview), and that is capable of adapting to the characteristics and particularities of the organization.

- To evaluate the degree of perfection of information-driven DMPs through a hierarchical scale of levels associated with specific requirements and metrics (model) that allow classifying organizations according to their degree of maturity.

- To conduct tests for the validation and improvement of the organizational maturity model of information-driven DMPs to between 6 and 8 companies divided into blocks in a range of 3 to 4 companies per year (two blocks in total).

## 1.5. THESIS STRUCTURE

Chapter 2 presents a study of the state of knowledge and comprises a chronological review of how technological advances have impacted on the evolution of DMPs with a strong interaction between them that led to a greater understanding in this application domain. This allowed the role of information for a better decision-making in businesses to be highlighted, which has opened up a wide range of possibilities and opportunities at the organizational level to take advantage of the data. The findings show that there is still a gap between current technical possibilities and organizational needs, which means the commercial solutions for business intelligence, analytics and other related technologies are not fully adapted to organizational needs, while many organizations do not fully understand what to do with their data. Therefore, adapting the different data-based technologies to particular types of processes, information and decisions would represent a big improvement opportunity for them.

In Chapter 3, a novel maturity model for the information-driven DMP in organizations is developed along with an in-depth description of its structure of dimensions and attributes. In a publication in the *International Journal of Management and Decision Making* [55] the "*Circumplex Hierarchical Representation of Organization Maturity Assessment*" (CHROMA) model was presented for evaluating organizations regarding their competence and readiness in using information to support decisions. This model groups the most important informed decision factors, which are distributed in a logical sequence into five dimensions: data availability, data quality, data analysis and insights, information use, and decision-making. The model addresses these dimensions in an organized and systematic way, providing a framework for characterizing the organization's use of information in DMPs from an uninitiated stage to a completely embedded one. This model was tested in a pilot study on three small/medium-sized enterprises (SMEs). The assessment involves interviewing key company personnel and evaluating the attributes and dimensions of the CHROMA model. Results confirmed the ability of the CHROMA model and its associated assessment tool to collect useful information for assessing and establishing objectively the level of maturity of information-driven DMPs in order to guide companies to improve their decision-making processes whilst causing minimal inconvenience to the organization. However, in its current form, this model is better suited to medium-large companies and must be simplified in order to be applied to SMEs.

Chapter 4 presents the "*Simplified Holistic Approach to DMP Evaluation*" (SHADE) variant of the CHROMA model for the information-driven SME. This is a simplified, customized version of the CHROMA model used to address the results of a pilot study and adapted to SMEs to evaluate their competence, readiness, and maturity in making better-informed decisions. The dimensions and attributes of this version of the model are classified into five dimensions, which in turn are subdivided into three attributes, according to the results of the findings achieved during the pilot studies carried out and explained in the previous chapter. The assessment tool was improved and unified to better adapt it to the particularities of this type of organization while keeping the same stages used in the CHROMA model framework hierarchy. The assessment comprises interviews plus a shorter web questionnaire addressed only to key company personnel and evaluates the attributes and dimensions of the CHROMA SHADE model. The results of its application indicate that the model is adaptable to both family and non-family SMEs and is useful in identifying strengths and weaknesses, thereby providing insights for prioritizing improvement actions.

Chapter 5 presents the experience of the CHROMA model application throughout a campaign that included a total of six small/medium-sized family businesses. The first three collaborating companies were part of a pilot study intended to validate the CHROMA model suitability, while the later three companies were subject to the application of the CHROMA SHADE model. The findings highlight the applicability of both versions of the model to these types of companies to evaluate them and objectively establish their level of maturity in the context of the information-driven DMP. The results also allowed strengths and weaknesses to be identified, thereby providing insights for prioritizing improvement actions without causing disruption. Likewise, the improvements applied to the assessment tool reduced the time invested in the application of the whole evaluation methodology without causing disruption to the organization. Such improvements facilitated not only the interviews and their corresponding analysis but also the subsequent interpretation required for implementing the model's output. These findings highlight the potential capacity of the CHROMA and SHADE models to comparatively analyze and categorize the organizations within well-defined domains (typology, geography, economic sector, generation, size, etc.).

Finally, Chapter 6 presents the conclusions and a discussion about the implications, and the foreseeable subsequent research lines regarding the topic of this thesis are presented.

Supporting documents and the detailed CHROMA model scheme are included in the Appendix.

# 2

# Chronological Evolution of the Information-Driven Decision-Making Process

## 2.1. Evolution of the Decision-Making Process

To understand the elements involved in the DMP, first, some definitions are required. In 1947, the noun "*decision process*" was reported from the perspective of organizations by Herbert A. Simon [56], a pioneer of scientific administration based on decision-making. Simon argued that the organization is a reflection of its decision-making.

A decision can be defined as the moment in which, through a continuous process of evaluation of possible alternatives, inherent to a given target, the appropriate choice takes place driven by the expectation associated with a course action [57]. Other definitions include the particular commitment that leads to action, often associated with resource allocation for a purpose. Therefore, the DMP is immersed within actions and variables under an integrated approach that starts by identifying a stimulus for action whose output is associated with a commitment to act accordingly [58]. On this basis, decision-making is a dynamic, complex and potentially ambiguous process that occurs under uncertainty and risk [7].

Over several decades, most authors have agreed that decisions are the result of a dynamic process through which a goal is achieved. Thus, the DMP is an integral and critical part of the organization's management aimed at choosing, among a set of possibilities, the alternative that may lead to resolving a situation in a satisfactory way for all stakeholders [2, 3, 7, 56, 59–63].

Naturally, the way to tackle DMPs has evolved through time, adapting to the needs, challenges and technologies of every age [1]. In the following sections, we present a chronological review starting in 1950 and progressing through decades.

### 2.1.1. From 1950 to 1959: A rational approach to bounded rationality

In this decade, the DMP was understood as a system through which information flows and started the use of statistical tools for the design of decision models. Two main criteria were introduced: "*maximize expected profits*" and "*minimize the maximum risk*" as well as the concept of "*sequential decision*" for planning each stage of complex decisions [59].

In 1953, Irwin D. J. Bross [59] proposed a decision model based on data and statistical principles, distinguishing the real world from the symbolic and the importance of measurements as a validation element. Thus, data quality started to be considered an important issue. In addition, the first reported use of the terms "*individual decision*", "*administrative decision*" and "*group decision*" are to be found in [59]. Later, the term "*management by objectives*" was coined and refers to "*finding opportunities rather than focusing on problems based on the pursuit of the organization's mission*". Later, this approach would be called "*business strategy*" [64].

On the other hand, the rational behavior of the decision maker was discussed and the term "*bounded rationality*" was coined. It was proposed to model human behavior as a social agent that act influenced by emotional impulses rather than rationality. In consequence, the DMP was rationalized from the perspective of finding a mechanism of choice, leading to the adoption of "*satisfactory*" decisions of existing needs, rather than optimal solutions according to the classic posture of rational behavior [61, 63].

It is noteworthy that during this decade important research that greatly expanded the field of application of game theory became evident and laid the foundation for the study of decisions in environments that interact and the understanding of human cooperation. The dilemma "*social choice and individual values*", the dimensions of uncertainty for decision-making and the dynamic of the group decision theory, were studied [65]. The same happened with the influence of factors such as leadership, authority, guidance risk policy and the interests of stakeholders on decisions. It was an attempt to understand the mechanisms used by individuals, groups, organizations and society to make decisions [66].

At the end of this decade, the axiom of choice was raised under the domain of probability theory, which states that in a group of many items, the probability of selecting an item over another is not affected by the presence of other elements. This phenomenon was called "*independence of irrelevant alternatives*" and allowed the DMP to be modeled from an approximately rational approach and provided the basis for modeling the tendency of consumers to prefer a product or brand, laying the basis of "*individual choice behavior*" [67].

### 2.1.2. FROM 1960 TO 1969: SYSTEMATIZATION AND HIERARCHIZATION OF THE DMP

This decade brought together the DMP and problem-solving. The problems were classified into "*structured*" or "*unstructured*" for decision-making [7, 62]. In addition, theories and concepts related to the underlying judgment of psychological processes and choice were presented. The similarity between alternatives in choice behavior was introduced [68].

In the middle of this decade Charles Kepner and Benjamin Tregoe [69] proposed four rational processes for problem-solving and decision-making: 1) Assessment of the situation: 2) Problem analysis, 3) Analysis of decisions and 4) Analysis of potential problems (opportunity). Their now classical method gives a set of systematic procedures to identify the root cause of a problem and find a solution. These procedures are based on critically analyzing data, information and experience.

A few years later, Peter Drucker [60] lead the development of a systematic DMP based on clearly defined elements addressed through a sequence of steps: a) Classification and definition of the problem, b) Specification of the response to the problem, c) Establishing what is right against what is acceptable in the context of meeting the conditions given by the environment, d) Building on the basis of the decision, the action to carry out, and e) Testing the validity and effectiveness of the decision. This increased the effectiveness of executives in decision-making.

In this decade, the scope of the decision was extended to all areas of the organization, including the idea that decisions are made by individuals and groups at all levels of the organization. Decisions were classified into four categories, represented in a pyramidal hierarchical scheme associated with the organizational levels: a) Strategic Planning, whose decisions are addressed by senior management, b) Management Control, whose decisions are aimed at controlling the proper development of the efforts undertaken, c) Operational control, whose decisions seek to control the effectiveness of the organizational actions, d) Operational performance, whose decisions are related to those made in daily work of the functional units focusing on the implementation of strategic decisions, functional tactics and operational activities [7], as shown in Figure 2.1.

At the end of this decade, the techniques of flow diagrams and decision trees were developed. A discussion regarding the cost of imperfect sampled information versus the worth of perfect information was presented, providing an approach for deciding under uncertain real-world complex conditions. These advances have been widely used since then [70].


Figure 2.1: Categories of organizational decisions. According to the hierarchical perspective, the number of decisions decreases as the pyramid level increases. The scope of the decisions made by the higher pyramid levels is broader and less precise, while towards the base of the pyramid the decisions become detailed and precise [7].

A last important development of this decade is the SWOT analysis model (Strengths, Weakness, Opportunities, and Treats) proposed by Learned et.al. The method, based on achieving a strategic adjustment between the internal capacities and the external possibilities of an organization, is useful for making decisions and prioritizing actions in complex situations [71].

### 2.1.3. FROM 1970 TO 1979: THE EARLY STAGES OF COMPUTER-AIDED COMPLEX METHODS

At the beginning of this decade, the term "*groupthink*" was proposed to explain a process that can lead to making wrong and irrational decisions by groups in which, through an apparent consensus, make decisions influenced by peer pressure, affecting rational judgment, efficient thinking and the evaluation of the situation to solve [72].

Tversky [73] introduced a general theory of choice that became the basis for the development of decision models sustained on a process of covert removal. The idea is to evaluate the different alternatives taking into account a number of aspects, and the use of an iterative selection process. The procedure proceeds thus: an aspect of each option is evaluated at the time, beginning with the most important one. When an option fails to meet the established criteria, it is eliminated. This process is repeated until only one alternative remains. This model of choice by aspects solved the main problems concerning the assumption of independence of irrelevant alternatives. In parallel, "*the garbage can model*" was presented as an alternative to the normative models of rational choices. It proposes making decisions despite the conditions of "organized anarchy" by assessing the problems and their solutions as choice opportunities [74].

The many developments of the early years of this decade represented a paradigm shift. The organization is no longer seen as a set of isolated elements but as a complex system of interrelated elements. This new paradigm considers that humans bring their skills and knowledge to the growth of the entire company and decision-making is considered an essential management skill [75]. Other approaches, based on intuition and creative strategy rather than on the rational and analytical component, emerge. The idea is that the role of the manager immersed in the organization chaotic environment is to be fast, creative and adaptive [76].

Vroom and Yetton [77] developed a model to explain how leadership style influences the degree of participation of the subordinates in decision-making. This model was presented as a decision tree to be analyzed by the leader according to the magnitude of various types of problems that should be delegated as tasks that lead to their resolution.

In the middle of the decade, Mintzberg et al. [58] drew attention to the fact that non-routine decisions, namely the ones more common at the highest level of the organizational hierarchy, are frequently taken by unstructured DMPs. Furthermore, they detected a lack of attention to these types of decisions. Considering that DMPs were dynamic, highly complex and dependent on a conceptual framework, they identified a gap between the decision process and the organization structure. The reduction of this gap is fundamental to improving the functioning of the organization.

In line with the advent of the computing era, the classification of decisions as "*programmed*" was used for repetitive decisions, while "*unscheduled*" refers to those unstructured decisions that require complex processing of information. Along this line, four interdependent phases were presented for DMPs: intelligence, design, choice and revision [78].

The idea of bounded rationality was maintained. It suggests that the mechanisms of human rational choice involve using their information processing capabilities to look for alternatives. A satisfactory solution is then found by calculating the consequences, in the presence of uncertainty, of each choice. Bounded rationality sustained that human behavior for fully rational decision-making was conditioned by the complexities of the environment and by the limited capabilities of the computational resources available at the time. The theory opened up new horizons in the mathematical modeling of decision-making [79, 80].

By the end of the decade, Preference Trees, or the "*Petree*", emerged as an evolution of the elimination-by-aspects model and maintains the basic principles of covert elimination but represented hierarchically in a tree structure [81].

The organizational behavior model of Mintzberg [82] consolidates the hierarchical principles of the DMP. This model describes the parts of organizations, ranging from the "core operations" in which the activities for the realization of the product or service take place, a "*middle line*" for the intermediate chain of command, the "*strategic apex*" formed by senior executives, the "*technostructure*" represented at the level of the middle line that was not part of the operational structure, and the "*support staff*", also located at level of the independent middle line of the operational base. This model is graphically shown in Figure 2.2.

Mintzberg's model is based on the idea that the company must have an internal consistency that would allow it to face the competitive conditions in the external environment. The model also identifies the flow of information at the different levels: operating work, vertical information and of decision-making (which are illustrated as circular arrows in Figure 2.2 to represent the feedback through information flowing from different instances), and staff information [82].

By the end of the decade, the "*prospect theory*" is developed as an alternative model to the theory of expected utility for decision-making under risk. Prospect theory models how people make decisions in situations of uncertainty present in the real world. It proposes a model of choice in which instead of assigning a value to the final outcome, it is assigned to the profits and losses, replacing the probabilities by decision weights [83].

### 2.1.4. FROM 1980 TO 1989: THE BEGINNING OF THE INFORMATION AGE

Earlier in the decade, interest was centered on the study of the DMP in unstable environments and on studying how to manage the risk associated with decisions [84]. There was also interest in the cognitive implications influencing DMPs and the way in which inherent tasks are performed under uncertainty [85]. A greater emphasis on the use of information and the technology for decision-making is evident; its importance in gaining competitive advantage appears as a key aspect in the near future [86].

With regards the progress of hierarchical approaches for multi-criteria decisions, this decade witnessed the managerial application of the Analytical Hierarchy Process (AHP), a mathematical technique developed at the end of the 70s. AHP proposes a prioritized structure that facilitates ranking alternatives according to their degree of fulfillment of several predefined conditions to quantitatively achieve a consensual group decision. AHP has received criticism and multiple fixes were proposed in the years to come, such as the REMBRANDT method, developing it into a rather well-stablished technique due to the simplicity and intuitiveness of its application [87–90].

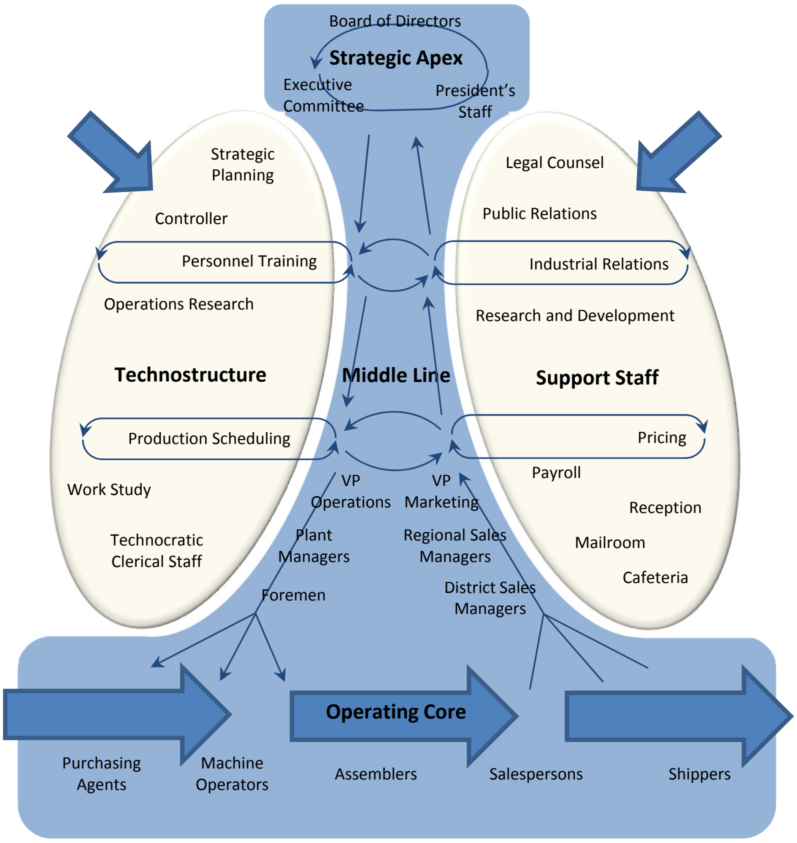


Figure 2.2: Mintzberg's [82] model. The interaction between the basic components of organizations is shown. Several information flows are identified: the operating workflow, the flow of control, information and decisions, the flow of staff information and the flow of intelligence information (information to the external organization).

Likewise, with the widespread adoption and scope of Decision Support Systems (DSS), a classification framework, including communications-driven, data-driven, document-driven, knowledge-driven and model-driven DSS, was used to better explain their application domain. Moreover, it was recognized that DSS could be designed to support decision-makers at any level in an organization. In the particular case of DSS for strategic decisions, they had to be designed taking into account their compatibility with the type of strategic decision-making models used in the organization and their ability to handle and share intersubjective and consensual information in a flexible way [7, 89, 91, 92].

By the end of this decade, March [93] conducted an analysis of the use of information systems for decision-making in the presence of ambiguity, uncertainty and incomplete data. He concluded there was a gap between decision theory and information engineering. It is not surprising that in this context, some researchers like Simon [94] thought that it was very common for organizations to be faced with situations in which the best strategy for making decisions in complex environments was to rely on the good judgment of its managers. According to Simon, a manager of good judgment has completed a psychological process of acquisition and improvement of "*intuition*". Managers' intuition is understood as their ability to create mindsets that unconsciously automate a quick and rational response, but with the inherent limitations of available information [94].

Another study conducted in different companies identified several types of strategic decisions and their influence at the departmental level. It also established that the influence of senior management on all decisions made in companies was moderate; each department makes, almost independently, their own decisions. The study also evaluated the influence of departmental attributes in the types of strategic decisions, concluding that environmental scanning represented the largest source of influence for product-market decisions, while technological and managerial decisions were influenced by hierarchy and access to resources [95].

### 2.1.5. FROM 1990 TO 1999: CREATING ORGANIZATIONAL KNOWLEDGE AND INTEGRATING ITS COMPONENTS

A framework integrating the multiple developments made during the eighties helped to consolidate the foundations of DMP and to provide guidelines for future research [96, 97]. Theoretical and empirical arguments allowed the identification of three factors that influence the strategic DMP [96]: environment (uncertainty and complexity), organizational (related to the structure and characteristics of the organization, personnel, key work equipment, performance and strategies) and other specific (impetus, urgency and risk).

Negotiation appeared as an important management area and Bazerman and Neale [98] established principles for decision-making during the negotiation process based on the correct use of information and on the opponent's study.

Novel and useful applications of the AHP method in multi-criteria decisions to fine-tune the DMP as a support tool that allowed business, industry and government executives to organize their thinking processes in a logical manner while establishing clearer priorities [99]. Issues and practical and computational challenges in the use of the AHP method for scientific and engineering applications were also examined [100].

The introduction of the concept of "*Knowing Organization*" (KO) had a high impact. The idea is that organizations with the ability to use the information to gain a better understanding of their activities and their environment gain a competitive advantage by making better decisions and having clearly defined courses of action. The model proposed to represent the KO consists of three concentric layers of information: interpretation (sensemaking), conversion (knowledge creation), and processing (decision-making), respectively (Figure 2.3). Each inner layer takes as its input the output of its outer layer to progressively focus the information towards the organizational action courses [101].

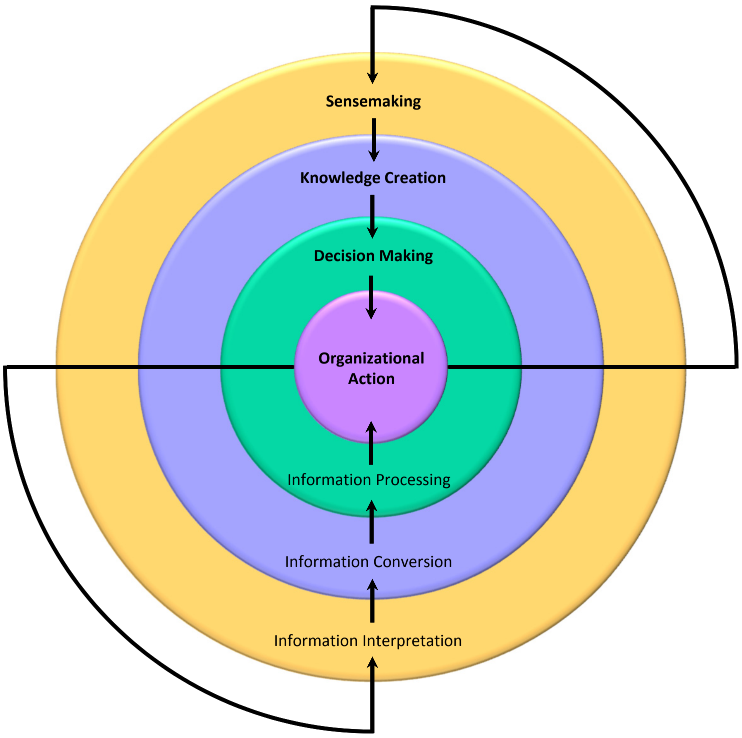


Figure 2.3: The Knowing Organization [101].

This decade was also characterized by greater research in the DMP from a heuristic approach rather than rational. An exploratory study that analyzed mental models identified several key elements of the DMP, among them self-learning to adapt quickly to changing environments [102].

Until the late 90s, despite the advances in strategic management, research on DMPs in small businesses was scarce. A study found that small firms base their decisions more on intuition than on conventional rational approaches. Notions of rationality were applied only to collect external information to support such decisions. This was explained by the innovative nature of these types of companies, which can take greater risks in their enterprises [103].

At the end of this decade, new elements related to the organizational context which influences the DMP were discussed, such as national culture, the corporate governance structure, the role of information systems, and the need for a more integrated approach [104].

### 2.1.6. FROM 2000 TO 2009: BREAKTHROUGH IN INFORMATION AND ITS MANAGEMENT

In the early 2000s, research on DMPs continued to be interested in the use of information to reduce uncertainty. The mechanisms of data collection and verification were empirically studied. Two types of information that benefited decision-making were identified: "*Soft*" (related to the subjective and qualitative aspects) and "*hard*" (objective, systematic and quantitative). The importance of acquiring information from external sources as a mechanism to achieve better organizational alignment with the environment was highlighted, together with the fact that its search must be done through a structured but flexible process [21].

Despite the huge amount of data available and the technological advances such as data warehousing and data mining, a critical study emphasized the existence of problems that limit the capability of organizations to have the information needed to handle the internal and external complexity and dynamism. This study argues that the root cause of this situation was the lack of clear information requirements for organizational management. Specifications for the technologies were provided as guidelines for managing the information requirements in organizations [105].

Throughout this decade, Evidence-Based Management (EBM) was developed. EBM was defined as "*the conscientious*, explicit and judicious use of current best evidence in making decisions" that emerged as a branch of "*Evidence-based Medicine*", a widely praised movement that reached clinical practice as well as healthcare management [106]. In the general DMP context, EBM encourages the adoption of a determined and committed approach to collecting the data necessary to make informed and intelligent management decisions. This trend was slow to grow due to the difficulty in transferring the EBM fundamentals from the clinical field to management, especially with respect to the characteristics of what is considered evidence in each case and the particularities of each organization [10, 107, 108].

In the middle of this decade, the development of complex systems for computer learning to assist in the acquisition of skills that lead to making good decisions was also published. Such systems were designed to train professionals in decision-making in order to change unstructured and multivariate environments in order to provide theoretical and practical knowledge with framed routines in solving real problems. It differentiates between learning focused on decision-making in businesses with respect the methods and tools to support business decisions, since the latter does not give the decision, but supports the decision-maker [109].

Another development was the introduction of the stakeholders in the organization's DMP. The diversity of stakeholders provides the ability to perceive multiple dimensions and interconnections. In addition, then the DMP becomes a mechanism to understand stakeholders needs and to address ethical concerns [110, 111].

The second part of the decade was characterized by a growing interest in the development of methods for making group decisions based on multiple criteria and attributes. Proposed methods include multi-criteria decision analysis (MCDA), fuzzy logic and, game theory, among others. MCDA methods evaluate and compare several alternatives with a number of criteria for selecting the best path of action based on aggregation rules while resolves the potential conflict found in the analysis performed. Furthermore, under uncertain and imprecise conditions, fuzzy sets are used along with MCDA to provide techniques for modeling, aggregating, selecting and categorizing preferences and alternatives. Those advances contributed to optimize the evaluation of management alternatives with respect to multiple and ambiguous criteria, preventing the deviations due to individual preferences or to inherent limitations of the human capabilities when it comes to process such amount of heterogeneous scenarios [89, 111, 112].

Throughout this entire decade, management experimented a rapid change and one of the areas where this change was greatest was DMP. Researchers and organizations tried to find newer and better ways to make decisions through innovative ways of managing information. Information was seen as a valuable asset for the organization. The scope of information taken into account in the DMP expanded to include non-financial and external data. Likewise, large companies started to invest in developing infrastructure and technological solutions to integrate their systems and get the most out of the available data, as well as becoming more "*transparent*". Transparency begins to be considered a help in making better decisions and a way of gaining a competitive advantage. The major challenge foreseen in this decade is the development of advanced analytics to extract knowledge from data and information, with special attention to risks. Learning from similar situations in the past helps ensuring that organizational goals are placed before the goals of the business units, as well as to developing a better understanding of individual customers' needs to offer them tailored products and services [113–115].

This decade also brought a new paradigm: the use of prospective-retrospective. The idea is similar to the "*pre-mortem*" approach, as opposed to the "*post-mortem*" one. This method comprises group techniques for identifying, in advance, the risks and problems that may arise in a project prior its inception. This prior evaluation of scenarios and anticipating potential failures allows the DMP to be strengthened and to avoid impulsive decisions [116, 117].

Additionally, Davenport [4] states that very few organizations focus on a systematic analysis of their DMP. According to Davenport, attention should be given to the DMP in order to "*re-engineer*" and/or improve it. His framework covers all organizational components (technology, information, organizational structure, methods, and personnel) and proposes four steps to improve the decision-making: 1) prioritization of key decisions; 2) characterization of the decisions and elements involved; 3) intervention through the design of roles, systems, processes and behaviors necessary for DMP improvement; and 4) institutionalize decision tools and assistance. In the same manner, managers should: beware of analytical models that they do not understand, maintain broad perspectives for the decision-making and evaluate the quality of the decisions made regarding outcomes, the DMP, and information.

At the end of this decade, an interesting study was conducted on the role of information in strategic DMPs, comprising an analysis of the value and the quality of information, the strategies to prevent overload of information at the executive level, and the changes experienced by management due to information and communication technologies. This study highlighted the importance of information and how different technological advances have facilitated and improved the acquisition, availability, and analysis of information useful in supporting DMPs. Moreover, Citroen [2, 3] proposes a model that includes the preparation, analysis, specification, limiting and assessments stages that would lead to rational decision-making, concluding that information helps reduce uncertainty and provides better conditions for rationality (Figure 2.4).

### 2.1.7. From 2010 to date: Better decisions in the time of Big Data

This decade is characterized by an even stronger relationship between Information Technology (IT) and DMPs. An important line of research was developed that aimed at driving IT management decisions from a business perspective. That is, in investigating the relationship between the IT function and the value of the business that it generates measured through business indicators such as benefits, costs and customer experience. There was also a great interest in developing technological solutions embracing problems of various domains with an interdisciplinary approach, trying in this way to reproduce human decision-making [118].

Similarly, the results of a large survey conducted during the early years of this decade showed a statistically significant direct relationship between data-driven decision-making and company performance. Company performance was measured in terms of productivity (return on assets, return on equity and asset utilization) and market value [119].

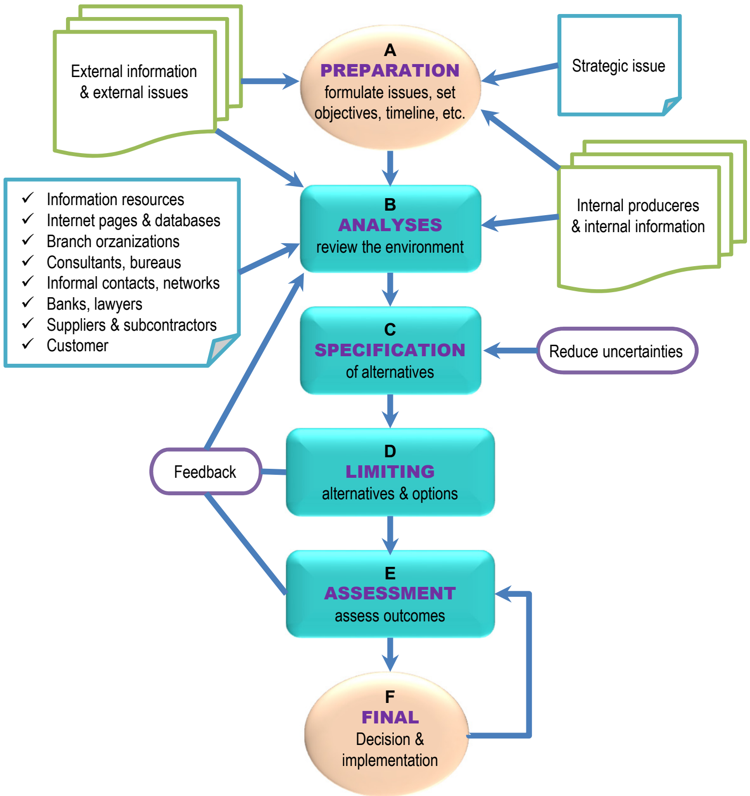


Figure 2.4: Model of the phases of a rational DMP. Rounded boxes indicate the phases in the DMP; square boxes contain elements that provide input for the indicated actions. Arrows indicate the main direction of interactions [2, 3].

Teal [120] developed a conceptual framework for strategic decision-making under uncertainty that tries to bring together contributions from psychology, creativity and management, including the temporal dimension (past, present, and future).

In parallel, Kester et al. [121] proposed a general model for DMPs of new product portfolios. The model foundation is that the portfolio decision-making is the result of the systematic interaction between three elements: evidence, power, and opinion. Depending on the balance among the three elements, decisions will be better or worse.

Following the idea to extend the Evidence-Based Medicine to general management, Tort-Martorell et al. [11] distinguished between internal and external evidence, and argued that organizations should concentrate their efforts on internal evidence-based management, which is easier to implement than the external one and has proved effective as one of the pillars of TQM, Excellence Models or Six Sigma. This led to the use of scientific methods to gain knowledge and of data quality and analytics as important elements.

Malakooti's [122] model for DMP is based on evaluating and ranking the alternatives of the possible actions derived from the decision, and in specifying four dimensions used by people to make decisions. The four dimensions, each defined by two opposite types are: information processing (concrete or abstract), alternative generation (adaptive or constructive), alternative assessment (moderate or bold) and decision closure (organized or flexible). A web-based questionnaire was used to test the model. The conclusion claims the proposed dimensions are reliable and have a low correlation with each other.

Recent research conducted at the University of Cambridge has led to what is currently known as "*Total Information Risk Management*" (TIRM) [123]. TIRM is a holistic framework of concepts, methods and techniques developed to systematically manage the effects of uncertainty arising from the quality of information on the objectives of the organization. It is based on the evaluation of information from all possible sources and types, using as a reference the widely accepted precepts of risk management of the ISO 31000 standard [124].

The current trends in DMP are very much related to the rapid changes in analytics and big data developments. In order to determine whether data-driven decision-making improves business performance, a joint team from the MIT Center for Digital Business, McKinsey's business technology office and collaborators conducted a survey to test that hypothesis. The methodology involved structured interviews with executives at 330 companies about their organizational and technology management practices and gathered performance data from their annual reports and independent sources. Despite the broad spectrum of approaches found regarding data-driven decision-making, this study concluded, with statistically significant evidence, that "*the more companies characterized themselves as data-driven, the better they performed on objective measures of financial and operational results*" [125].

Provost and Fawcett [126] conducted a critical study on the relationship between data science, big data technologies, and information-driven decision-making. Their idea was that understanding and embracing the inherent relationship between these concepts would allow the field of data science to achieve its full potential for improving business performance through better information-driven decisions. They concluded that there are two types of decisions that can benefit from data science: 1) those for which "*discoveries*" are made within data, and 2) decisions that repeat at a massive scale, and so decision-making can benefit from even slight improvements in accuracy based on data analysis. They also remarked on the current and future relevance of automated decisions performed by computer systems, concluding that big potential lies in applications such as adaptive advertising, high-frequency trading, and credit scoring and fraud detection, among others.

In general, an excellent source of information on big data and analytics is the research conducted at the Massachusetts Institute of Technology (MIT). A special collection of papers on "*making better decisions*" have recently been published by the MIT Sloan Management Review. Among them, we would like to highlight [127–129], which we believe provide an overview of the current situation.

One trend is to look for DMP alternatives that would lead to the broadening of perspectives and making smarter and faster decisions. The idea is to evaluate all scenarios, evident and subjacent tendencies, assess emergent technologies and use them for critical and constructive discussions that would lead to gaining knowledge and better decisions [129].

Another is to take advantage of the access to large amounts of data to make better predictions on which to base decisions. In essence, it is about basing decisions on statistical findings and developing decision models supported by data. However, empirical evidence shows that the increasing amount of data available makes the analysis more complex, hindering the proper communication of analytical results to decision makers, who do not fully understand these results. To overcome the problem, the author proposes a method of "*simulated experiences*", which would allow executives an intuitive interpretation of statistical information [127].

Moreover, the explanation of the psychological mechanisms that lead us to decide in the way we do remains an open subject of great interest. Work has been done on: "*psychological distance*", the balance between "*exploitation*" and "*exploration*", active decisions versus ruled decisions, spontaneous decisions versus deliberated decisions, and the improved perception of competence in decision-making thanks to the willingness to seek advice, among others. The findings of B. Posner [128] suggest that a greater understanding of the psychological phenomena would allow the creation of strategies to address the DMP more effectively.

Finally, most parties agree that DMPs can be significantly improved by combining both data-driven decision models and critical and creative thinking. An appropriate balance between the exploitation of decision models and human managerial skills is required to understand their benefits and limits. This would allow what will happen to be predicted more accurately, as well as influencing directly the desired outcome to making it happen, and also use predictions to influence indirectly the courses of action for achieving specific goals [26].

## 2.2. Chronology of Information Technology that Supports Decision-Making

Through the analysis of the evolution of the DMP, it was shown that much of its progress is closely related with that of information technology and DSS. In turn, DSS also underwent strong development that resulted in a great variety of advanced methods allowing and encouraging more complex analysis to make better decisions [2, 3].

As with DMP, we are going to review briefly the major milestones in the evolution of data-based technologies in businesses at intervals of decades. The review starts with the arrival of computing, which clearly represented a paradigm shift in terms of how to manage businesses, as it opened up a wide range of possibilities and opportunities at the organizational level [2, 3, 7].

### 2.2.1. Before 1960

These years were marked by the beginning of the computer age. The first advances at the hardware and software level started with the implementation of linear programming in experimental computers by George Dantzig of the Rand Corporation in 1952, the start of the System Dynamics Group at the Sloan School MIT and the first steps in developing the first data-driven DSS conducted at the MIT Lincoln Lab [2, 91]. During these years, Hans Peter Luhn [130] coined the term Business Intelligence (BI) in a visionary article that appeared in an IBM scientific publication. In it he discussed the problems of acquisition, dissemination, storage, retrieval and transmission of information in organizations. Indeed, he foresaw an automated way to communicate using the electronic devices available at the time, considering the organizational changes experienced after the arrival of computing. He also predicted an increased demand for information, which would require methods to manage it in order to address the new challenges of decision-making [130].

### 2.2.2. From 1960 to 1969

This decade saw remarkable advances in interactive computer systems. In the early sixties, the first developments in programming language and database management systems marked an important milestone. However, the construction of information systems on a large scale was still an expensive affair. By the mid-sixties, the development of more powerful computer systems by several research groups from both the academic and business world allowed the development of Management Information Systems (MIS) aimed at providing managers of large companies with structured periodic reports based on information from accounting systems and transactions [2, 7, 91, 131].

Other remarkable advances were made in human-computer interactions. Many were due to the work and vision of Douglas Engelbart [132], which among other improvements in the interface and general interaction with the computer promoted the development and incorporation of aid accessories such as the mouse. He also designed the first integrated online "*hypermedia-groupware system*", called oN-Line System (NLS), which allowed meetings supported by computers, teleconferencing, file sharing, digital libraries, hyper-email, online communities, etc. to be conducted. [91].

During this decade, a new type of information system, a precursor of DSS and referred to as Management Decision Systems (MDS), was developed and implemented. In addition, researchers at Stanford University developed the SPSS statistical software package. One of the ideas behind it was to use statistics to transform data into information useful for promoting decision-making. Additionally, the Ph.D. thesis of Scott Morton marked a milestone in computer display systems and how computers and analytical models could lead the organization to make key decisions [7, 91, 133, 134].

All this research contributed to important developments in terms of the graphical user interface (GUI): operating systems with multitasking and multiuser approaches, the MEDIAC model to support decisions on marketing management through a dynamic programming approach [91], the development of information systems based on models to guide decision-making on new products through better marketing strategy [135, 136], as well as conducting experiments on a programmed system for computer-assisted decision-making [137].

### 2.2.3. FROM 1970 TO 1979

These years were characterized by the development of more complex computer-assisted methods aimed at solving problems of decision-making in organizations by means of supporting individual managers rather than the organization as a whole [91].

Scott Morton's research at the beginning of the decade produced the first steps in the implementation, definition and research test of a model-based DSS [138, 139]; furthermore, he was the first to use the term of DSS in a scientific journal. Simultaneously, Gerrity [140] developed a system for managing the portfolio, laying the foundation for DSS in this field, while John Little identified four criteria: robustness, ease of control, simplicity, and completeness of the design of DSS, which remain relevant in assessing modern DSS [7].

Other relevant advances of the early seventies were the first enterprise resource planning (ERP) system developed by SAP and the design of a complete set of network communications protocols currently known as TCP/IP [91].

The middle of this decade brought great interest and significant developments in management information and planning systems and computer-assisted decision-making, all of them supported by ever faster hardware improvements [91]. Examples of such advances were the first OLAP (online analytical processing) and the appearance of VisiCalc (Visible Calculator), the first spreadsheet or more powerful computing devices such as the minicomputers from Digital Equipment Corporation [87, 89, 91].

All this led to the formal birth of personal DSS and a surge in interest in the idea [2, 7, 91, 141, 142]. At the end of this decade, Peter G.W. Keen and Michael Scott Morton's book [143] provided greater understanding and guidance to the design, analysis, implementation, evaluation and development DSS. Research led by J. F. Rockart [144] at MIT into the definition of management information needs required by the chief executive officer (CEO) through the method of Critical Success Factors (CSF) was a breakthrough in academia. The main proposition of Rockart's paper was the solving of problems of managing large amounts of information by focusing on what is really significant for businesses and decision-making.

### 2.2.4. FROM 1980 TO 1989

This decade marked the widespread acceptance of DSS [2] from both the academic and practical point of view. The personal DSS of the 70s gave rise to systems intended to assist in organizational DMPs, comprising the Intelligent DSS (by considering artificial intelligence and expert systems), Executive Information Systems (powered by database theory and OLAP) and Group DSS (incorporating aspects from social phycology and group behavioral process) [87, 89].

This happened in part because of the many publications from the seventies and Steven Alter's book, which expanded the conception and consolidated the description and identification of the DSS [91, 145] , and in part because it was the right time, which heralded the wide availability of hardware with the fast expansion of PCs and the beginning of globalization.

Along the same line as setting the conceptual framework of DSS [7], Bonzek, Holsapple and Whinston's book [146] showed the significant influence of Expert Systems technologies in developing DSS and identifying the essential components that are common to all DSS. At the same time, research was conducted aimed at analyzing how advances in computational technologies and DSS influenced the way information reached CEOs and was used for decision-making [147, 148].

The mid-eighties saw important software developments aimed at supporting project collaboration through the enhancement of digital communication. These were generically referred to as group decision support systems (GDSS) [149, 150]. At the same time, Houdeshel and Watson [151] reported the success, in terms of benefits and the frequency of use and customer satisfaction, of Lokheed-Georgia's management information and decision support system (MIDS). They attributed it to the right combination of several factors: senior executives' commitment, carefully defined information requirements, a team approach using carefully selected hardware and software systems and an evolutionary development.

Following the increase in data and information availability, MIDS, GDSS, and organizational decision support systems (ODSS) evolved from the single-user model-driven DSS to relational database products [2, 7, 91]. This movement gave way to business information systems architectures based on data warehouses structured on relational databases and designed to provide easy interfaces and access to business data [152].

At the end of this decade, Howard Dresner, an analyst at Gartner Group, coined the term business intelligence (BI). Its use has been growing ever since and is meant to cover all support system methods aimed at improving decision-making by gaining knowledge through accessing and analyzing business information [91, 153].

### 2.2.5. FROM 1990 TO 1999

The beginnings of this decade were characterized by the emergence and consolidation of technologies that extended the capabilities of existing support decision-making tools such as business intelligence (BI), data warehousing or online analytical processing (OLAP), which implied major changes in the way information and organizational knowledge was managed [7, 154, 155]. The need to deal with the rapid growth in the number and size of databases brought the development of tools and techniques such as knowledge discovery and data mining, which were aimed at an automatic intelligent understanding of data [156].

New desktop OLAP tools appeared and the emergence of client-server DSS left behind the systems based on mainframe data-driven DSS. These early years were characterized by the strengthening of object-oriented technological solutions to reuse the decision support capabilities, extending the approach based on online transaction processing (OLTP) for database management with real OLAP capabilities [91, 154].

The middle of this decade was marked by the possibilities created by the arrival of the World Wide Web and technological breakthroughs in data warehousing. Many organizations began to develop corporate intranets, to implement enterprise resource planning (ERP) applications and basic decision support tools such as ad-hoc query, reporting tools and quantitative models. Independent data marts were a widespread alternative to data warehouses [7]. All this interest led to major advances in research and development in the fields of knowledge discovery and data mining, which were seen as tools that integrated statistics, databases systems, machine learning and artificial intelligence to turn data into knowledge in order to achieve business results and appropriate customer relationship management [157–159].

Concerns about developing methods to assure and measure data quality grew. As a consequence, Wang et al. [160, 161] conducted a study that resulted in the production of a hierarchical framework of data quality based on "*data user's*" needs.

In parallel, throughout this decade, Intelligent DSS joined forces with a newly established discipline, knowledge management (KM). There were attempts to create AI-based DSS in the form of expert systems feed using organizational learning techniques [89].

At the end of this decade, two major landmarks can be noticed. On the one hand, the implementation of data warehouses and heterogeneous information systems represented the fundamental basis for achieving knowledge environments that integrated and allowed the sharing of information across the organization, thus contributing to improved decision-making [162]. This enabled the enhancement of the functionality of MIDS through balance scorecard (BSC) systems and enterprise management performance (EMP). In addition, the late nineties saw the development and introduction of new web-based analytical and business intelligence applications [7]. On the other hand, DSS embraced KM and, henceforth became what it is currently called knowledge management-based decision support systems [89].

### 2.2.6. FROM 2000 TO 2009

This decade represented an accelerated growth in the use of information in an integrated or distributed manner and also through the web. There was great interest in measuring and ensuring data and information quality and an important evolution in the development, improvement and implementation of BI solutions [2, 7, 91].

Early in this decade, applications service providers (ASPs) introduced software tools across the network and more sophisticated models of web services. They incorporated into their portals greater capabilities to support decisions by integrating knowledge management, business intelligence and communications-driven DSS into their interface [7, 163]. This triggered the development of more powerful techniques of data mining able to find hidden patterns in large databases; moreover, remarkable progress was made in transactional data. Their use was adopted by an increasing number of companies that expected that collecting and analyzing data about customers would enable the development of quantitative models to predict their preferences. In turn, this would allow companies to offer customized products and services to their clients [164].

The results from the research program "*Quality Program and Total Data Quality Management (TDQM)*", initiated during the past decade at MIT, aroused a lot of interest in the academic and professional world. This led to the development of new methods aimed at measuring, evaluating, managing and improving data and information quality. Data started to be seen as an important and valuable asset to gain business insight, improve efficiency and increase competitive advantage in dynamic business environments [165–169].

The term business analytics (BA) was introduced at the beginning of this decade and represented the key analytical component in business intelligence. It also represented an extension of its capabilities through advanced and automated data analysis using the databases of the company and the web, sophisticated quantitative techniques and presentation of dynamic reports, among others [170]. The adoption of these techniques by large corporations increased considerably and this gave a boost to research aimed at achieving the maximum value of the data available and transforming it into a greater organizational knowledge. Knowledge of the customers and their needs, how to increase business effectiveness or of new business or innovation opportunities [5] was gathered thanks to this analytic approach.

However, not all organizations managed to successfully undertake the path of BI and BA. Many found obstacles to their adoption. This led to several initiatives by the academic and professional community to analyze and identify appropriate methodologies adapted to different contexts in order to solve the problems that constituted a barrier to the successful implementation of BA [6, 22, 171].

The growing technological advances and changes at the technical and organizational level are reflected in the classification of data as structured, semi-structured and unstructured. An increasing number of data sets included image and voice, which required new techniques to manage and improve the data quality of these new types of files. Furthermore, the wide adoption of mobile devices generating and displaying data also required new service-oriented technologies for delivering, over the internet, the information required for making decisions everywhere, leading to was later known as ubiquitous decision support systems [172–174].

From the organizational and project management field, the concept of maturity models was embraced to assess the degree of adoption and use of BI. These concepts would experience a major upswing in the next decade [50].

At the end of this decade, big data polymorphism was evident. In the same extent that algorithms and solutions to process a big volume of data were developed, new challenges arose for the storage, processing and analysis of new data streams and higher volumes. This dynamism led to thinking about taking full advantage of big data as a moving boundary out of our reach to the same extent that it imposes a positive constant drive to innovate and take advantage of such data [175].

### 2.2.7. FROM 2010 TO DATE

The early years of this decade have been characterized by further consolidation of BI and BA solutions at the organizational and academic level, as well as by interest in ensuring that technologies are aligned and complemented with the flourishing trend to adopt big data [176]. This is due to the revolutionary potential of big data for creating useful knowledge for timely actions that improve the business and offer better products and customer service. This potential has placed BI and BA tools as a technological priority for the chief information officer (CIO) [25, 177].

Among the main consequences of the current use of big data are greater granularity of the data sources thanks to the rise of social networks and mobile devices, increased computing capabilities through the power of the cloud, the migration to search engine technologies applied to business systems, a more objective interpretation and insights into the feelings of group by means of opinion mining, applying techniques of social recommendation to provide consumers with predictive suggestions based on their preferences and the preference of their contacts and peers [25].

Retrospective studies identified an increasing trend in the amount and impact of the scientific production with terms of BI, BA and big data, which in turn is associated with a greater presence of these words on the web and an improvement in the webpage ranking of sites discussing those subjects [176]. Moreover, experimental applications had become more common. For example, taking as input a historical time series data, Varshney and Mojsilović [178] used signal processing techniques to develop a predictive model.

Some concerns and ethical-legal questions gained greater relevance due to the universalization of the internet of things. Ownership of data generated by users via sensor networks and the multiplicity of devices being used worldwide at every moment is an issue currently being debated. Alternatives and different views on privacy, the right to be forgotten as well as the use and strategies for the proper protection of confidential data from users are being proposed [179].

## 2.3. DISCUSSION ON THE EVOLUTION OF THE ROLE OF INFORMATION IN THE DMP

When the evolution of DMPs and data-driven technologies in businesses are simultaneously analyzed, the interaction between them is evident. Figure 2.5 shows a timeline which summarizes the major milestones previously mentioned in sections 2.1 and 2.2. The upper line represents a summary of the evolution of the DMP throughout the decades covered by this review. The lower line represents the evolution of data-driven technology in businesses. The gap between them represents their degree of interrelation and how the DMP evolved thanks to the development of technological capabilities, highlighting the most outstanding landmarks that allowed their convergence. The steps correspond to the most important milestones that influenced the development of DMP.

In terms of the chronological evolution shown in Figure 2.5, the first interactive information systems developed in the 60s significantly influenced advancement in the DMP. This gained momentum once the first computer-aided complex methods were introduced in the 70s, which provided new tools to improve the relevance, importance, and timeliness of information. Their deployment during the 80s was transcendent on the path to making better decisions. Figure 2.5 also illustrates the influence of the advances in data-driven technologies, especially those deployed from the 90s in DMPs. These technologies allowed data on the different factors that surround a decision to be obtained, reducing uncertainty and associated risks. This represented a shift towards a deeper knowledge of the organization, customers, suppliers and competitors in order to detect business opportunities.

Likewise, Figure 2.5 shows that in many instances technologies emerged or were adopted as an answer to the managerial needs of the time. One could argue that was the general trend before the 2000s. Conversely, in the most recent 15 years the progress of information technologies is what has truly pushed forward the data-driven managerial paradigm. Indeed, progress in the field of information technology and computer science is faster than it has ever been, surpassing the corresponding advance in the theories and techniques of making management decisions. This means a major breakthrough in the way companies make decisions have to take place, and perhaps this is about to happen.

In the same vein, Figure 2.6 presents a cause-effect diagram used to show graphically the relationship between all the successive managerial and technological advances that took place between 1950 and 2015 and that led to our current state regarding information-driven DMPs. Through Figure 2.6, it can be seen that as managerial and technological streams become increasingly closer as time advances, the convergence between DMP and DSS has led to major organizational transformations, emerging new data-driven business models, with start-ups leveraging data as the key resource of their business. Those big data and analytics

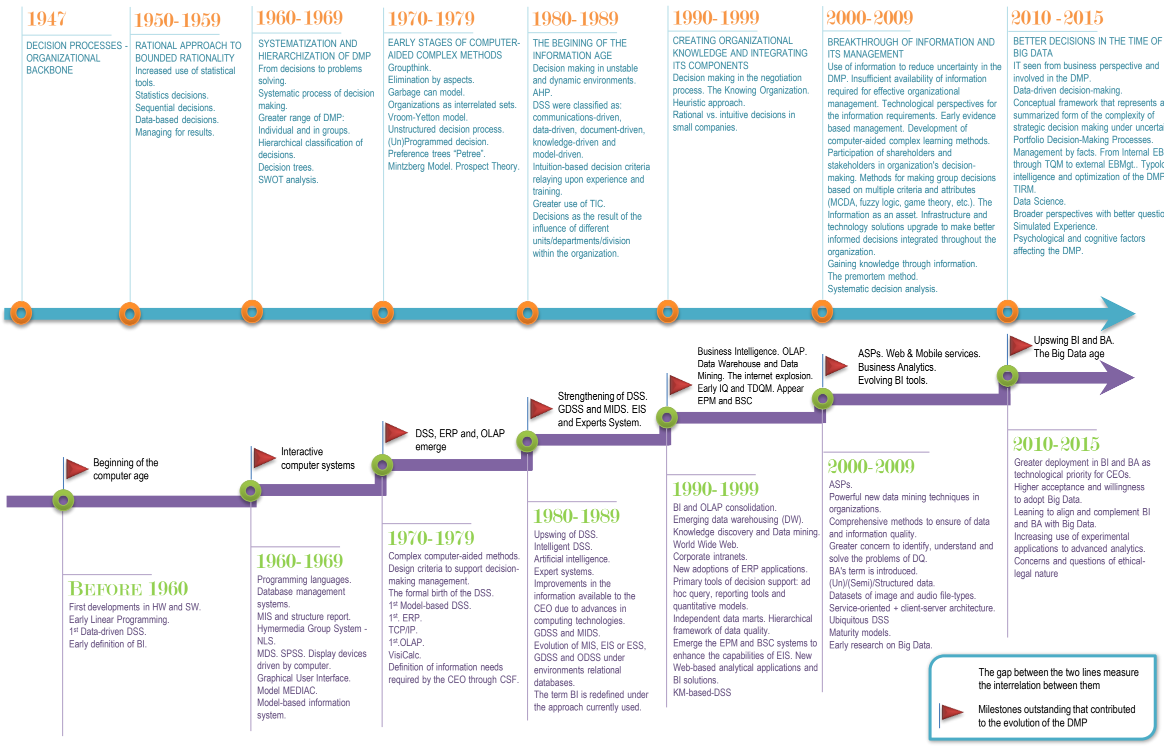


Figure 2.5: Timeline of the evolution the DMP and the information technologies that support them.

business models use data to create differentiated offerings, the brokering of the information and the building of networks to deliver data anywhere and anytime [180, 181]. Nowadays, organizations can obtain benefits from analyzing data not only for making single strategic decisions of large impact but also through making autonomously minor decisions on a large scale. In this regard, the big internet-based companies such as Google, Amazon or Facebook, as well as many others big companies worldwide, rely more than ever on autonomous algorithms for making decisions, and the numbers seem to validate the success of their practice.

Despite the profound transformation of the DMP as a result of the information resources available, it is noticeable that this transformation is slower and smaller than that taking place in the technological field, which is represented and reaffirmed by the outstanding milestones in Figure 2.5 and Figure 2.6, respectively. This disparity in evolution is also reflected in the adoption of these technologies (DSS and DMP) by businesses. Many organizations are ahead in the adoption of information technologies than in the development of the management systems needed to take advantage of them. They are, thus, not getting the most out of the massive amounts of data at their disposal.

A study conducted in 2010 revealed that 60% of executives interviewed claim to have more data than they know how to manage and use effectively [22]. This has been a recurrent fact in successive years. Those who lead organizations usually do not have the information needed, although they may have the data necessary to provide it to make key decisions [14]. This indicates that they are not yet fully matched with emerging technologies that are in continuous evolution. In order to compete successfully, organizations need to become more efficient and differentiate from the competition. This reveals that it is easier to buy the needed technology than to change the way organizations make decisions and are managed. Important factors inherent to this problem include the lack of adaptation by management to the technological solutions, lack of adaptation by the technological solutions adopted by the company to the needs and particularities of the organization, data quality problems, ineffective information governance and of the cultural and management nature [22].

The majority of successful cases are found in organizations that develop their own technologies or have reached maturity in the action-reaction cycle integrated in all areas, also called "*managing the information*

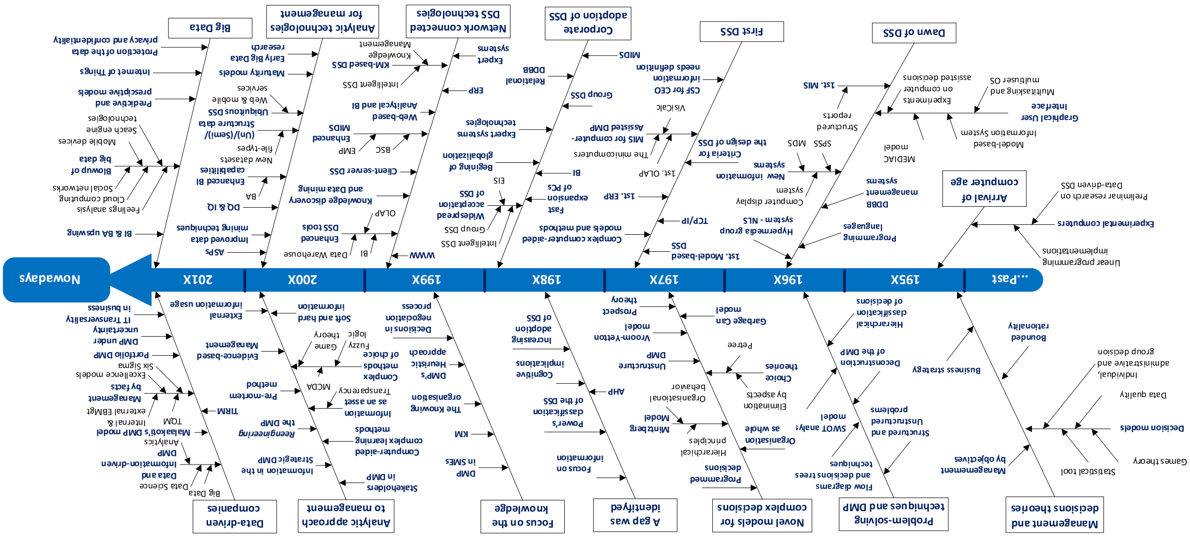

Figure 2.6: Cause-and-effect diagram of the chronological evolution of the information-driven DMP.

*transformation cycle*", which has led them to achieve the know-how to make better use of their information in order to make different types of decisions [14, 24].

In this sense, academic and professional communities have important implications for further work and collaboration in order to align the DMP with the data-driven technology solutions so they can achieve greater integration in order to close the gap between them, following which organizations can achieve a better-adapted toolset of technological resources in their DSS that are suitable to their real needs and particulars that allow them to consolidate the organization's business strategy. From a pragmatic point of view, this will require relevant, timely information, which should be disseminated widely and globally, to support their decisions and lead to real organizational knowledge and competitive differentiation.

When researchers, organizations and the managerial community finally come to bridge the ever existing gap between information technologies and the theory and practice of decision-making, there will be a major breakthrough in how companies and businesses are run. Recent experiences point to the evolution from data-driven to algorithm-driven organizations, which means providing automated and intelligent algorithms with the sufficient authority to make decisions across all levels of the organization with or without supervision. Similarly to many other preceding advances, algorithm-driven management is surely a matter of discussion and is not immune to risks and criticism. Yet, it seems reasonable to think that if the gap between DMP and DSS technologies is due to the human factor, relying more on algorithms rather than on the experience-based (biased) judgment of managers would help bridge it more easily. Therefore, one of the most relevant discussions in the forthcoming years will be about the role of managers in the DMP of algorithm-driven organizations.

# 3

# CHROMA: A Maturity Model for the Information-Driven Decision-Making Process

The previous chapter made clear there is a need for mechanisms for systematically identifying the key factors involved in information-driven decision-making processes. Consequently, it is important to develop methodologies to measure, evaluate and determine the level of sophistication of information-driven DMP in organizations as a first step to identify and implement improvement actions. Hereafter, this thesis embraces the maturity models as the alternative to this end.

In this sense, a maturity model was designed to evaluate and determine the level of organizations regarding their competence, readiness and maturity in the use of information to support decision-making. This model is graphically represented as a chromatic circle, as shown in Figure 3.1. The model is referred to as the "*Circumplex Hierarchical Representation of Organization Maturity Assessment (CHROMA) model for information-driven DMP*", based on the idea that the information-driven DMP requires the coexistence of a set of differentiated key factors that contribute to an organization's proficiency in making better-informed decisions.

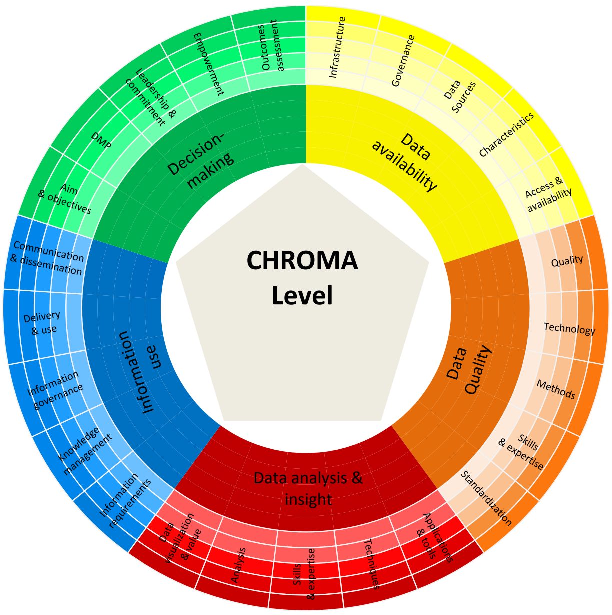


Figure 3.1: CHROMA model for information-driven DMP.

The CHROMA model's foundation is that an appropriate use of data will lead to more objective and better-supported decisions [4–6, 8, 14, 20, 27]. Therefore, business success can be gradually and systematically augmented by increasing an organization's maturity in its information-driven DMP.

From a general perspective, the CHROMA model uses as input the variables and factors that determine how decisions are driven based on the data, which in turn allows establishing a hierarchical reference framework to categorize the organization according to results of the evaluation of their information-driven DMP, providing as output an overall understanding of the organization that is useful for planning, re-directing and improving their performance (See Figure 3.2). The CHROMA model's objective is to help companies of any type in this process by providing insights that translate into a company self-knowledge and the accompaniment to guides them in the journey to improve their ability to innovate, gain a competitive advantage as well as identify business opportunities through the intelligent use of information.

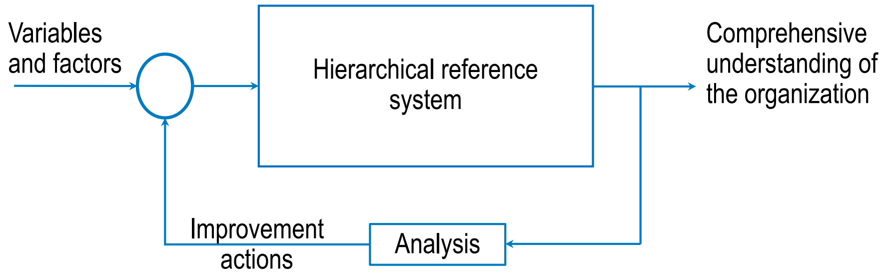


Figure 3.2: General process of CHROMA model.

The CHROMA model is prescriptive in that it provides a methodology for determining the current status of the organization, the requirements of each stage and a roadmap to advance from one stage to the next on the maturity scale. The following explanation of the model is divided into three sections: section 3.1 presents the model structure; section 3.2, the maturity stages and section 3.3, the assessment system. Finally, section 3.4 briefly describes the aspects considered during the pilot study to test the model.

## 3.1. STRUCTURE OF THE CHROMA MODEL FOR INFORMATION-DRIVEN DMP

The aspects contemplated by the model are classified into five dimensions which in turn are divided into five attributes. The dimensions and attributes were selected based on a review of state-of-the-art and successful managerial practices, and together they cover in a clear and organized way the specific aspects by which maturity in information-driven DMP is measured [3–6, 8–10, 14, 21, 22, 24, 45]. The five dimensions are represented in a chromatic circle where each one is a fundamental (spectral) component of maturity, as shown in Figure 3.1. The five attributes of each dimension are represented by different intensities of the dimension's color.

A brief description of each dimension and their corresponding attributes follows:

### 3.1.1. DATA AVAILABILITY

This is the ability of the organization to make accessible and available to end-users the necessary and relevant data in a timely, efficient and accurate way in order to support business processes and decisions [8, 14, 53, 54]. Several factors (attributes) influence this dimension:

1. `Infrastructure`: covers and describes the technology, architecture and integration available in the organization to ensure adequate availability and access to data supporting business processes and decisions [53, 54, 182, 183].

2. `Governance`: describes aspects, processes, controls and practices of data governance needed to ensure

a coherent strategy with clear standards and accountability in terms of business rules, data definitions, and data assets management to provide well-governed and flexible data access [51, 53, 54, 184].

3. `Data sources`: this attribute is related to the sources of data used and the sharing and integration of the data throughout the organization [54, 182, 184]. In the early stages the data comes basically from internal processes (internal data) and is not shared or integrated. Advanced organizations incorporate external data sources (government, markets, social networks, etc.).

4. `Characteristics`: this is related to those qualities, elements, characteristics or formats in which the data is presented or allows it to be defined. This includes the variety, volume, and speed of data used. Moreover, this attribute is also related to access to and availability of metadata (data that describes other data) in order to determine the source of the data and make it traceable [182, 184].

5. `Access & availability`: this attribute describes the ability of the organization to give users the means to access and to have to hand the data they need in a timely and expeditious manner [53, 54].

### 3.1.2. DATA QUALITY

Data quality is a fundamental matter to be considered by organizations in order to support business processes and decisions based on correct, accurate, relevant and reliable data. Ensuring data quality is a complex issue that requires a good combination of methodology, standards, people skills and technology [165, 168, 174].

Data quality problems are frequent in many organizations and their consequences go beyond leading to bad decisions, —they also generate a negative data-driven culture [54, 172, 174]. This dimension consists of the following attributes:

1. `Quality`: this attribute describes the degree to which the data quality issues are considered and addressed by the organization [54, 165, 168, 185].

2. `Technology`: describes the tools and technological resources of the organization and the degree of sophistication of these for proper management of data quality [166, 172, 186].

3. `Methods`: this attribute provides a description of the structured and systematic set of techniques and protocols applied to ensure organizational data quality [166, 172, 186].

4. `Skills & expertise`: this attribute includes people's knowledge, abilities and skills to ensure the quality of data, as well as the degree to which these capabilities are extended and consolidated throughout the organization [54, 165, 168, 185, 186].

5. `Standardization`: this attribute raises the requirements for a standardized definition and implementation of data definitions, data taxonomies and data elements in accordance with commonly used business terms, as well as metadata that is up-to-date and integrated across the company [165, 168, 186, 187].

### 3.1.3. DATA ANALYSIS & INSIGHT

Data analysis involves processing data to transform it into useful information and discovering the hidden value that lies in it, thus providing insights that support decision-making [4, 6, 8, 14, 22, 24, 180, 182, 184, 188]. The associated attributes that are key to analyzing the data to provide a global view of the business processes of the organization include:

1. `Applications & tools`: describes the tools and technological applications available to the organization for analyzing data, as well as their capacity to allow more specialized analysis and the possibilities to evolve [8, 14, 15, 54, 180, 184].

2. `Techniques`: describes the set of procedures, standards and protocols applied and their degree of sophistication in performing data analysis [8, 14, 15, 54, 180, 184].

3. `Skills & expertise`: this attribute describes the knowledge, capabilities and analytical skills that staff should have in order to take advantage of their data. It also includes training to develop and broaden these skills, as well as the degree to which these capacities are extended and consolidated through the organization, thereby promoting a data-driven culture [8, 14, 20, 22, 54].

4. `Analysis`: this attribute describes the purpose and approach of data analysis, ranging from purely descriptive and looking to the past, to predictive and innovation encouraging [6, 8, 14, 20, 22, 54, 180].

5. `Data visualization & value`: this contemplates how data is visually represented and presented, and the support in which it is presented. It assesses whether it is understandable, useful and efficiently usable by all users in the organization [8, 9, 54, 180].

### 3.1.4. INFORMATION USE

The use of information in this context is defined as the way in which an organization's information (processed data that has a meaning: relevance, purpose, and context) is used to support decision-making [3, 10, 11, 14, 21, 22]. In this regard, the five attributes associated with this dimension are:

1. `Information requirements`: this attribute is associated with the degree to which the information requirements are defined and integrated with business processes in support of the organization's objectives [3, 8, 14, 24].

2. `Knowledge management`: includes the elements that are essential to identify, capture, develop, share and effectively utilize the organization's knowledge, clearly defining roles and responsibilities, as well as standardizing strategies, processes and approaches to its implementation, monitoring, and improvement [46, 52, 189].

3. `Information governance`: describes the set of policies, structures, processes, standards and procedures to manage, enhance and leverage information. Encompasses compliance with immediate and future requirements at the regulatory, legal, privacy, security, risk, and operational levels of the organization in alignment with business goals [51, 53].

4. `Delivery & use`: this attribute contemplates the ways and means through which the information is presented, offering a clear, updated, understandable and useful view of key elements to support the company strategy and decision-making [14, 22, 24, 180].

5. `Communication & dissemination`: covers the degree to which key information is disseminated and shared transparently across the organization, ensuring that it is consistently updated, measured, revised and improved [8, 14].

### 3.1.5. DECISION-MAKING

Information-driven decision-making assesses the way in which organizational decisions are made under a systematic and planned process supported by useful and usable information resulting from the analysis of verifiable data [1, 4–6, 8, 13, 14, 20, 22, 27, 129, 190, 191] Amongst the factors (attributes) to be considered in the DMP, the following were established:

1. `Aim & objectives`: this describes the degree to which the purpose, objectives, policies and strategies are established in terms of relevant data, both internal and external to the organization. It also considers the continuous revision and improvement of it on the basis of well-established and standardized metrics throughout the organization [52–54].

2. `DMP`: this attribute describes the elements that must be present for the decision-making process to be carried out accurately, objectively and efficiently, thereby promoting the development of an information-driven culture and adequately managing the risks associated [3, 4, 6, 8, 14, 22].

3. `Leadership & commitment`: considers leadership involvement in promoting analytical skills and a data-driven culture across the organization [8, 14, 54].

4. `Empowerment`: this attribute contemplates the willingness to delegate authority and power to make decisions throughout all levels of the organization [8, 14].

5. `Outcomes assessment`: this evaluates how the organization assesses the outcomes of the decisions made, which is a crucial aspect to determine the degree of effectiveness of decisions and to identify opportunities for improvement. It includes how the metrics to do so are established and measured [4, 6, 8, 14, 20, 22].

## 3.2. MATURITY STAGES OF THE CHROMA MODEL FOR INFORMATION-DRIVEN DMP

As with models of excellence [192–194], the evaluation of maturity in the CHROMA model is conducted from bottom to top. That is, each attribute is evaluated according to five well-defined stages of maturity. The evaluation of the five attributes of each dimension is then combined to provide the dimension's degree of maturity. The overall evaluation is, in turn, obtained by combining the five dimensions.

The attributes' stages of maturity are defined as: 1) Uninitiated, 2) Awareness, 3) Proactive Adopting, 4) Integral Embracement, and 5) Completely Embedded. These five stages provide a good balance between resolution and a manageable number of levels. Figure 3.3 schematically shows these maturity stages. The requirements to reach each of these levels are widely specified and clearly described in the CHROMA framework (See Appendix A), which is the basic reference during the evaluation of the organization.

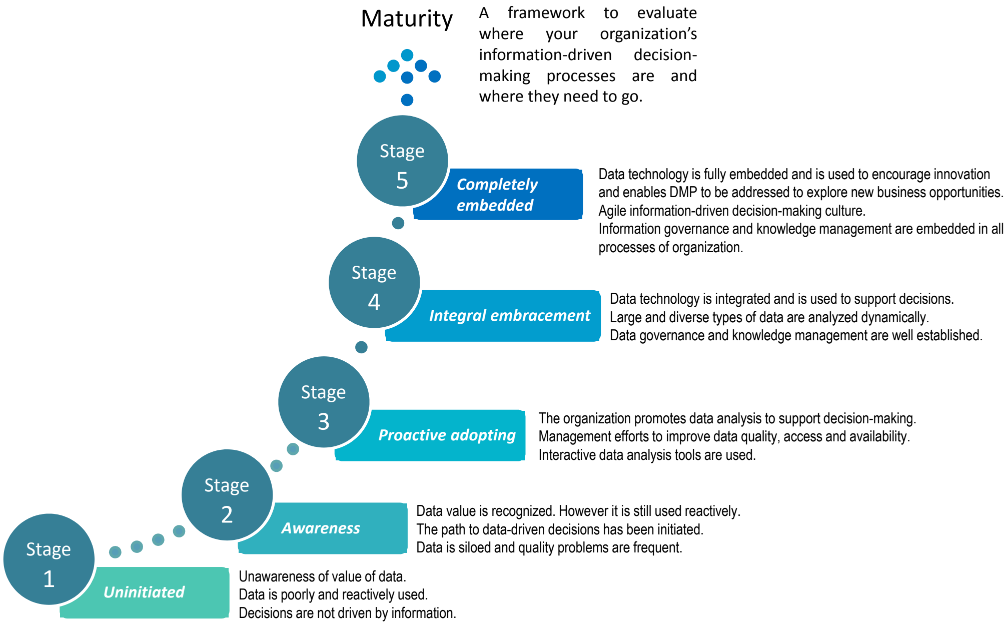


Figure 3.3: Generic description of the maturity stages of the CHROMA model for information-driven DMP. A detailed description can be found in Appendix A.

## 3.3. SCORING OF THE CHROMA MODEL FOR INFORMATION-DRIVEN DMP

The CHROMA model assessment process is divided into two phases, which are schematically represented in Figure 3.4. Those two phases are intended for gathering the necessary information for performing the evaluation whilst causing minimal inconvenience to the organization in terms of the disruption of their normal working and managerial processes.

The first phase consists of between four and five semi-structured face-to-face interviews, each one comprising between 24 and 46 predefined open-ended questions which are written down in a set of

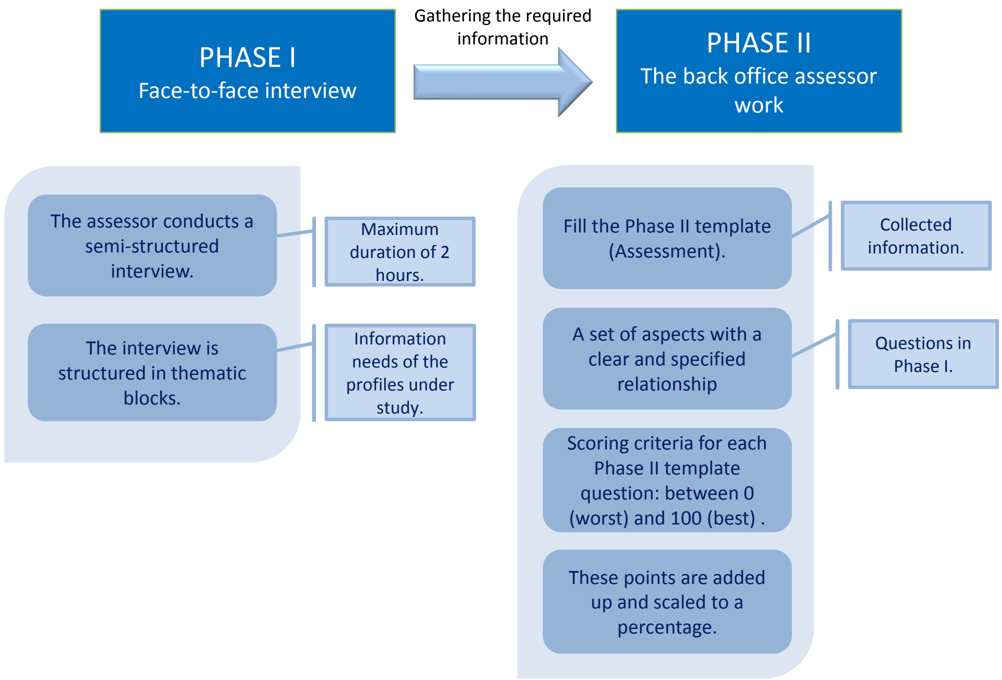


Figure 3.4: Phases, structure, method and application criteria of the assessment tool.

information gathering templates, plus a short web questionnaire of twelve questions addressed to all staff. Interviews are carried out with key personnel of the organization involved in the information-driven DMP, for example, the project coordinator, the head of IT (or equivalent), the CEO or a senior manager, and the head of one or two processes (or departments).

The answers of the interviewees are audio recorded for their posterior analysis and notes regarding the highlights are taken during the interview. Interviews are intended to be conducted by an expert which must be able of guiding the interviewees whenever more details are required for achieving a sufficient comprehension of the organization under assessment [195].

It should be noted that in no case, the result of the web questionnaire (survey) influences the evaluation carried out by the external expert since both must be done independently. In other words, the intention of the survey was to compare the results obtained from applying the CHROMA model with the self-assessment carried out by the company.

The second phase corresponds to the scoring process which is carried out by the external expert evaluator based upon the information collected in phase I. In that sense, phase II pose a set of closed-ended questions that must be answered external expert evaluator using the framework of the CHROMA model as the standard reference. Each individual questions must be given a score between 0 (worst) and 100 (best). This implies the expert has to compare the results and rank the organization using the framework of the CHROMA model for the different attributes, which ensures an objective, consistent and adjusted assessment of the level of organization maturity for each attribute.

Naturally, the scoring done in phase II is closely linked to the assessment conducted. Figure 3.5 shows that first, the interview questions are used to score the disaggregated aspects assessed for each profile (interviewee). The disaggregated scores are then combined to obtain a scaled attribute score. Next, those attribute scores are averaged to obtain the dimension score, and in turn the overall score is obtained as the mean value of the dimension scores.

The importance (weight) a given question has in the overall assessment of maturity depends on the number of attributes over which it has influence. Independently of the number of questions that are related to each attribute, they have the same weight in the dimension's score. Likewise, each dimension has the

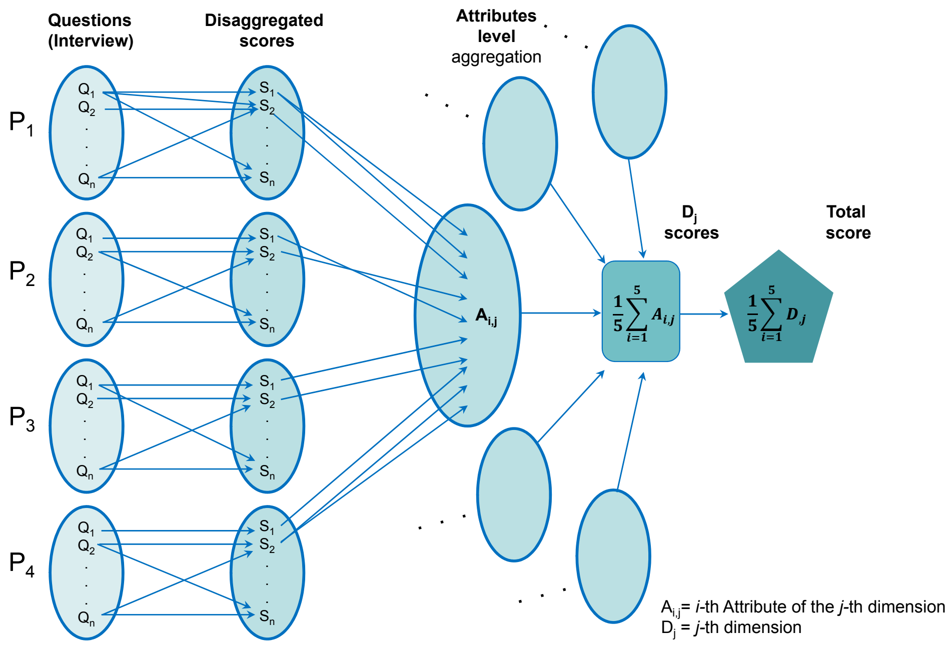


Figure 3.5: The CHROMA model scoring process.

same weight in the overall CHROMA score. Also, the result of the assessment will be presented at different levels of detail, simultaneously providing an index of maturity for the attributes and dimensions, as well as a total index.

Obviously, the feedback is provided at a detailed level along with a score for each dimension and attribute, which is a source of valuable information to detect areas or elements requiring improvement actions.

These results are graphically represented in order to facilitate a global analysis of the situation of the data-driven DMP. Figure 3.6 shows an example of how the CHROMA model structure is used to simultaneously display the results of the evaluation of the maturity stages: The attributes score is represented by the length of bars arranged in a circle, the dimensions are represented by a pie chart, and the global score appears inside the central pentagon.

## 3.4. PILOT STUDY

To test the model and to gather feedback on improvement points in terms of the assessment and the usefulness of the reports and feedback provided, we conducted a pilot study. The study was also intended to evaluate the capability of the assessment tool to measure properly the level of an organization's maturity in its information-driven DMP. The conclusions of the pilot study reflect the opinions of companies and assessors.

In line with the above, and in order to delimit appropriately the pilot study to be carried out, it was decided to center the pilot study on the family-owned SMEs. This, given its importance in the Spanish economy and the fact that their peculiarities impose additional challenges to data-driven DMP. In conducting the pilot study, the "*Instituto de la Empresa Familiar*" (Spanish Family Business Institute), the Associació Catalana de l'Empresa Familiar (ASCEF), and the Association of Internationalized Industrial Enterprises (Amec) provided significant support.

Through them, different companies in Catalonia were contacted, being finally selected three of medium size [196]—two industrial and one from the service sector. This selection was based both on the size of the company and on the typical characteristics of family businesses: Ownership, control, governance and voting rights [38, 197], as well as their willingness to participate in the study.

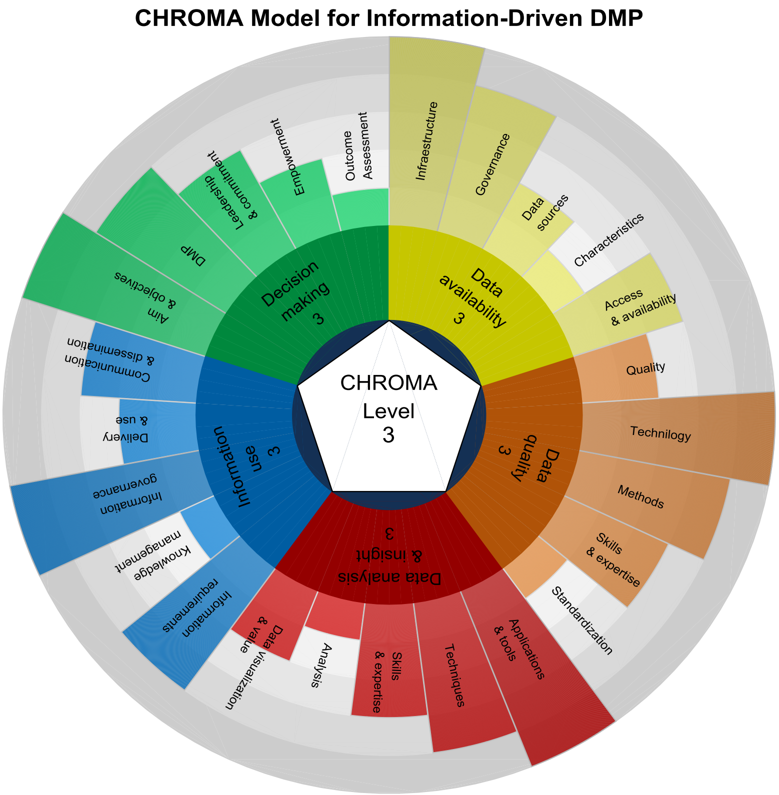


Figure 3.6: An example of the graphical representation of the application of the CHROMA model.

In this regard, a comprehensive analysis of the results of the pilot study will be given in Chapter 5. However, it is necessary to provide in advance the outcomes from this pilot study that justified the development of a simplified version of the CHROMA model, which will be presented in the following chapter.

At a general level, three important opportunities for improvement were identified in the evaluation methodology of the CHROMA model (from the point of view of the assessment tool and the model itself), namely:

1. The assessment tool needs to be simplified in terms of linking it more closely way with the dimensions and attributes of the model and improving its adaptability with respect to the particularities of each organization. This simplification should allow us to generate more focused questions for an accurate collection of information relevant to the study, and linked to the dimensions and attributes of the model to improve and facilitate the evaluation process.

2. Although the initial intention was to design a model suitable for any type of company (except the largest), through the pilot study conducted with companies ranging from 60 to 110 employees, it was found that the use of the CHROMA model might not be able to fully adapt to SMEs, so it can and should be simplified.

3. The idea of complementing the managers' interviews with a short web questionnaire addressed to all personnel did not yield the expected results, as the number of responses was extremely low. This may require a shift in focus, through the development of an even shorter survey (between 5 and 6 questions) and closely linked to the model's dimensions and attributes, addressed only to decision makers to obtain their perception of how information is used to drive the company's decisions and strategy.

# 4

# CHROMA SHADE: A Maturity Model for the Information-Driven SME

The previous chapter presented the Circumplex Hierarchical Representation of the Organization Maturity Assessment (CHROMA) model for information-driven decision-making process (DMP), which was developed and tested through a pilot campaign on three family-run SMEs [55]. Among other things, the results revealed that the CHROMA model offers a high-resolution vision regarding the complexities inherent in the multiplicity of factors that combine at the technological and management level in making better-informed decisions. This resolution level is better suited to medium- to large-sized companies, whose processes of information transformation and decision-making are distributed further across the different levels of the organization, allowing them, from a novel and holistic approach, to detect and guide efforts and investment towards specific improvement areas.

In line with the above, a simplified derived version has been developed, the "*Simplified Holistic Approach to DMP Evaluation (SHADE) of the CHROMA model*" for the information-driven SME. The CHROMA SHADE model seeks to provide a coherent and simpler assessment methodology adapted to the characteristics of SMEs, whose information transformation and decision-making processes are mainly concentrated in the senior level management of the organization.

The CHROMA SHADE model embraces the factors covered by the CHROMA model but with a reduced set of attributes, which were merged and summarized consistently to ensure that the assessment output and the reality were aligned, thereby facilitating their interpretation and understanding. SHADE is also an analogy to remind users that the new model is a projection of the original CHROMA model. Accordingly, the CHROMA SHADE model is also conceptually and graphically represented as a chromatic circle, as shown in Figure 4.1, in which an overall set of elements that influence the information-driven DMP are distributed in an orderly manner.

In this context, based on the same principles as its predecessor, the CHROMA SHADE model is useful in assessing and determining the level of the SME in terms of competence, readiness, and maturity to making better-informed decisions.

## 4.1. Structure of the CHROMA SHADE model for the information-driven SME

The CHROMA SHADE model is classified into five dimensions, which in turn are subdivided into three attributes representing together in a clear and organized way the concrete aspects by which maturity is measured in the context of the information-driven DMP in SMEs. The dimensions and attributes of this version of the model are the results of the findings achieved during the pilot studies carry out for the original version of the model [55]. Similarly, these dimensions are represented according to a range of colors reminiscent of a chromatic circle in which each color constitutes a fundamental (spectral) component of maturity and the different intensities of the color of each dimension correspond to its attributes.

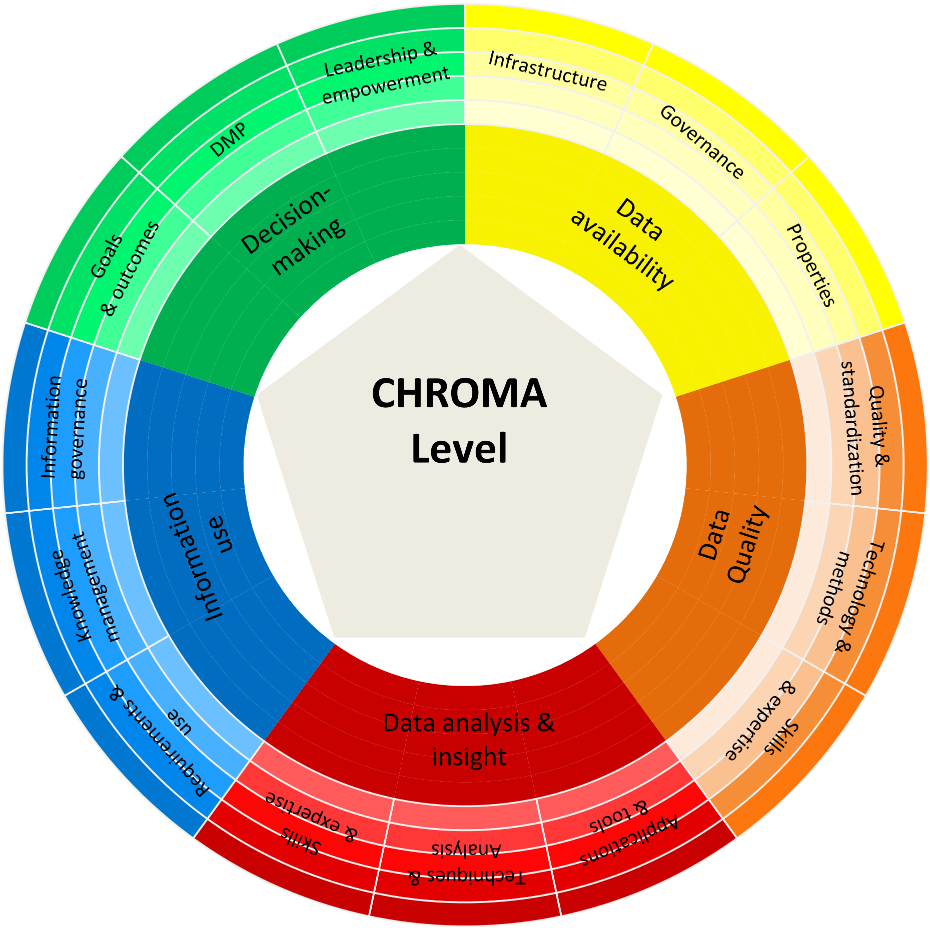


Figure 4.1: Simplified version of the CHROMA model for the information-driven decision-making process.

Under a broader approach, the five dimensions that make up both models are distributed following a logical sequence in terms of information-driven DMPs [198]. The idea raises the notion that, for information-driven decision-making, it is first necessary to ensure that end users gain the appropriate access and availability to relevant data (data availability). It should also ensure that business processes and decisions are supported by good quality data (data quality). Next, this data must be processed to transform it into meaningful and relevant information (data analysis and insight), which will be used to support decisions and encourage organizational continuity (use of information), promoting the making of better-informed decisions under a planned and systematic process that contributes to improving their performance, innovation, and achieving a greater competitive advantage (decision-making).

The CHROMA SHADE is a "*mutation*" of its predecessor that emerged from the need to adapt to the conditions inherent to SMEs. Although the CHROMA model and its SHADE variant are in different branches with regards to the typology of organizations to which they are targeted, they share most of their core characteristics. To avoid redundancy, only the aspects that were modified from the original model will be explained in the following sections.

### **4.1.1.** DATA AVAILABILITY

Several factors (attributes) influence this dimension:

1. `Governance`: this describes aspects, processes, controls and practices of data governance to ensure a coherent strategy, with clear standards and responsibilities for efficient data asset management that

enable the organization to be able to provide users with the required accessibility in a timely, flexible and expeditious manner [27, 51, 53, 54, 184].

2. `Properties`: this attribute is related to those qualities, elements, particularities or formats in which the data is presented and range from its definition, characteristics and origin sources to the degree in which it is shared. Likewise, this attribute is also related to the access to and availability of metadata (data describing other data in order to standardize its content and structure for a more effective understanding of it) to determine the source of the data and make it traceable [54, 182, 184].

### 4.1.2. DATA QUALITY

The attributes that influence data quality are:

1. `Quality & standardization`: this attribute addresses how the organization discovers, addresses, and prevents data quality problems. This includes, therefore, the establishment of data taxonomies and standards for definition, coding and data exchange [54, 165, 168, 185–187].

2. `Technology & methods`: this describes the technological tools and resources of the organization and their degree of sophistication for an adequate quality management of data, specifying for this the structured and systematic set of techniques and protocols applied to ensure the quality of data of the organization [166, 172, 186].

### 4.1.3. DATA ANALYSIS & INSIGHT

The associated attributes that are key to analyzing the data to provide the big picture of the organization's business processes include:

1. `Applications & tools`: this describes the tools and technological applications available in the organization for analyzing data, contemplating its upgrade and capacity level to allow more specialized analysis, as well as the way in which data is visually represented and presented for ensuring it is understandable, useful and efficiently usable by all the organization's users that allow them to obtain a greater value and insight about the data through its analysis [8, 9, 14, 15, 27, 54, 180, 184, 191].

2. `Techniques & analysis`: this describes the set of procedures, standards and protocols applied and their degree of sophistication in performing data analysis as well as the purpose and approach under which the different types of analysis are carried out to contribute in decision-making across the organization [6, 8, 14, 15, 20, 22, 27, 54, 180, 184].

### 4.1.4. INFORMATION USE

The five attributes associated with this dimension are:

1. `Requirements & use`: this attribute is associated with the degree to which the information requirements are defined, established and integrated with business processes in support of the organization's objectives by providing relevant, updated and reliable information according to the needs of the users. It includes the ways and means through which the information is presented, offering a novel, agile, understandable and useful perspective as well as its effective use and exploitation to support the company's strategy and decision-making, thereby promoting an information-driven culture [3, 8, 14, 22, 24, 180].

2. `Information governance`: this describes the set of structures, policies, processes, and standards required to manage, integrate, enhance and leverage organization-wide information through clear guidelines and responsibilities under a transparent, shared-learning and research on best practice approach. It encompasses effective compliance with immediate and future requirements at the regulatory, legal, privacy, security, risk, operational and business levels across the organization in alignment with business goals [8, 14, 20, 27, 51, 53, 184].

### 4.1.5. DECISION-MAKING

Amongst the attributes involved in the information-driven DMP, the following were established:

1. `Goals & outcomes`: This describes the extent to which the purpose, objectives, policies and strategies are established and continuously improved in terms of relevant data, both internal and external to the organization. It also considers defining and implementing standardized metrics across the organization for the measurement, monitoring, and evaluation of the degree of effectiveness of decisions, the fulfillment of objectives and to identify opportunities for improvement [4, 6, 8, 14, 20, 22, 27, 52–54, 190].

2. `Leadership & empowerment`: This describes the conditions of leadership, commitment and willingness to delegate authority functions with different degrees of power and autonomy that must exist in all levels of the organization to consolidate a data-driven decision-making culture throughout the company [8, 14, 54, 184].

## 4.2. ASSESSMENT OF THE CHROMA SHADE MODEL FOR THE INFORMATION-DRIVEN SME

In order to properly categorize organizations, the CHROMA SHADE model is deployed through the same five well-defined stages of maturity (see Figure 4.2), which provide a good balance between resolution and a manageable number of levels [55]. Likewise, the requirements to reach each of these levels are widely specified and clearly described in the CHROMA SHADE framework (see Appendix B).

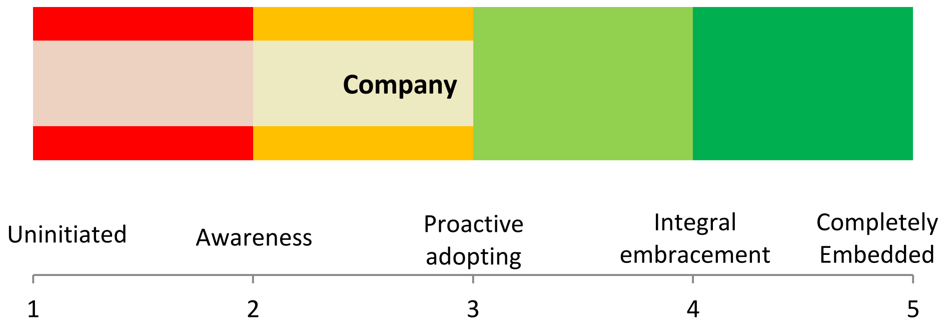


Figure 4.2: Stages of maturity of CHROMA model and its SHADE variant for the information-driven DMP.

As with the CHROMA model, the evaluation of maturity in the CHROMA SHADE model is conducted from bottom to top. That is, each attribute is evaluated according to the five stages of maturity. The evaluation of the three attributes of each dimension is then combined to provide the dimension's degree of maturity. The overall evaluation is, in turn, obtained by combining the five dimensions. This evaluation is carried out through an enhanced version of the CHROMA model assessment tool (see Appendix C).

This assessment tool was simplified and merged according to findings of the previous pilot test, with the aim linking it more closely with the dimensions and attributes of the model and improving its adaptability with respect to the particularities of each organization, especially SMEs. Likewise, the built-in improvements made it possible to unify the assessment tool into a single template that is sufficiently robust to be applied indistinctly for both the CHROMA model and its SHADE version. For this, more focused questions were designed for the accurate collection of information relevant to the study and linked to the dimensions and attributes of the model to improve and facilitate the evaluation process [55].

In this sense, this assessment tool aims to gahter the necessary and relevant information to the study, causing minimum inconveniences to the organization and thus allowing an appropriate and pragmatic evaluation in a reduced time frame. This enhanced version of the assessment tool is based on two semi-structured interviews with key personnel (profiles) of the organization involved in the information-driven DMP:

- The head of IT (or equivalent) or, in his absence, a project coordinator, who provides key information regarding the data management technology used, the available databases and the way information is made accessible to users. Moreover, they should be the liaison and contact person between the organization and the assessor, providing an initial general perspective of the organization and its functioning. They should also help organize the assessment process. When the organization does not have this profile, a project coordinator should be assigned to carry out these liaison functions, and technical issues should be addressed to the CEO or a senior manager.

- The CEO or a senior manager, who provides the perspective on how well the organization uses the information to make decisions. The interview also allows top management expectations to be aligned with the scope of the study and the output that will be delivered.

Additionally, a brief web questionnaire of six questions was designed that was closely linked to the dimensions and attributes of the model, directed only to decision makers (heads of processes or departments) to obtain their perception as to how information is used to drive decisions and company strategy (see Appendix D). This survey constitutes a complementary validation mechanism to compare with the results of the application of the CHROMA model. Therefore, the results of the surveys are not combined with those of the interviews, they are independent of each other.

The application of the assessment tool of the CHROMA model and its SHADE version is divided into two phases. In phase I, a set of semi-structured face-to-face interviews comprising 60 predefined open-ended questions which are written down in the information gathering template (Appendix C) are conducted. Moreover, the interviews are conducted with key personnel corresponding to each profile. Each interview has an approximate duration of one and half hours. Also, the interview is structured into thematic blocks associated with the dimensions and attributes of the model. Next, the phase II evaluation process is made on the basis of the information collected in phase I, which is in turn checked against the framework of the corresponding model for the different attributes and scored according to a specific set of evaluation criteria ranging from 0 (worst) to 100 (best) according to the rules shown in Table 1 to ensure an objective, consistent and adjusted assessment. These scores are added up and scaled to a percentage. Figure 4.3 shows the methodology of the CHROMA model assessment process.

Table 4.1: Scoring criteria for phase II of the CHROMA model assessment tool

| **SCORE** | **CRITERIA** |
|---|---|
| 0 | Does not exist |
| 25 | Something exists |
| 50 | Exists at a minimum acceptable grade |
| 75 | Exists to a good degree |
| 100 | Exists to an excellent degree |

As already indicated, the scoring carried out in phase II of the assessment tool is closely linked to the dimensions and attributes of the model. In this regard, as shown in Figure 4.4, the interview questions are used to score the disaggregated aspects assessed. The disaggregated scores are then combined to obtain a scaled attribute score. Next, those attribute scores are averaged to obtain the dimension score and in turn the overall score is obtained as the mean value of the dimension scores. In a similar way to its predecessor, the importance (weight) a given question has in the overall assessment of maturity depends on the number of attributes over which it has influence. Therefore, independently of the number of questions that are related to each attribute, they have the same weight in the dimension's score. Likewise, each dimension has the same weight in the overall CHROMA score.

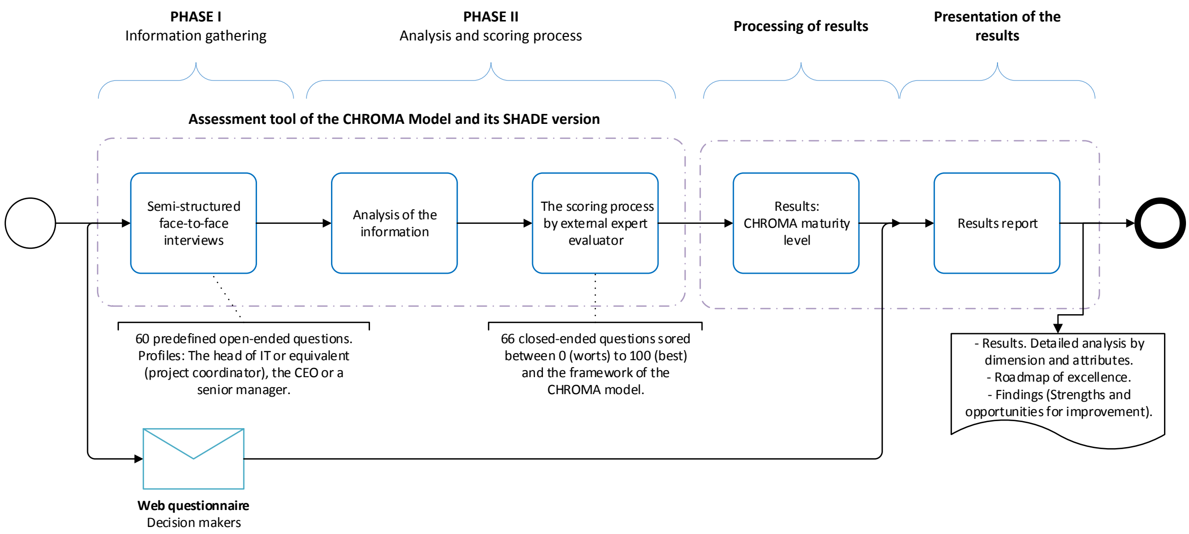


Figure 4.3: The CHROMA model assessment process.

In this regard, the results of the application of the CHROMA SHADE model will be presented at different levels of detail, simultaneously providing an index of maturity for the attributes and dimensions, as well as a total index, which is a source of valuable information to detect areas or elements requiring improvement actions.

These results are graphically represented in order to facilitate a global analysis of the situation in the information-driven DMP context. Figure 4.5 shows an example of how the structure of the CHROMA SHADE model is used to simultaneously display the results of the evaluation of the maturity stages: The attributes score is represented by the length of the bars arranged in a circle, the dimensions are represented by a pie chart, and the global score appears inside the central pentagon.

## 4.3. PUTTING THE CHROMA SHADE MODEL TO WORK IN FAMILY-OWNED SMES

In order to validate the applicability of the CHROMA SHADE model, it was put into action in a further three SMEs. The model's usefulness, evaluation process and adaptability were verified in each study case. To ensure the homogeneity necessary for later comparisons with the prior findings, it was decided to continue focusing on family-owned SMEs. At the same time, this study aimed to evaluate the ability of the assessment tool to measure appropriately and consistently the level of an organization's maturity in its information-driven DMP using the dimensions and attributes of the model.

For all the above, the research once again was supported by the "*Associació Catalana de l'Empresa Familiar*" (ASCEF) and by the "*Instituto de la Empresa Familiar*" (Spanish Family Business Institute). Through these institutions, several Catalan companies were contacted and three medium-sized companies [196] were selected, which had the typical characteristics of a family business: shared ownership, control, governance and voting rights [38, 197] and agreed to participate in the study. With these three companies from the service sector, the application of the CHROMA SHADE model assessment tool was carried out.

Additionally, for this second block of field studies, a group of four students from the Universitat Abat Oliba CEU was recruited and selected for training in the CHROMA SHADE model to participate as trainees during the field study campaigns.

It is important to emphasize that the application of the CHROMA SHADE model was very useful in keeping with the purpose initially established. The results obtained through this study are presented in chapter 5.

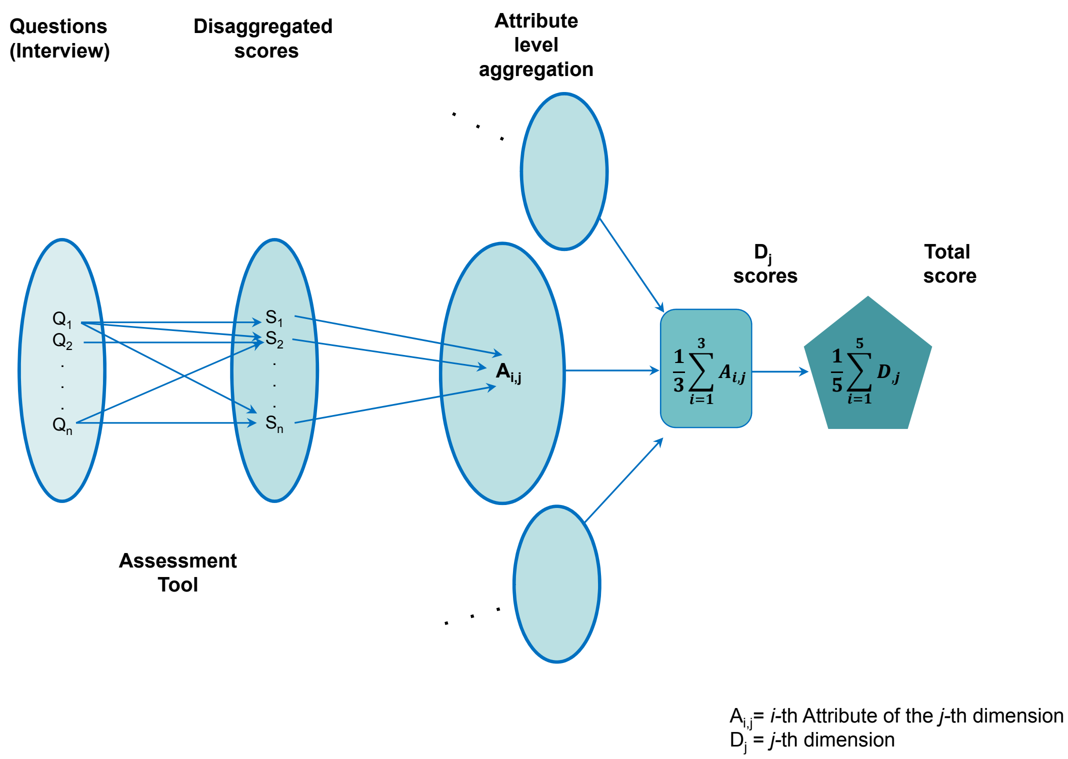


Figure 4.4: The CHROMA SHADE model scoring process.

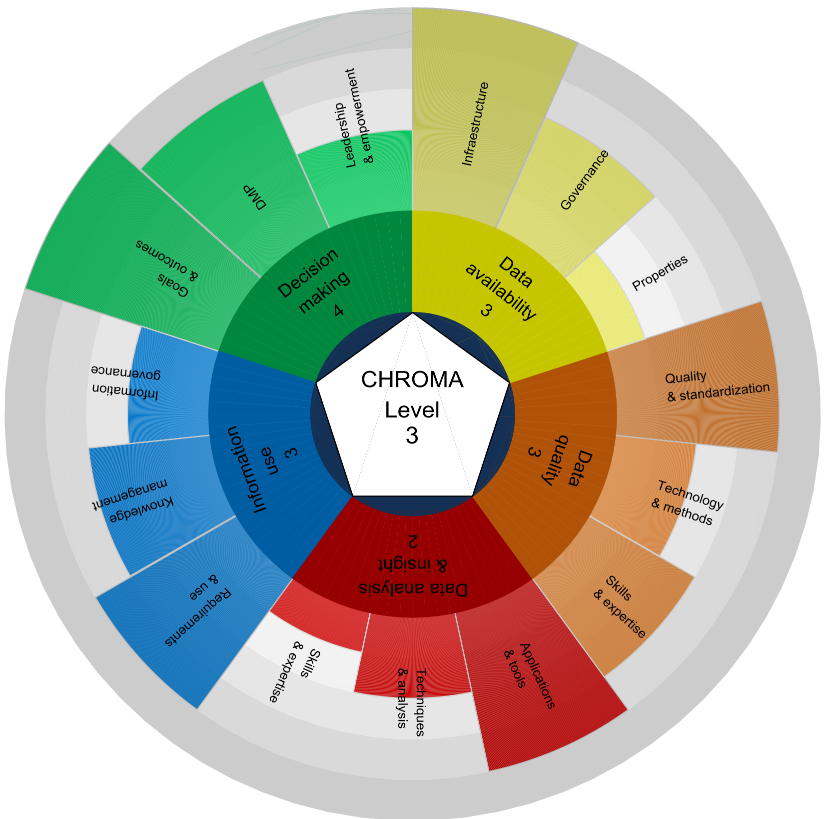


Figure 4.5: An example of the graphical representation of the application of the CHROMA SHADE model.

# 5

# RESULTS

This chapter details the main results derived from the application of the CHROMA and SHADE models throughout a campaign that included a total of six SMEs. This chapter is organized into three sections. The first comprises the results obtained from each model for each SME. The next section presents a comparative analysis of the SMEs involved in the study. The last two encompass the lessons learned and improvements made to the models along with the contributions to the growth and success of the companies through their application.

## 5.1. FIELD TEST RESULTS

In this section, the results of the application of the CHROMA and SHADE models to the family-owned SMEs that collaborated with the study will be summarized. It is important to note that the results obtained from the evaluation (section 5.1 of this chapter) were presented to each of the companies under study through a detailed report of the results that contained confidential information that cannot be disclosed. In this report, the results of the application of the corresponding model are presented in detail, highlighting in turn the strengths and opportunities for improvement, the maturity assessment achieved with a roadmap to guide them to evolve to higher maturity levels and the conclusions and recommendations.

### 5.1.1. RESULTS OF THE APPLICATION OF THE CHROMA MODEL FOR THE INFORMATION-DRIVEN DMP

The following is a summary of the results obtained by means of the CHROMA model application in the first block of three small/medium size enterprises that collaborated with the pilot study in terms of the purpose set out in Chapter 3.

#### COMPANY 1

Company 1 is a family business of 72 employees that offers specialized services in asset management (properties, communities and rental), property commercialization and real estate consultation. Company 1 has almost sixty years of experience in the real estate sector. In this company, four interviews were conducted with the following profiles:

- Project Coordinator (head of quality).
- CEO/Senior manager (3rd generation and member of the Steering Committee).
- Head of the Patrimonial and Commercial Departments.

It is noteworthy that this organization does not have a defined profile of Head of IT or its equivalent within its workforce; all its technological support needs are therefore managed and covered through outsourcing.

As a result of the evaluation of this organization, it was found that its current level of maturity falls into the category of "*Integral Embracement*" with a consolidated information-driven decision-making process, highlighting some improvement opportunities in order to be able to evolve to the stage "*Completely Embedded*". Figure 5.1 presents the results of the application of the CHROMA model to Company 1.

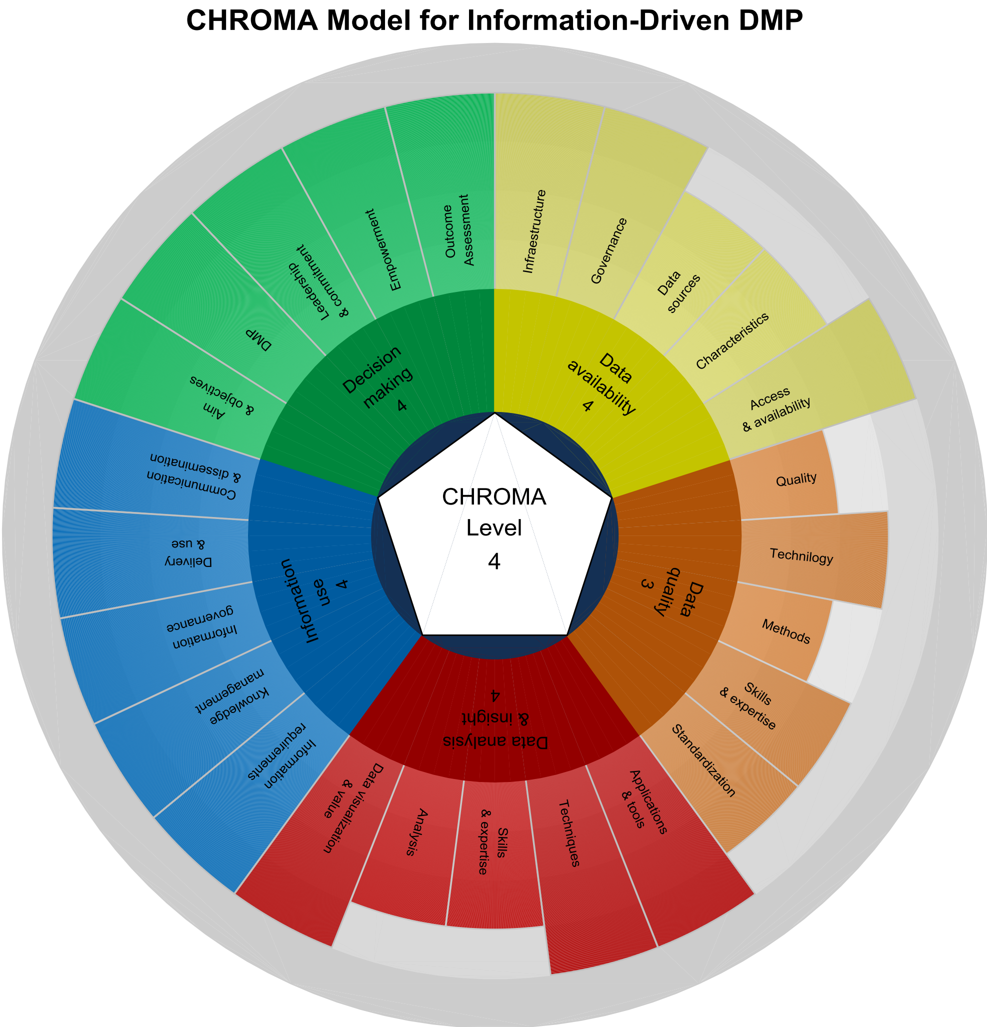


Figure 5.1: Results of the application of the CHROMA model to Company 1.

The following were identified as outstanding aspects:

- A strong commitment by management to data usage to support the decision-making, which has been gradually increasing since 2000.
- They have consolidated an information-driven DMP culture through senior mandate.
- Wide experience accumulated as a result of many years of growth in the sector.
- Cloud-based data technology, which they say represented a positive and successful change for their organization, constituting a breakthrough and a novel differentiating aspect for companies of this type.
- They have implemented algorithms to improve their management and gain competitive advantage.
- Data technology is integrated throughout the organization and is used to support decisions.
- They are founders, owners and beta-testers of a software company specialized in the real estate sector with which they have the possibility to test everything and to ask for improvements in their system and applications, thereby staying at the forefront of their sector.

- They have ISO 9001 certification.
- They enjoy an international presence.
- They promote the transparent handling of relevant information with all the interested parties of the organization.
- Customer focus and satisfaction, dealing with their complaints and needs in a timely manner.
- They maintain close collaborative relationships with suppliers to guide them and provide them with information that allows them to work in an aligned way.
- They have well-established knowledge management and information governance. However, this needs to be properly documented.

An interesting aspect that can be appreciated with regards to this company is that although its strategy is based mainly on internal data, which still presents quality problems and the analysis of the data is concentrated mainly in the top management and does not extend to the whole organization, it can be seen that they make good use of the available data to transform it into information they use to support decision-making.

The most relevant improvement opportunities were identified at the level of data quality management, the use and analysis of new types of data and the strengthening and enhancement of the staff analytics capabilities, which are the aspects that are unbalanced (see Figure 5.1) requiring special attention to undertake this path of evolution.

### COMPANY 2

Company 2 is a family business of 61 employees whose economic activity is oriented at the manufacture and export of machinery for the hotel and catering sector and specializing in the manufacture of professional dishwashers, cookers and fryers. In this company, four interviews were conducted with the following profiles:

- Project Coordinator (Head of the Financial Area).
- CEO/Senior manager (2nd generation, Export and Marketing Manager).
- Heads of Factory and Warehouse.

This company does not have a defined profile of Head of IT or its equivalent within its workforce; these efforts and activities of technological support are therefore outsourced.

As a result of the assessment process carried out on this organization, it was found that its current maturity level lies in the "*Uninitiated*" category, showing that it has not yet embarked on the journey to becoming an information-driven company. In other words, it is an organization whose decision-making process is not driven by information resulting from rigorous data analysis and is facing a path of great challenges ahead in order to progress to stages of higher maturity once the basic minimum actions related to the documentation, systematization, and integration of its processes are initiated. Figure 5.2 presents the results of the application of the CHROMA model to Company 2.

The following were identified as remarkable aspects:

- Strong commercial relations at the national and international level.
- Strong international presence of its products.
- High technical and creative capacity in the manufacture of its products.
- They also offer technical advice as part of their customer service.
- Wide experience accumulated as a result of many years of growth in the sector.
- They maintain good relationships with their distributors and suppliers.

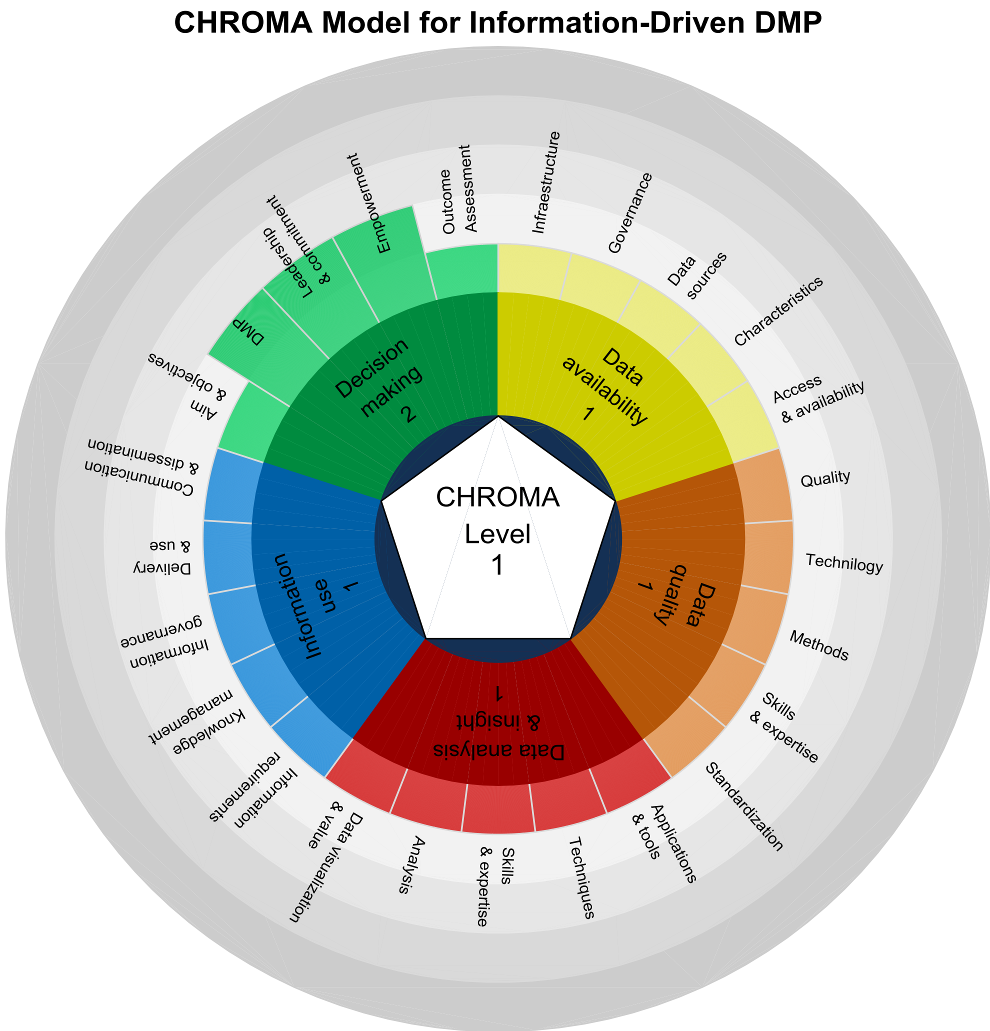


Figure 5.2: Results of the application of the CHROMA model to Company 2.

Although this company is aware of the importance of the data, it is not properly collected, and those who have access to it do not use it or analyze it appropriately to support decision-making and therefore simply making decisions based on the information resources available at the time.

The most relevant improvement opportunities were detected at the level of documentation, systematization and integration of its processes, access and availability of data, data quality management, data analysis, knowledge management, use and governance of information, as well as in the strengthening and enhancement of analytical skills and staff management, which, being gradually addressed, will allow them to begin to perceive significant improvements in their management in order that their organization can evolve.

## COMPANY 3

Company is a family business with more than 100 employees and with many years of experience in the field of design, manufacture and assembly of cutting-edge technology for the meat industry. In this company, three interviews were conducted with the following profiles:

- Project Coordinator (Intelligence Manager).
- General Manager.

- Production & Operations Manager.

As a result of the assessment of this organization, it was revealed that its current maturity level falls into the category "*Integral Embracement*", which is reflected in the consolidation of its information-driven decision-making process, with some opportunities along the way to evolve to a "*Completely embedded*" level. Figure 5.3 shows the results of the application of the CHROMA model to Company 3.

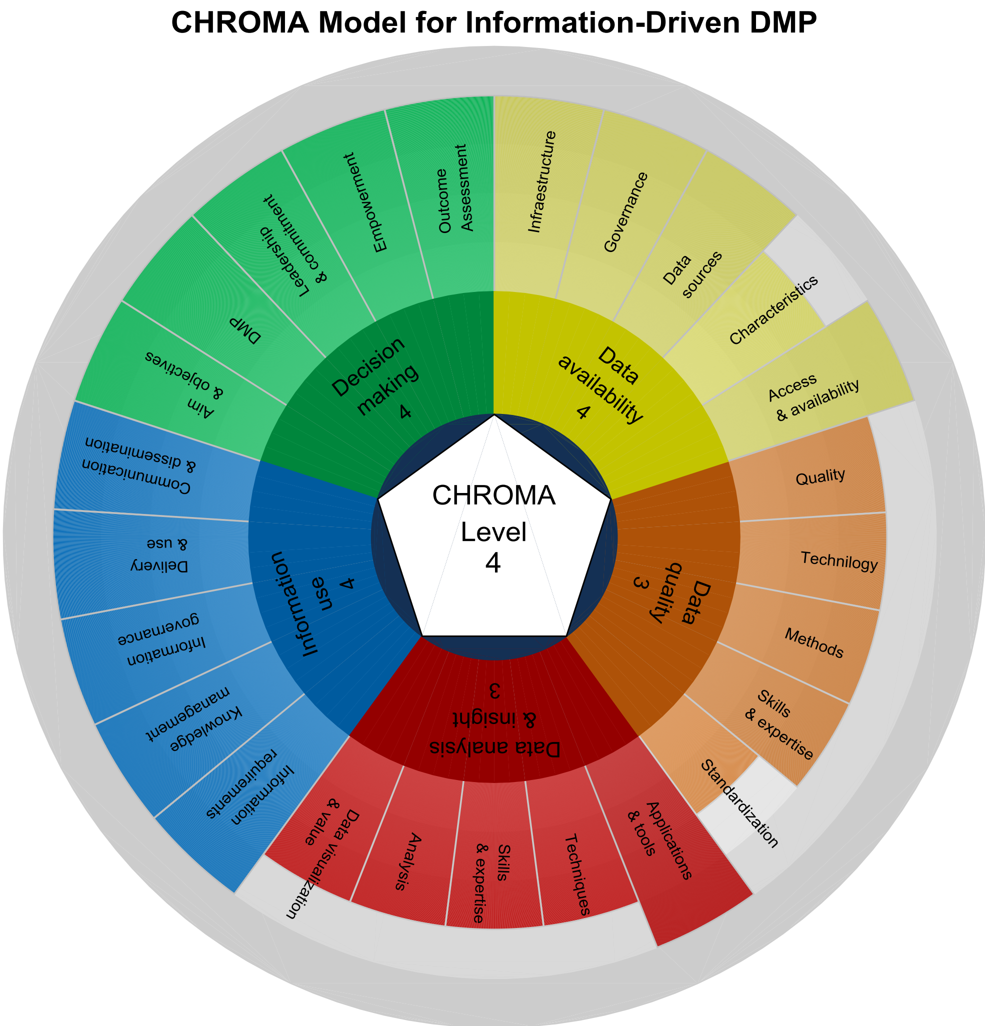


Figure 5.3: Results of the application of the CHROMA model to Company 3.

The following were identified as outstanding aspects:

- Strong international presence of its products.
- High technical and creative capacity in the manufacture of its products.
- Extensive accumulated experience as a result of many years of growth in the sector.
- A strong commitment by management to data usage to support the DMP, which has been gradually promoted throughout the organization for the last 12 years at least.
- They have consolidated an information-driven culture in their DMP through senior mandate.
- Consolidated data management strategy.
- Data technology is integrated and used to support business processes and decisions.

- Large and various types of mainly internal data are analyzed dynamically.
- Knowledge management and information governance are well established but need to be documented appropriately.
- They have developed and implemented innovative and scalable process improvement projects, upgrades and enhancements of technological functionalities to expand the availability of useful information to internal and external staff (providers), who are continually reviewing, expanding and improving it.
- They have ISO 9001 certification with a process-based approach.
- Customer focus. They have established policies and procedures to ensure customer satisfaction and provide timely response to their complaints and needs.
- They maintain close collaborative relationships with suppliers to guide them and work in an aligned way.
- Staff participation in decision-making is promoted.
- They have consolidated an improvement and innovation culture.

The most relevant improvement opportunities that were observed to be unbalanced (Figure 5.3) were detected at the level of data quality management, use of new types of data, data analysis, and insight, as well as in the strengthening and enhancement of staff analytics capabilities, which is necessary to achieve the organization's balance and evolve to the next level of maturity.

### 5.1.2. RESULTS OF THE APPLICATION OF THE CHROMA SHADE MODEL FOR THE INFORMATION-DRIVEN SME

The following is a summary of the results obtained through the application of the CHROMA SHADE model to the three small/medium size enterprises that collaborated in the second block corresponding to the validation of the model.

#### COMPANY 4

Company 4 is a family business with around 70 employees and is dedicated to the transport of complete loads with a national scope, both peninsular and island. It has accumulated extensive experience as a result of many years of reinventing itself and growing within the sector. In this company, two interviews were conducted with the following profiles:

- CEO/Senior manager (3rd generation, and Logistics and Operations Manager).
- Senior manager (3rd generation, and Administrative and Financial Manager).

It is noteworthy that this organization does not have a defined profile of Head of IT or its equivalent within its workforce; all its technological support needs are therefore managed and covered through outsourcing.

As a result of the evaluation of this organization through the application of the CHROMA SHADE model, it was found that its current level of maturity falls into the category of "*Proactive Adopting*", which means they are on the way to becoming an information-driven company. Some improvement opportunities were identified to help them evolve to stage of "*Integral Embracement*". Figure 5.4 presents the results of the application of the CHROMA SHADE model to Company 4.

The following were identified as remarkable aspects:

- Great interest and commitment by senior management in the use of data to support decision-making, which has been consolidating since 2010 in a systematic and structured way.
- Data technology, which is in the process of being integrated and used to support business processes and decisions.

- It is on the path to consolidating the organization's data management strategy.
- They have established and implemented knowledge management and information governance strategies; these, however, need to be appropriately documented.
- Strong national presence of its services.
- Strong commercial relations with multinational companies (customers).

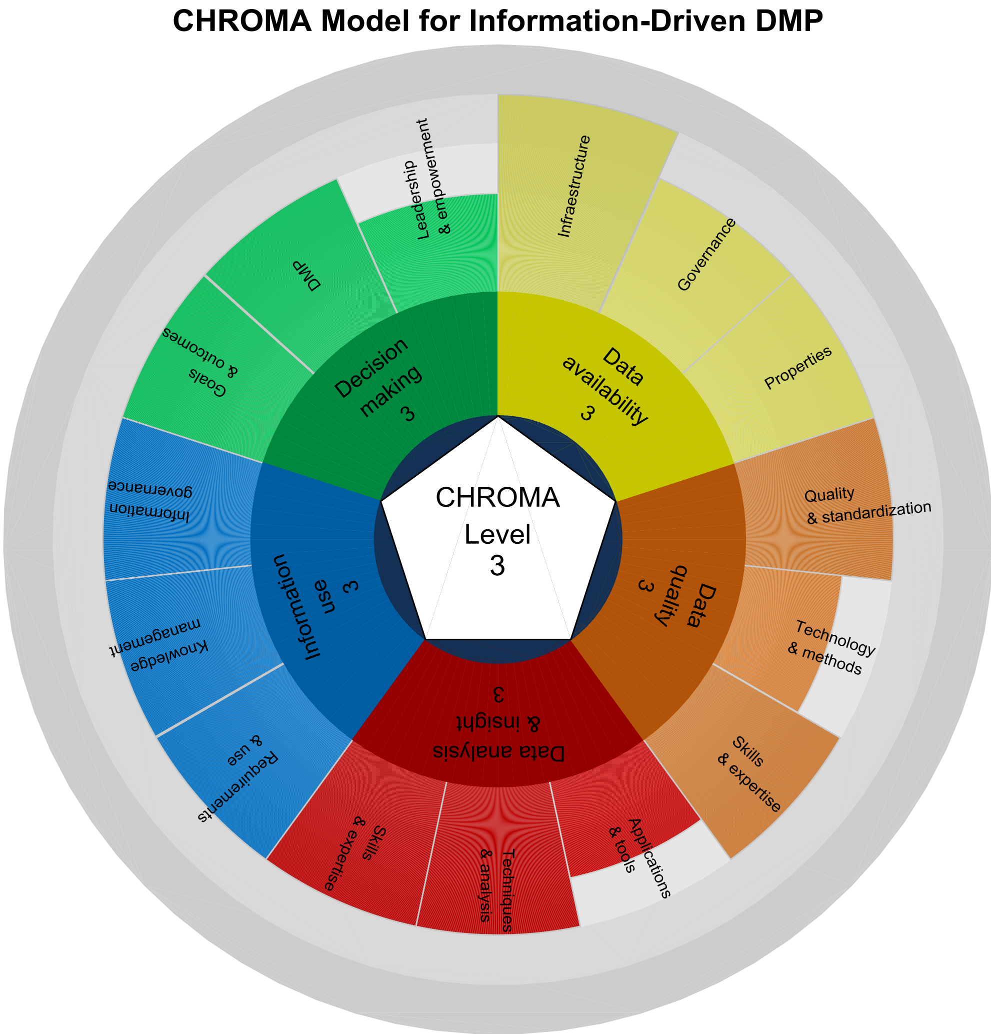


Figure 5.4: Results of the application of the CHROMA model to Company 4.

The most relevant improvement opportunities are detected at the level of collection, integration, and use of new data types, leadership and empowerment, linking and establishing strategic alliances with startup companies for the improvement and incorporation of new technological functionalities to the current information systems for data quality management, data analysis and insight, and information use. Other identified improvement opportunities include the development, strengthening and enhancement of the analytics capabilities of key personnel, which is necessary to continue advancing along this path of evolution.

### COMPANY 5

Company 5 is a family business with 28 employees, made up of a group of three companies with well-differentiated lines of business in the media and advertising stands sector specializing in outdoor advertising services and digital marketing. In this company, one interview was conducted with the following profile:

- Deputy Director (2nd generation).

Although this company has a defined profile of IT Manager within its workforce, information on the technical aspects to support the DMP was directly collected by the deputy director, who is responsible for the consolidation of this process.

As the result of the evaluation process carried out on this company, it was found that its current maturity level lies in the "*Awareness*" category, which means that they have started on the path to becoming an information-driven company. Some opportunities for improvement have been identified to evolve to the stage of "*Proactive Adopting*". Figure 5.5 presents the results of the application of the CHROMA SHADE model to Company 5.

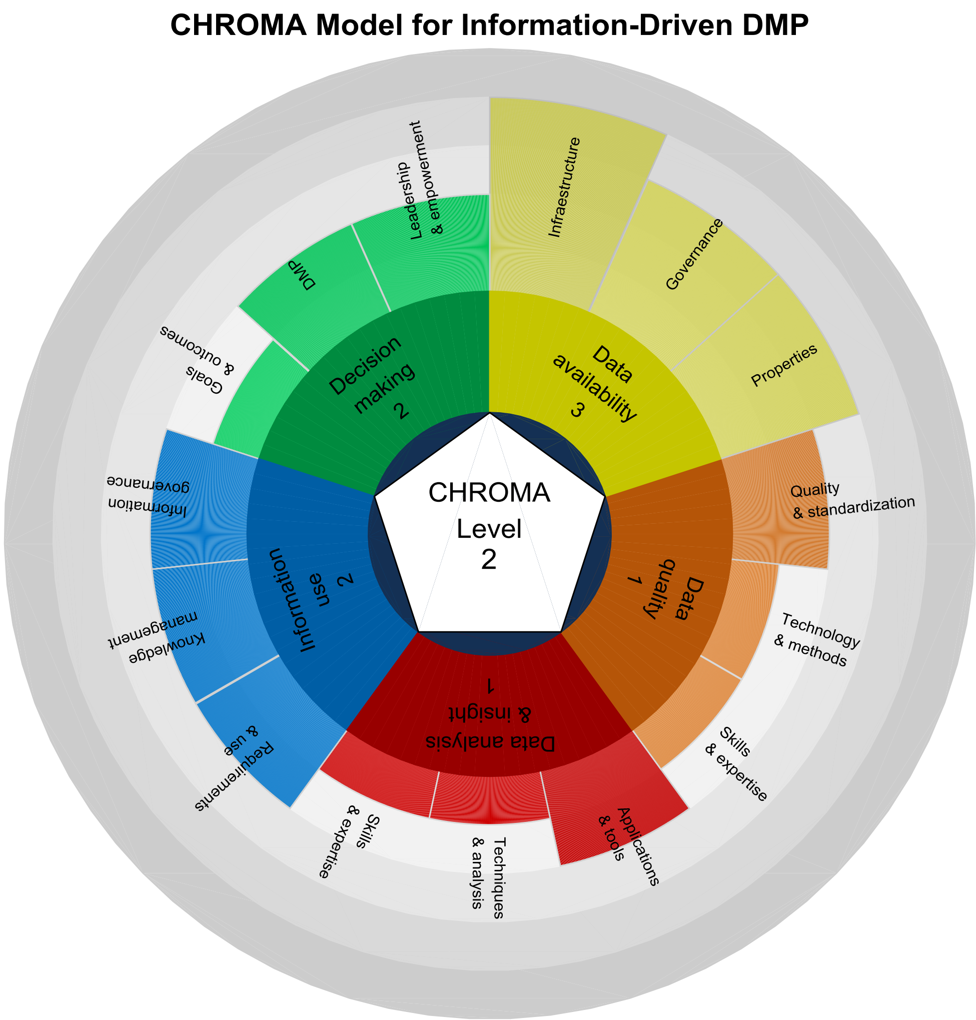


Figure 5.5: Results of the application of the CHROMA model to Company 5.

The following were identified as outstanding aspects:

- There is awareness by top management of the importance of information and an interest in starting to use it to support decision making.
- It is currently devoted to establishing a standardized set of procedures and processes in the organization.
- They are in the process of consolidating the implementation of a set of technological management tools (Business Intelligence, ERP and CRM) to ensure the interconnection of their processes and better use of their data to transform it into useful information.

- Data technology is in the process of being integrated and used to support business processes and decisions.
- They have their own custom-made software that works online using geolocation data to manage advertising stands, with coverage at the regional and national level, and which represents a differentiating element in their sector with customer-added value.
- On the path to establishing the organization's data management strategy.
- Wide experience accumulated as a result of many years of growth in the sector.
- Important national presence of its services.

The most significant improvement opportunities are detected at the level of standardization and integration of the organization's vision, its processes and the hierarchical structure with succession protocols to establishing roles/responsibilities, collection, integration and use of new data types, data quality management, data analysis and insight, knowledge management, use and governance of information, decision-making based on information promoting leadership and empowerment. Other identified improvement opportunities include the strengthening and enhancing of the analytical and management skills of the personnel, which is necessary to achieve the organization's balance and evolve to the next level of maturity.

### COMPANY 6

Company is a family business of 37 employees that offers professional services in the field of real estate management, including financial, patrimonial and legal advice. It has more than eighty years of experience in this sector. In this company, two interviews were conducted with the following profiles:

- CEO/Senior Manager and owner (4th generation).
- Project Coordinator (Vertical Property Manager and IT Requirements Coordinator)

It is noteworthy that this organization does not have a defined profile of Head of IT or its equivalent within its workforce; all its technological support needs are therefore managed and covered through outsourcing along with the area manager (Vertical Property Manager), who serves as the liaison person.

As a result of the evaluation of this organization, it was found that its current level of maturity falls into the category of "*Awareness*", which means they are on the way to becoming an information-driven company. Some improvement opportunities were identified to help them evolve to stage of "*Proactive Adopting*". Figure 5.6 presents the results of the application of the CHROMA SHADE model in Company 6.

The following were identified as remarkable aspects:

- There is awareness by top management of the importance of information, which is reflected in a great interest by the management in data usage to support decision-making, which has been carried out for at least 5 years.
- Wide experience accumulated as a result of many years of growth in the sector.
- Data technology is in the process of being integrated and used to support business processes and decisions.
- They have established and implemented knowledge management and information governance strategies but need to be widely extended and appropriately documented throughout the organization.
- Working in the organization's structuring and standardization with a process-based approach.
- Staff participation in decision-making is promoted with a staff empowerment vision.

The most relevant improvement opportunities were detected at the level of documentation, systematization and integration of its processes, access and availability of data, data quality management, data analysis & insight, knowledge management, use and governance of information, decision-making under a structured and planned process, and the strengthening and enhancement of the analytics capabilities of key personnel, which is being gradually addressed and will allow them to begin to perceive substantial improvements in their management that will lead them towards their organization's evolution.

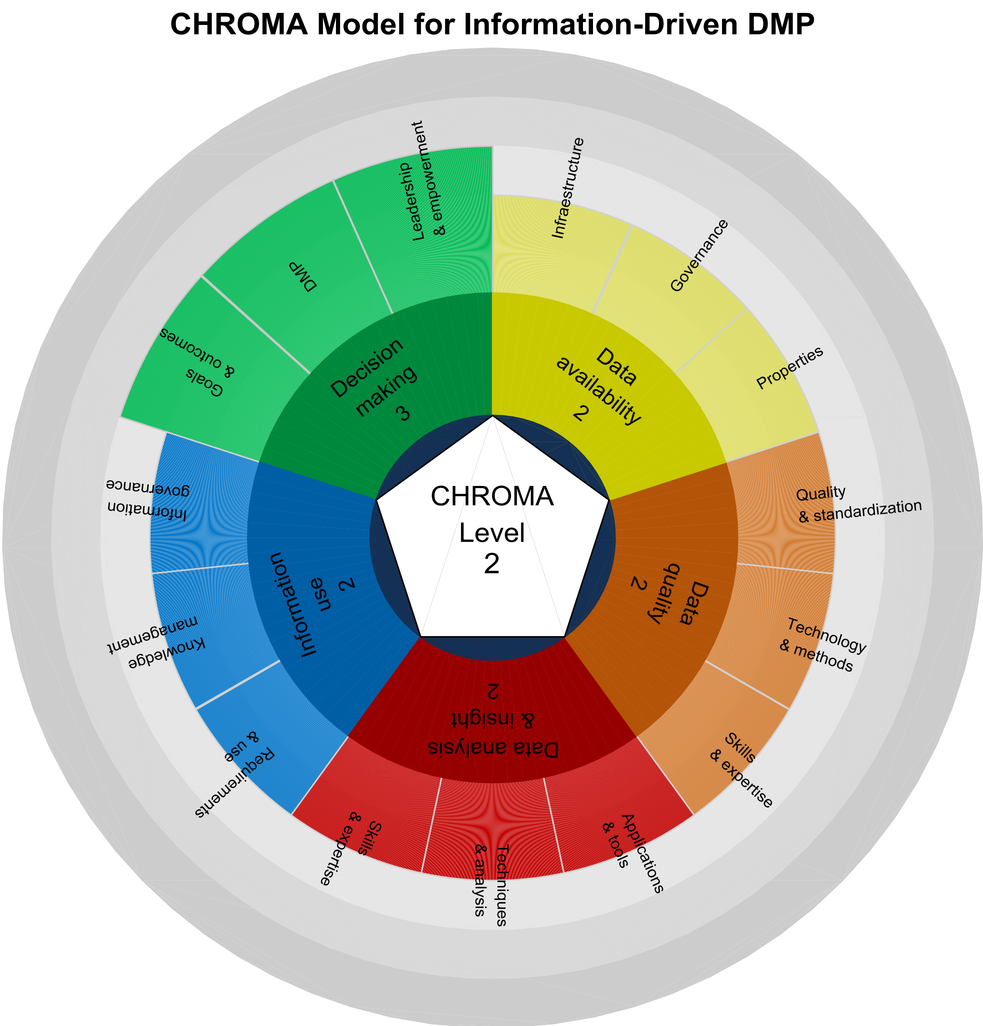


Figure 5.6: Results of the application of the CHROMA model to Company 6.

## 5.2. COMPARATIVE ANALYSIS

In order to analyze the complete set of results from all the companies evaluated, the overall level of maturity and the disaggregated dimension scores were compared among these companies. Comparisons at the attribute score level were not possible due to the difference in the number of attributes defined for both maturity models. Figure 5.7 shows the results according to dimension that were reached by the companies evaluated.

Figure 5.7 reveals several interesting insights. In the first place, it is noteworthy that none of the companies reached a maturity level of 5 in any of the dimensions. This suggests that these organizations still have a long way to go to become information-driven companies.

Secondly, another notable aspect observed in these results is that the companies that obtained the best values maintain a balanced valuation in all their dimensions. This makes a lot of sense, and to corroborate this observation, the correlation coefficient between the maturity indexes of every pair of dimensions was calculated, obtaining a strong correlation in all cases [0.73; 0.95].

Other important aspects to highlight in these results are related to the dimensions with the best and worst maturity indexes. In this regard, by analyzing the average maturity score by dimension obtained in each of the companies evaluated (Figure 5.8), the "*data quality*" dimension was found to obtain a lower score. It is therefore clear that data quality problems are still the most challenging unresolved issue in these companies.

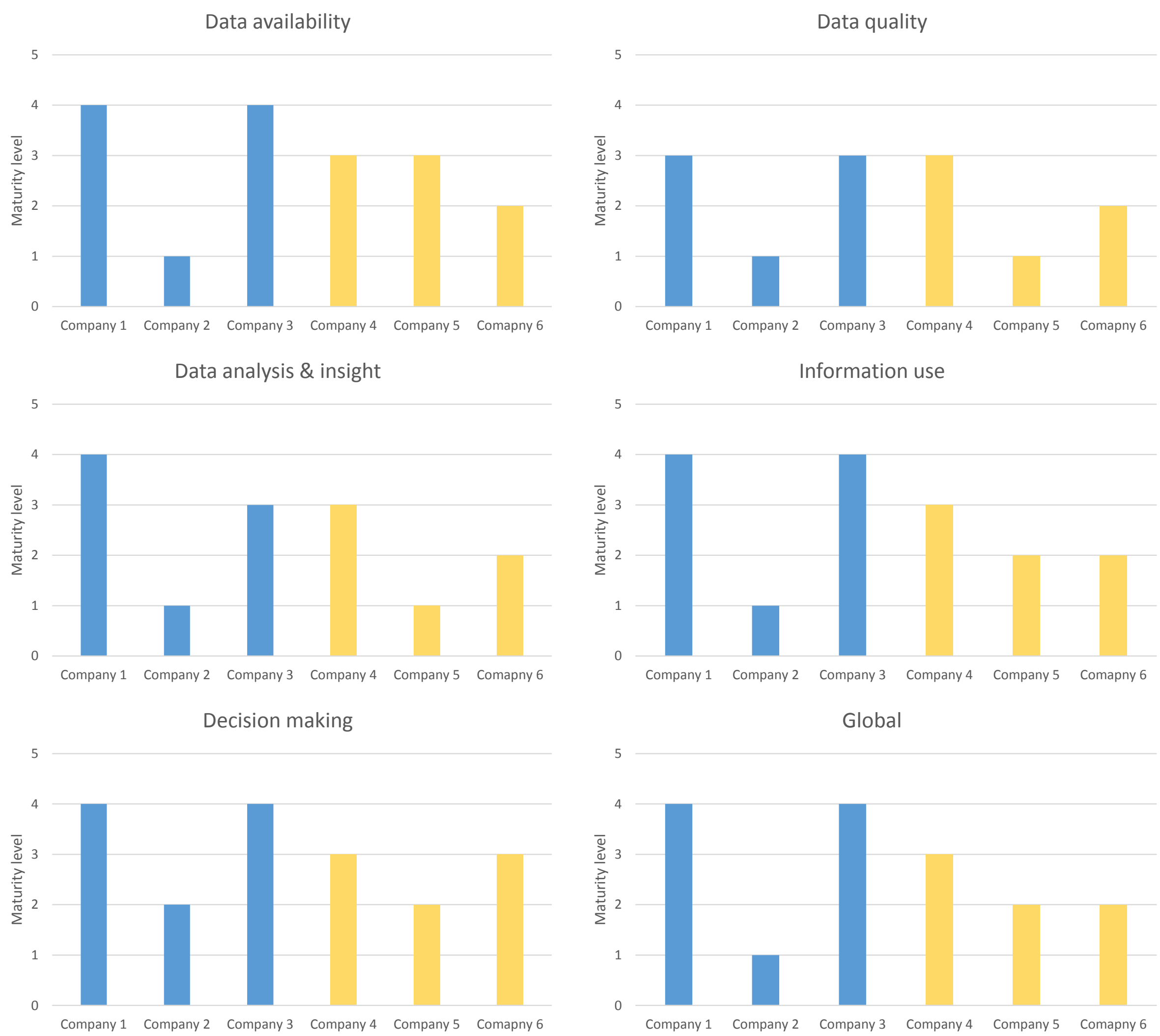


Figure 5.7: Results per dimension reached by the companies evaluated.

In line with the above, the "*decision-making*" dimension turned out to have the highest score. This suggests that these companies have been able to take advantage of their available information resources to support decision-making; in other words, to a greater or lesser extent they have made good use of the data available.

Another interesting aspect to highlight is that the "*data analysis and insight*" dimension yielded the second lowest score. This could be verified throughout the field studies, since in most of the organizations the insufficient data quality management was accompanied by poor data analysis. The analyses were mostly descriptive and reactive without further exploitation including multivariate analysis, clustering and predictive/prescriptive models that could offer them a deeper insight into their organization and the way forward to ensure their consistent and sustained growth.

Finally, although 6 companies is a very small sample and the comments we make do not have any statistical value, we have detected some points that we believe are worth noting:

1. The use of data to support the DMP in an organization is directly related to the level of professionalization of the senior management and their familiarity with the use of technological tools. In this regard, they will promote it through a trickle-down effect to the rest of the organization.
2. Data analysis is mostly used at the senior and middle management level. At the operational level, data analysis is very scarce.
3. Skills in data analysis are rather limited, being restricted to track indicators, dashboards and tailored spreadsheets.
4. Managers are aware of the analytics and big data revolution but do not feel an urgent need to adopt them.
5. Risk management is a little considered and neglected issue in SMEs.
6. An interesting aspect to note is that, independently of their results, the six companies analyzed have been able to recognize their limitations by taking advantage of their available information resources. Thus, these companies, through detailed knowledge of the industry, their sector and the market, have been recognized by the high quality and technical capacity of their products and services, which is reflected by a strong national and/or international presence and by solid relationships with partners and suppliers. This reinforces that notion that family-owned SMEs are very efficient in their innovation processes and that these results can serve as the impetus to continue their evolution, improve their performance and achieve greater competitive differentiation.

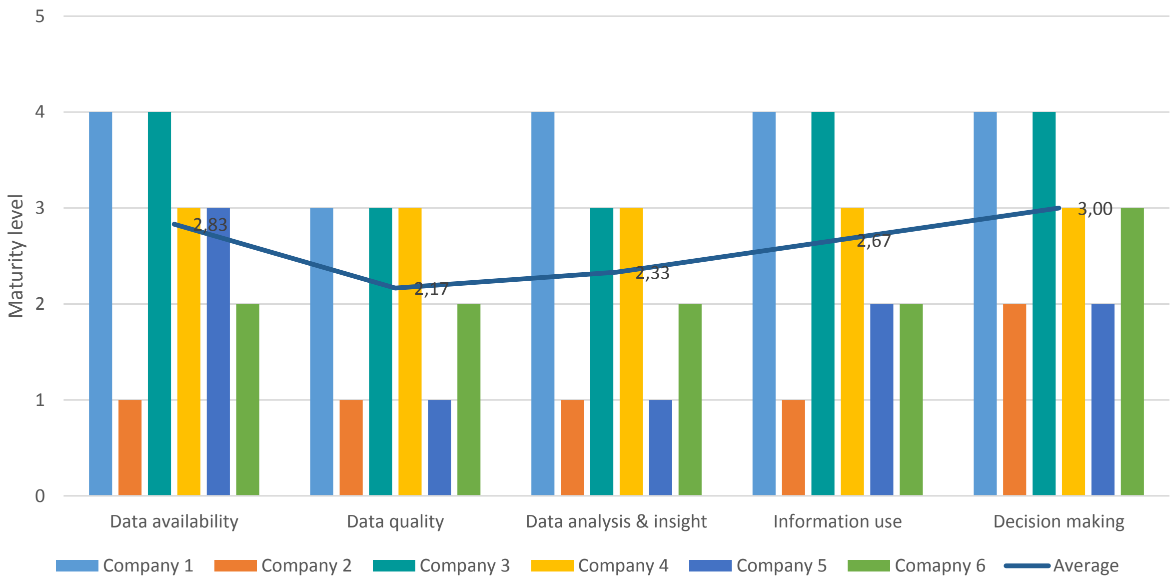


Figure 5.8: Mean maturity score per dimension in the SMEs studied.

## 5.3. LESSONS LEARNED AND IMPROVEMENTS TO THE MODELS

Beyond the actual quantitative and qualitative outcomes from the study carried out in the pilot and in the validation campaigns, many valuable lessons were learned from the close interaction with the SME, which enabled the maturity models and their assessment tool to be improved. These lessons learned will be described in detail in the following subsections.

### 5.3.1. INTERVIEWS VERSUS SURVEYS

The interviews conducted through the assessment tool were fundamental and of great value in carrying out this study effectively. They were a means of establishing a closer relationship with the decision-makers and obtaining first-hand information about their needs and concerns.

Conversely, the short web questionnaire did not yield the expected results, as the number of responses was extremely low. As a direct consequence, it was evident that the applicability of such survey-based assessment methodologies is rather unfeasible and unreliable given the disinterest of the organizations' representatives in answering it, in spite of the valuable information that this complementary tool would be able to collect.

Indeed, this observation made it necessary to rethink what organizations and those who run them are really looking for. In the first place, the interviews worked more effectively than the web questionnaires, which may indicate that decision-makers feel more confident and willing to participate when it comes to a face-to-face interaction. During interviews, decision-makers can raise their concerns by showing an open interest in receiving more feedback to keep improving.

In the same vein, the number of questions in the survey seems not to influence the willingness of the decision makers to answer them. For example, during the first campaign the questionnaire contained 12 questions, while for the second campaign those questions were summarized into 6 multiple-choice questions and this made no change in the success ratio of its application. Therefore, it would seem that decision-makers are looking for a more personalized treatment instead of standard predefined approaches, even if this means dedicating a little more time.

Obviously, time is a company's matter of concern, but it is clear that they will be willing to devote more time if this is going to generate customized recommendations that address their needs and problems. Instead, when they are asked to fill in an online survey, they are most likely to consider it a waste of time.

### 5.3.2. TIME-INVESTMENT IN THE EVALUATION PROCESS

Figure 5.9 shows the time invested in the evaluation process carried out in the six SMEs involved in the study. To recap, the first block of three SMEs were analyzed using the CHROMA model and the preliminary version of the assessment tool. Then the second block of three companies was analyzed using the SHADE model and the improved version of the assessment tool.

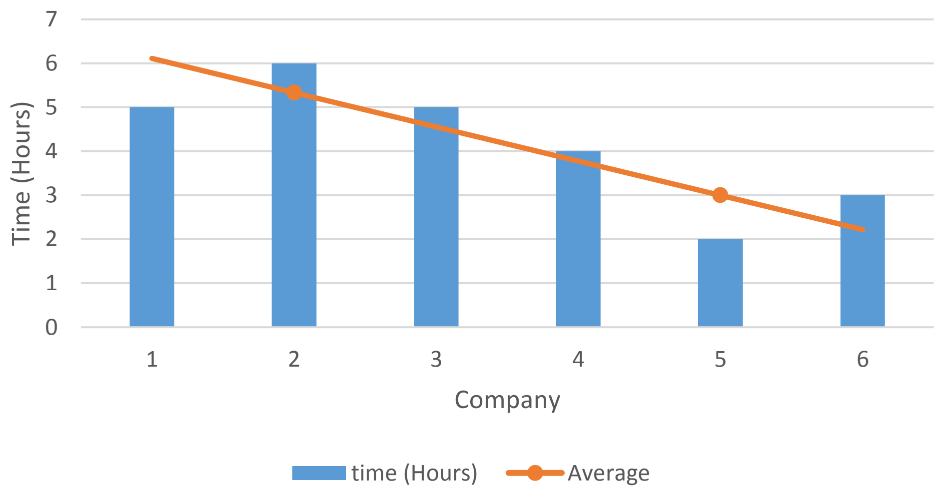


Figure 5.9: Total time invested in the evaluation process.

In accordance with the above, it is important to note that both assessments tools allowed the application of the corresponding maturity model, causing minor disruptions to the organization's workflow. In this regard, each of the interviews conducted during the first block of SMEs lasted from 1 to 1.5 hours per interviewee (less than the 2 hours initially forecast), with a total elapsed time of 5 to 6 hours per SME. On the other hand, the second round of SMEs benefited from the simplifications and improvements made to the assessment tool through a reduction in the interview time, which lasted approximately between 2 and 4 total hours per SME.

In this respect, as can be seen in Figure 5.9, the mean time invested in the evaluation of the first block of SMEs was 5.33 hours, while the average time invested in the evaluation of the companies that formed the second block was 3 hours. Although the original version of the evaluation tool caused only minor disruptions to business processes, the later version reduced even more the invested time. This improvement was due to the unification of the different interviewee questionnaires. This in turn allowed time to be gained in order to spend it into the office work as needed.

Likewise, it was also possible to reduce the time needed to perform the evaluation, analysis, and interpretation of the results to provide companies with a report that offered them useful feedback with added value. In both cases, the information gathered through the interview questions (Phase I) was sufficient to address the questions and complete the templates of the scoring phase (Phase II).

### 5.3.3. THE ROBUSTNESS OF THE ASSESSMENT TOOL

Ideally, the assessment tool is intended to provide coherent outcomes independently of the evaluator. In order to verify the robustness of the evaluation with the assessment tool, one of the students that participated as a trainee accompanied the expert evaluator during the interview carried out with SME 5. Both evaluators then independently scored phase II of the assessment with regards to the collected information. In this regard, the results were compared at the level of questions, attributes and from a general approach, that is, the disaggregated and aggregated scores. The findings of the analysis performed in this experiment are detailed in the following section.

Figure 5.10 shows the differences registered between the expert evaluator and the trainee during the evaluation process. In this regard, several levels of coincidence were identified. In the first place, for 27 of the 66 questions (41%) of the assessment tool questionnaire, a perfect match was obtained, while 32 questions (48%) presented one level of deviation in the assessment, i.e. a difference, both higher and lower, in the response of a level of the value given by each evaluator. For 6 of the questions (9%), a difference of 2 levels of mismatch was observed and in only 1 question (2%), the difference corresponded to three levels of mismatch. There were no cases of total mismatch between the assessments made by each evaluator.

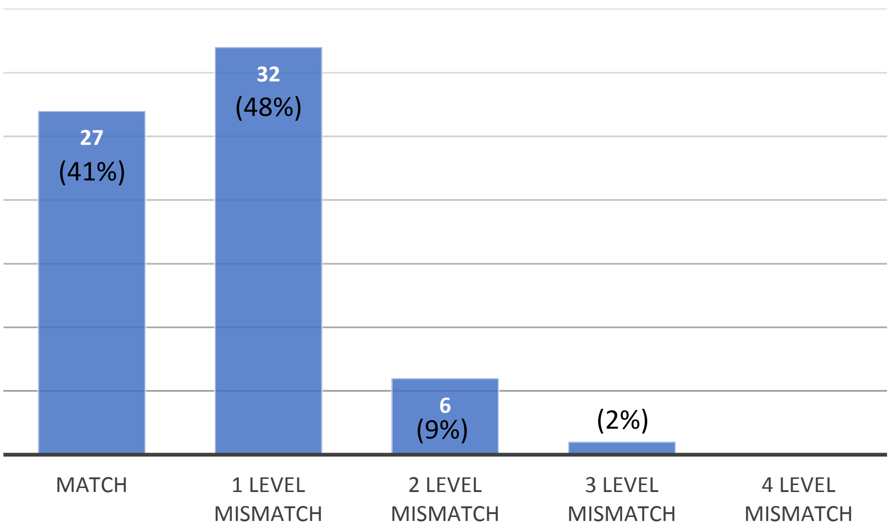


Figure 5.10: Histogram of the differences registered between the expert evaluator and the trainee. Case study: SME 5.

Likewise, Figure 5.11 shows the bivariate distribution of the disaggregated scores of the evaluator. In this regard, the scores for evaluating the organization using the assessment tool (Phase II) ranged from 0 to 100. As a result, a perfect match between evaluators when scoring the questions at 0, 25, 50 and 75 was 6%, 14%, 20% and 1%, respectively. 23% of the time, when the expert gave a question a score of 25, the trainee evaluator gave them a score of 50. In 9% of the cases, when the expert evaluator scored the questions at 0, the trainee scored them at 25 and so on.

Analyzing these results, the predominance of level 1 mismatches (48%) is noticeable in relation to the perfect match (41%), which exerts a strong influence on the overall results. These findings, analyzed together with those shown in Figure 5.11 and subsequently in Figure 5.12, suggest a more conservative tendency on the part of the trainee, probably motivated to a certain degree by the fear of being wrong, since their different assessments were generally narrowly ranged between the middle ranges compared with the expert evaluator, whose scores were distributed within a slightly wider range.

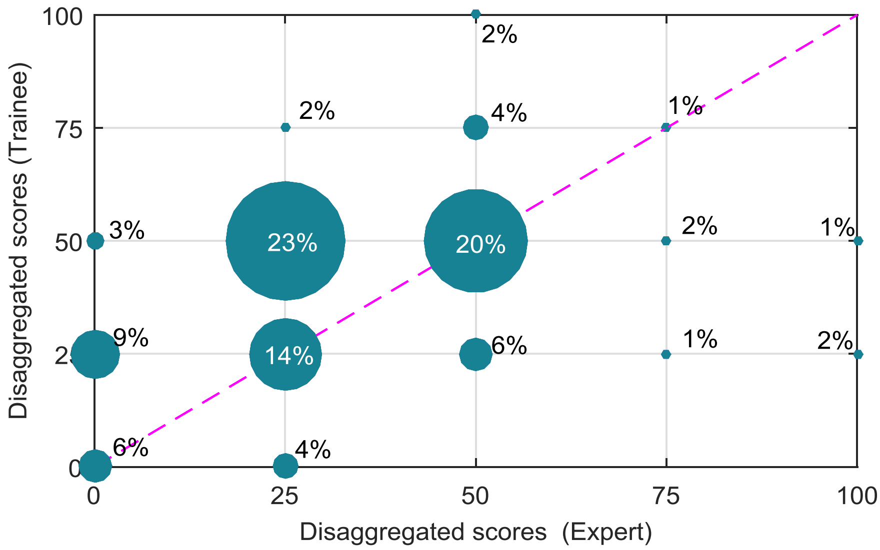


Figure 5.11: Bivariate distribution of the disaggregated scores of the evaluator. Case study: SME 5.

On the contrary, the results related to level 2 and 3 mismatches (Figure 5.10) are attributable mainly to the differences in the levels of knowledge and experience between the trainee and expert. Despite this, from a general perspective the overall maturity results reached by both evaluators were the same (maturity level 2 “Awareness”) with slight differences in terms of decimals that did not affect the final result.

Unfortunately, for the moment it was only possible to involve the collaboration of a trainee and to perform a single test. Despite this, several interesting results were obtained, which revealed the need to extend these experiments in order to validate this finding and to obtain more conclusive results.

### 5.3.4. SME PARTICIPATION RATE

This aspect represented a limitation to the study, especially during the deployment of the second block of field study campaigns. As first block was a pilot study, we focused on only three companies in order that, after identifying and incorporating improvements and learning lessons, a larger scale deployment could be carried out.

Once this phase of the investigation was completed, we then contacted about 8 companies of which only 3 decided to participate. The causes were related to the lack of knowledge of the topic, the model itself, and the benefit it would provide to them versus the effort required, as well as the motivations to implement it without profit.

Likewise, the need was observed for a closer relationship between the academic and business world in order to create greater conditions of trust between the parties, with the consequent increase in the willingness

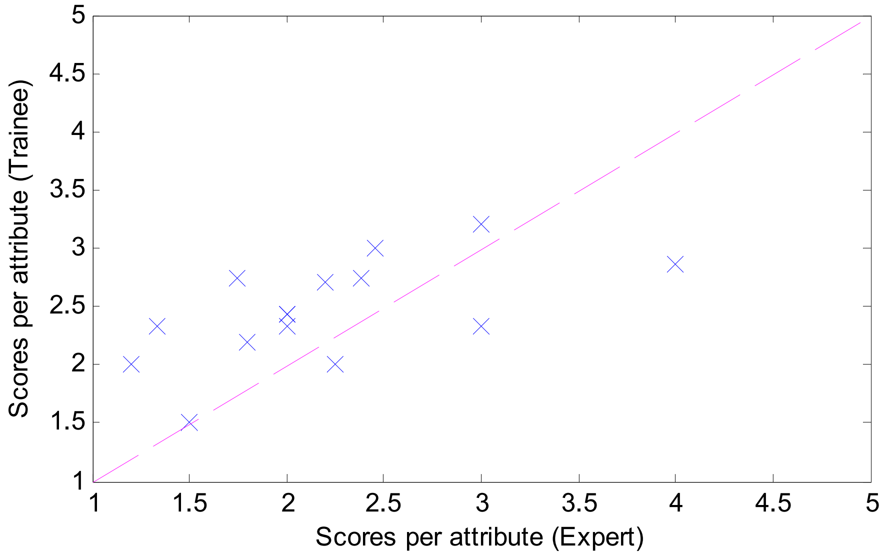


Figure 5.12: Expert versus Trainee scores per attributes. Case study: SME 5.

to be part of these types of research initiatives that seek the development of solutions with a direct application in a company.

## 5.4. CONTRIBUTIONS TO THE GROWTH AND SUCCESS OF THE COMPANIES

Much has already been said about the importance of SMEs to the Spanish economy and the advantage of boosting their development. In this sense, the growth that these types of organizations can achieve depends on them being able to embrace more rigorously the use of their data and analytics insights in order to boost their business through better and more supported decisions.

This implies a process of self-recognition to identify where they should focus all their efforts in order to be able to adopt better analytical practices that lead them to evolve and become information-driven companies. This can be achieved through the application of the CHROMA model and its SHADE version, which constitute a very useful methodology to support and to lead companies down this road. In this regard, both models were applied and tested, which allowed them to be assessed and to objectively establish the maturity level of the organizations analyzed. Therefore, the assessment tool, both in its original version and the improved version, proved to be useful for collecting useful and relevant information in order to establish the situation of the organizations with respect to how they use information to support decision-making, thereby allowing them to be evaluated with a better supported and objective criterion.

Accordingly, the model allows enables the organizations to be categorized and to be provided with a wider picture showing that there are improvement opportunities to help them evolve to higher maturity levels, thereby providing trustworthy accompaniment during their journey.

This could be corroborated and validated through the feedback received from the companies evaluated. In this sense, the companies stated that their organization was reflected in the results obtained and that they felt that they were consistent and adjusted to their reality. Therefore, the results of the model and the feedback provided were positively valued.

Likewise, the organizations were quite receptive to the study, mainly at the level of senior and middle management, largely because the information-driven DMP is a matter that concerns them. This underscores the great interest of decision-makers in gaining a greater understanding of how to better leverage their data and to broaden their perspectives in terms of adopting better analytical practices to make better decisions.

Managers found the interviews interesting and "*opened their eyes*" to areas of DMP they had not considered before. This revealed a need in organizations to have mechanisms that allow them to obtain an overview of their organization and the self-knowledge necessary to plan, redirect and improve their performance. In this respect, the structure under which both models are designed makes it possible to provide the results at several levels of detail, facilitating the organization the implementation of actions in a prioritized way.

In this vein, many of the improvements areas identified, which were necessarily quite generic, came as no surprise to the companies' management. They were, however, happy to see them ordered and interrelated from the perspective of DMPs.

Another positive aspect was that the structure of the interviews allowed us to provide the companies in advance with enough information to determine the organization's status, thereby making it possible for managers to raise awareness and recognize those aspects that needed to be better addressed. Managers were happy with the feedback and evaluated the process as a worthwhile experience.

All this makes it possible to confirm that these models are very necessary and valuable for the growth and success of the companies in which they are applied, by providing the route that will allow them to move towards excellence in decision-making through information.

In another vein, it was noted that both models, although tested only in family-owned SMEs, have great potential in that they are able to be adapted and applied to different types of organizations, whether family-run or not. This would allow a broader understanding of the behavior of organizations both individually and within a defined area through comparative analysis in order to improve our understanding of these companies and in terms of how to boost their growth and strengthening. Therefore, both models constitute a powerful tool for the economic and productive development of the country if its application were extended to a larger scale.

# 6

# Conclusions and Future Research

## 6.1. Conclusions

DMPs have evolved gradually, driven by the emergence of information technologies used in business and management. Such technologies have shown a progressive, accelerated growth mainly driven by technology solution providers, technologists and researchers and to a lesser extent by managers and decision-makers. The adoption of technology solutions by companies is fast, and in many instances is leaving behind the managerial DMP side, which often strives to adapt to the rapid, continuous changes. It is also worth noting that technology solutions related to gathering, storing and analyzing data, as well as presenting the results of this process have created and are an industry in itself. Unfortunately, so far the solutions commercialized are not fully adapted to the needs of organizations, who do not yet fully understand what to do with their data.

Over the last decades, it has been evident that large, medium and small companies have sought to improve their performance and competitiveness by using data to make better decisions. Nonetheless, organizations frequently fail, or not fully succeed, in the difficult task of aligning their data-driven technologies solutions with the adoption of good information-driven practices, and thus do not fully benefit from the advantages of better decision-making processes.

Maturity models, including CHROMA and its SHADE variant for SMEs, provide a framework that is used to assess and rank the level of organizations' proficiencies. However, the CHROMA model and its SHADE variant were created under a novel, holistic approach that embraces the complexities inherent in a multiplicity of factors that, at the technological and management level, converge to enable more objective and better-supported decisions to be made through the intelligent use of information. This is the main difference between the maturity models proposed in this thesis and their predecessors, which are more focused on the implementation of specific technologies, areas or policies such as business intelligence, business analytics, big data, information governance, knowledge management, etc.

The CHROMA model with its $5 \times 5 \times 5$ structure (5 dimensions subdivided into 5 attributes, each classifiable into 5 levels of aptitude), is better suited for medium to large companies, since it offers an excellent level of granularity in accordance with its functional scheme, in which the information transformation processes and decision-making are more distributed, thus favoring its appropriate implementation. Nevertheless, this level of granularity proved to be very complex when applied to SMEs, whose information transformation process and decision-making are more concentrated at the management level.

In this sense, CHROMA SHADE model emerged as a mutated and simplified version of its predecessor as a product of the need to adapt to the particularities of SMEs. For this, this model takes into account the basic conceptual and application principles that characterize to the original version but with a reduced number of attributes ($5 \times 3 \times 5$), which were unified and summarized consistently to provide better adjusted and understandable results according to the organizations' typology upon which it is focused.

With regard to the assessment tool, this also underwent transformations. In the first instance, certain problems were detected in the language used, redundancy in some questions due to the number of profiles, greater complexity to cross the scoring in phase I and phase II, the time invested in the entire evaluation process, etc. This led to the restructuring of the assessment tool, which in its final version consists of a single simplified, unified questionnaire sufficiently robust to be applied indistinctly to both models, capable of adapting to the particularities and functional structure of each organization. Accordingly, this improved version of the assessment tool includes more focused and better-formulated questions for a more accurate collection of relevant information, allowing a closer, direct link with the models' dimensions and attributes. All this enabled the evaluation process to be streamlined and optimized by offering as output the objective and adjusted results.

With regard to the methodology, two complementary strategies for collecting information were proposed. To that end, the most effective strategy was to conduct semi-structured interviews with key personnel of the company, which represented a means to engage more closely with decision-makers. This enabled a more accurate collection of relevant, firsthand information about their concerns. Therefore, it was important to carry out the study and offer better feedback oriented at the improvement of specific aspects that would consequently affect the performance and growth of the organization. However, the strategy related to conducting surveys, regardless of how brief they were, did not yield the expected results. In part, because this was considered a waste of time for the decision-makers but also because it is not perceived as a mechanism that offers them a close treatment or that makes a customized contribution that leads them to solve their particular problems.

In relation to the field study campaigns deployed, they were very significant in reaching a deeper understanding of the degree to which organizations are supporting their decisions vis-à-vis the information obtained from data analysis and their willingness to improve accordingly. In this sense, it could be seen in general terms that none of the companies managed to reach the highest level of maturity, which highlights that much remains to be done and the relevance of the model to help them continue to evolve. Likewise, addressing and strengthening one of the dimensions will have repercussions on the others, allowing them to be balanced. However, the findings reveal that data quality issues are the single biggest challenge facing organizations. Similarly, it can be seen that in general the data continues to be poorly analyzed, reactive and not very audacious, mainly concentrated in the upper management and middle managers and very scarce at operational levels. Despite this, the decision-making dimension achieved the highest average maturity score, which highlights that these organizations have, to some extent, been able to take advantage of their available data to support their decisions.

As a final remark, it is important to highlight the work of data scientists as experts who can support organizations, especially those who own data, on their way to becoming information-driven companies. On the one hand, data scientist are key for accelerating the organizational know-how regarding data processing and visualization for identifying and extracting the relevant information, the objective evidence, required to support efficient decision making. On the other hand, data scientists are a valuable for technology development organizations which can benefit from data analysis for adapting their products to the needs of users. In both cases, within multidisciplinary working teams, data scientist can help to reduce the risks of inappropriate technology deployments.

## 6.2. FUTURE RESEARCH

Future research related to this thesis will be directed at deploying more field studies involving organizations within a wider range of well-defined application domains. This will make it possible to perform more complex comparative analyses involving organizational behavior analysis according to their typology (large companies vs. SMEs, family vs. non-family, etc.), the economic sector to which they belong, their geographical location, antiquity, and so on. This would entail seeking greater links between academic and professional communities to focus efforts and ensure greater willingness to collaborate for the common benefit.

In addition, another aspect that needs to be further analyzed is the implementation of larger scale experiments to evaluate the robustness of the assessment tool in terms of ensuring its ability to provide consistent results independently of the evaluator. This may involve carrying out more case studies in which the results of the scores obtained by a greater number of evaluators are compared in order to obtain more conclusive results and to act accordingly.

Likewise, efforts should also be directed towards continuing to explore new and better alternative strategies for collecting complementary information regarding the overall vision of the decision-makers of the different organizations in order to have an additional information collection mechanism that adds greater value to the evaluation process and to allow the results of the models' application to be validated, identifying more opportunities for improvement without causing disruptions in the process.

In the same way, future research should have implications regarding the follow-up over time of the organizations evaluated, under the case study scheme in order to observe the evolution of organizations over time in order to verify that the actions implemented based on the opportunities for improvement and the roadmap provided have led to an evolution in the organizations' maturity.

Finally, although the model is sufficiently robust to adapt to different organizations, it could be of interest to develop new versions of the model aimed at different sectors, such as the sector health just to name one, with particular characteristics that may require greater customization to their particularities.

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# A

# THE CHROMA FRAMEWORK

This appendix presents the CHROMA framework, which describes the requirements by attribute to reach each of the stages of maturity of the CHROMA model, which is the reference guide employed during the evaluation process of the organization.

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | *Uninitiated* | *Awareness* | *Proactive adopting* | *Integral embracement* | *Completely embedded* |
| ***Data availability*** | Infrastructure | No management tools.<br>Lack of single, coherent data architecture. Neither a framework nor a standard architecture is defined. Processes are *ad-hoc* and localized. Spreadmarts. Siloed databases. | Some software tools for management reporting. No unified architecture across the enterprise. Basic architectural framework and standards defined. Processes under development. Siloed data warehouses and datamarts. | Management tools and technology are isolated. Architecture and standards identified and are being tracked and verified. Processes are documented across the company. On the way to unified architecture and cloud service. Centralized, common data warehouse and shared datamarts. | Management tools and technology are beginning to be integrated and operated throughout the organization. Enterprise architecture framework and standards are well defined, aligned and communicated with IT and business. Processes are managed and measured. Architecture is unified. Enterprise data warehouse. | Management tools and technology completely integrated throughout the organization. Unified architecture under an ecosystem approach. Continuously improved processes. Cloud services are widely used and usually under a hybrid scheme. Analytics environment are integrated and extended to suppliers and other external actors. |
| | Governance | *Ad hoc*. Unaware of data governance practices. Few or no policies, standards or ownership. | The value of data has been recognized. Data and its ownership begin to be defined and managed. | Department-focused data strategy and management. Policies and procedures are documented across the company. | Integral data governance program in place. Well-defined data strategy and management. Clear responsibilities. | Data governance program and strategies well established. Well-governed and flexible data access. |
| | Data sources | Historical internal data. Unaware of data source usefulness. Spreadsheets. | Identified and collected internal data. Mainly spreadsheets. Realize the usefulness of unified data resources. Shared data resources. | Internal data. Some spreadsheets. Data sharing as a collaborative activity. Awareness of the need to access multiple data sources and types. | Internal and external data. New sources of data absorbed as they emerge. Data sharing across the company. | Continually searching for and integrating new data sources, both internal and external to the company. Data sharing throughout the company and extended to suppliers and other external actors. |
| | Characteristics | Only structured data. Low volumes and/or disconnected silos. Manual, hard copy. Users cannot access any metadata. | Only structured data. Gradually increasing volume but still disconnected in silos. Departmental level. Metadata reports may be produced and distributed periodically. | Generally structured data. Volume increasing and centralized. Some data is siloed. There are several metadata repositories accessible to users. | Use of data in multiple forms: structured, unstructured and geospatial data. Large amounts of data. Siloed data is minimized.<br>There is a central repository accessible for users with updated metadata. | Data of all types, including real-time data. Huge and growing amounts of data. Users can easily access updated, relevant and integrated metadata. |
| | Access & availability | Data and information are not available when needed. | Data and information are not easily available when needed, and it is unclear who to ask for it. | Standards established regarding where and how data and information are made available. Usually, it is easy to find the data and information required. | Data and information are readily and consistently available when needed. Process availability is managed and measured. | Continuously improving the processes that affect data and information availability. |

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | ***Uninitiated*** | ***Awareness*** | ***Proactive adopting*** | ***Integral embracement*** | ***Completely embedded*** |
| ***Data Quality (DQ)*** | Quality | Poor quality and consistency. Problems with collecting data. No data management strategy in place. Useful data not collected. | DQ problems begin to be addressed reactively, discovering errors rather than eradicating the causes of defects. | Processes for identifying, quantifying and prioritizing DQ issues are established. There are still some problems. | There are few DQ issues that are being resolved proactively. | The DQ management process is continuously improved and evaluated. |
| | Technology | SQL and Excel or equivalent, in isolation. | Basic data profiling tools are adopted and available anywhere in the system development lifecycle. DQ technology and tools used to locate, match, link and assess data. Data parsing, standardization and cleansing are available. | DQ assessment and measurement tools are implemented. Business guidelines are employed for validation. Standardized technology components for implementing data validation, certification and reporting are in place. | Inspecting, monitoring and correcting DQ issues integrated into applications infrastructure. Automatic data correction guided by governance policies and defined business rules. Dashboard and reporting tools. | Tracking, remediation, and improvement of DQ issues both in databases, as in ETL and messages between systems. Non-technical users can define and modify DQ rules and dimensions dynamically. |
| | Methods | *Ad hoc* routines. Data values are corrected without coordination with business processes. Root causes are not identified. Same errors corrected multiple times. | Using different types of basic descriptive statistics. Ability to track down errors due to incompleteness and invalid syntax/structure. Root causes analysis by simple DQ rules and data validation. | Business impacts analysis, assessment using methods of data profiling and other statistical and analytical techniques and DQ reporting. Dimensions selected. Metrics and validity rules well-defined and mainly automated. Data flaws are manually inspected. Data contingency procedures in place. | DQ inspection and monitoring routines may include automated (checks during processing, data profiling, ETL tools) and manual processes (running queries or reports on data sources, data sampling). Basic methods of remediation of DQ issues with well-defined processes. Validation of exchange data in place. Auditable. | Tools for reporting, logging and tracking DQ issues. Root cause analysis. Data cleansing. Data controls across the enterprise. Remediation methods and, consequently, a remediation plan is established, ranging from process re-engineering to simple data corrections. Transparent DQ management practices. |
| | Skills & expertise | Quality depends on individuals or IT department. Identified data problems are fixed manually. This identification is based on its usability for a specific business task. | A small group of people trained. Starting to conduct data profiling, assess DQ, establish a baseline, identify improvements and investments in DQ. | The owner of the data is responsible for assessing and ensuring the quality of data within each department, specific business tasks or projects. | DQ experts are identified throughout the company and are engaged in all DQ improvement processes. | A DQ competency center (or equivalent) is funded and is in charge of continually assessing and improving DQ outside the system development lifecycle. |
| | Standardization | Files in different formats, without a naming standard or metadata. Similar data represented in different structures. | Different file formats with little to no standard naming or metadata. Data element definitions for commonly used business terms. Reference data sets identified. Guidelines for identifying information. Guidelines for standardized exchange formats. | Profiling and development of DQ standards are adopted. Data with standard naming or metadata at the departmental level. Structure and format standards defined for all data elements. Exchange schemas defined. | Integral DQ assurance program in place. Metadata attributes defined at division or company level. Master reference data sets identified. Exchange standards managed. Oversight of ongoing maintenance and compliance with internal and external data standards. | Metadata attributes defined in an updated, relevant and integrated way across the company. Master data concepts managed within a master data environment. Taxonomies for data standards are defined. Conformance with the defined standards is integrated into the company. |

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | *Uninitiated* | *Awareness* | *Proactive adopting* | *Integral embracement* | *Completely embedded* |
| ***Data analysis & Insight*** | Applications & tools | Spreadsheet program. | Low-cost investments are made in visualization and data analysis tools such as MIS, ERP, CRM, EPM, and tailored solutions for data management and reporting. | Unintegrated initiatives of BI, OLAP, data discovery, or analytics tools are in place. | Analytics tools integrated within the business process. Predictive applications. | Analytical software fully integrated and embedded throughout the organization. Predictive and prescriptive applications. |
| | Techniques | Descriptive analytics of processes and measures. | Reactive reporting for decision-making. | Proactive reporting for decision-making. Analysis of trends and benchmarks. Self-service tools that allow slicing and dicing of data and data visualization. | Predictive analytics is used to help the organization make decisions, identifying actionable solutions to maximize business value. Predictive analytics and text mining. | Development of predictive and prescriptive models. Risk analysis and mitigation. It can easily link the new data with existing assets. Scenario modeling. |
| | Skills & expertise | Understaffed. Analytical skills, usually confined to a department or line-business on a specific function, working in isolation. Best practices are not shared.<br>The culture is not data-driven. | Few isolated groups with analytical skills usually at departmental or line-business level. Beginning to gain greater awareness of data analysis potential and interest in training staff in this area. | Permeation of analysts in key business areas. Some specific expert groups in more advanced data analysis, such as risk analysis and predictive modeling, at the departmental or line-business level. There may be external consultancy support. | Analysts with higher levels of analytics skills, conforming centers of excellence or networks to support different parts of the organization. | The highest level of analytical skills. Centers of excellence (COE) are in place, with teams that innovate with analytics and that train other groups of beginners. |
| | Analysis | The analysis focuses on describing what has happened.<br>Focus on data accuracy, consistency and timeliness. | The analysis focuses on describing why something is happening. Focus on data analysis for cost reduction. | Analytical insight is used to predict the likelihood of what will happen to some current business activities or processes. Focus on their analytics applications is about compliance measures at the tactical and operational level. | More complex statistical analysis to solve business problems. More insights to predict gain and transform how they do business. A more strategic approach in their analytics applications | Analytical insight is used to encourage innovation and enables decision-making to be addressed in order to explore new business opportunities. Leverage innovation and search for new business opportunities. |
| | Data visualization & value | Manual reporting (spreadsheets).<br>Baseline process metrics. | Standard reports. | Dashboards and scorecards. | Dynamic graphing and dashboards. | Customizable self-service dashboards. |

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | ***Uninitiated*** | ***Awareness*** | ***Proactive adopting*** | ***Integral embracement*** | ***Completely embedded*** |
| ***Information use*** | Information requirements | Information requirements are not defined. The users do not trust or use data/information available due to quality problems or the time and effort required to gather the needed information. | End users define the information requirements and the applications/tools are adapted to the specified needs. Users trust their own departments/groups' reports. | Information needs to be linked to business processes that support organizational goals. Users partially trust data/information, but reconcile it with other sources in order to ensure consistency. | The necessary information is integrated across the company and meets user requirements. Users trust and use the data. | Enterprise information embedded. It is delivered or available when required. All reports are widely trusted and accepted. |
| | Knowledge management (KM) | The organization lacks the consistency and the documented processes and practices for identifying, capturing, sharing, transferring and applying appropriately its core knowledge. | Value of KM recognized. KM strategies, processes and approaches are implemented and tested. | KM strategies and processes are standardized. KM roles are created, defined and filled. Capturing/sharing lessons learned and skills are aligned with business needs. | The foundations for KM are established and standardized. Consolidated knowledge-sharing culture. Organization-wide KM practices are implemented. The effectiveness of KM is measured. | Strategies, processes and approaches to KM are embedded in all organizational processes. Continuous improvement of KM processes and practices. |
| | Information governance (IG) | Information is not systematically managed. There is no central oversight or guidance. IG is largely manual. May not effectively serve the business needs of the organization. Not sufficient to meet regulatory requirements. | A defined governance structure is established. Roles and responsibilities are established at the subject area level. The organization has defined policies, processes and standards. IG process begins to take place. Still vulnerable to scrutiny of its legal or regulatory requirements. May not meet the organization's business needs. | Organization-wide IG structures with executive sponsorship. All high-priority subject areas are represented. Policies and procedures are standardized, and core information is managed and protected. Governance targets and metrics are defined. The company meets business legal requirements. | An integral IG program is in place throughout the organization's operations, with policies for continuously improving it. Governance is managed using KPIs. The degree of confidence in information is reflected in decision-making. IG issues are integrated into the DMP. The organization easily meets its legal requirements. | IG is integrated within the organization's overall corporate infrastructure and business processes. Governance is continuously improved through better understanding of internal requirements and research in best practices. The compliance with requirements and legal responsibilities is routine across the organization. |
| | Delivery & use | Information is presented in static statistical reports that usually do not fully answer the questions or problems to be solved. Rely more on management experience than on the information provided by data analysis. | *Ad hoc* reporting. The information is presented in standard statistical reports used reactively at operational levels. Awareness of the importance of the information provided by data analysis. | Through the use of dashboards and other tools, users access updated information as actionable metrics and KPIs, used at the tactical level to improve processes and management. Becoming an information-driven organization. | Information is presented in easily shareable dynamic graphs and dashboards, which are proactively used to support business strategy. Intelligence is leveraged to optimize future performance. Relevant and key information is used as a competitive tool. | The user interacts with applications in real-time using customizable environments to visualize key updated information in an innovative and agile way. Information drives the company strategy. The information-driven culture is embedded. |
| | Communication & dissemination | Information is not communicated or disseminated timely throughout the organization. Email and documents (hard copy), poorly controlled and reactive. Bureaucratic processes. There is no emphasis on transparency. | Awareness of transparency in information dissemination at the departmental level. Email and information systems isolated. Some controls in place to ensure consistent information disclosure. Bureaucratic processes remain. | The information is beginning to be more centralized but is not yet fully integrated and disseminated across the organization. Transparency is important and the information is systematically available when needed. | The information is integrated across the company and supports business function and goals. Transparent information-sharing culture consolidated. The information is monitored and updated consistently. | The key information is embedded into overall corporate infrastructure, its culture and business processes, and is measured, reviewed and improved. |

| Dim. | Attr. | Maturity stages: *Uninitiated* | *Awareness* | *Proactive adopting* | *Integral embracement* | *Completely embedded* |
|---|---|---|---|---|---|---|
| ***Decision-making*** | Aim & objectives | Aims, objectives, policies and strategies are not consistently defined. Data and metrics unexplored. | Aims, objectives, policies and strategies begin to be defined on the basis of internal data at the departmental or line-business level. Metrics explored. | Aims, objectives, policies and strategies are defined and frequently revised and updated, taking into account data both internal and external to the organization but at the departmental or line-business level. Metrics defined. | Aims, objectives, policies and strategies are continually reviewed on the basis of relevant internal and external data across the company. Metrics are standardized and communicated across the organization. | Aims, objectives, policies and strategies have been implemented at the level of the entire company and are continually reviewed and improved in terms of relevant internal and external data. Metrics continually measured. Successes and failures identified. |
| | DMP | Decision-making is random or improvised rather than a deliberate and coordinated process. Decisions are made based on gut instinct or experience instead of facts. No considered potential risks, issues or consequences. | Decision-making is deliberate only in situations of crisis or high risks. There is no structured decision-making process. Aware of the need to become data-driven for decision-making. React reactively only to imminent risks. | Decision-making begins to take place under a systematic, coordinated and deliberate process on the basis of available data. Working to become more data-driven for decision-making. Beginning to consider risks and consequences. | Decision-making is done under a clearly articulated strategy throughout the organization and on the basis of objective, reliable and relevant data. Organization proactively considers and manages risks and potential consequences before decision-making. | Decision-making process is fully embedded into business strategy and objectives of the company. The information-driven decision-making culture is fully consolidated. Risk management is used as a differentiator for decision-making. |
| | Leadership & commitment | There is no data-driven culture among leaders. | Leaders begin to recognize the importance and encourage the use of data for decision-making at the departmental level. | Strengthening analytical skills. Work together across the organization in the use of data for decision-making. | Engagement and collaboration for data-driven decision-making. | Commitment, collaboration and strong promotion of information-driven decision-making across the enterprise. |
| | Empowerment | Power centralized within the top management level. Reluctance to delegate responsibilities or activities or to share information. | The degree of autonomy and responsibility unclear or limited to routine, common and simple activities to ensure functioning at the departmental or line-business level. | Leaders begin to delegate more activities and responsibilities to downstream levels of the organization. Differentiated degrees of autonomy and responsibility. | Decision-making with clear prioritization and guidance, moving through the different levels of the organization. | Decision-making delegated throughout the company with approach strongly oriented at innovation, as well as identifying and exploiting new business opportunities. |
| | Outcomes assessment | The outcomes of decisions are not measured or evaluated. | Metrics for outcomes of decisions begin to be defined. | The organization has established specific goals and metrics to measure the outcomes of decisions but at the departmental or line-business level. | The organization has integrated goals and metrics to continually measure the outcomes of decisions across the company. | The organization's goals and metrics have been met, forming the basis to improve and innovate, and has an established process to ensure they are routinely reviewed and revised. |

# B

# THE CHROMA SHADE FRAMEWORK

This appendix presents the CHROMA SHADE framework, which describes the requirements by attribute to reach each of the stages of maturity of the CHROMA SHADE model, which is the reference guide employed during the organization's evaluation process.

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | ***Uninitiated*** | ***Awareness*** | ***Proactive adopting*** | ***Integral embracement*** | ***Completely embedded*** |
| ***Data availability*** | Infrastructure | No management tools. Lack of single, coherent data architecture. Neither a framework nor a standard architecture is defined. Processes are *ad-hoc*. Spreadmarts. Siloed databases. | Some software tools for management reporting. No unified architecture across the enterprise. Basic architectural framework and standards defined. Processes under development. Siloed data warehouses and datamarts. | Management tools and technology are isolated. Architecture and standards identified and are being tracked and verified. Processes are documented across the company. On the way to unified architecture. Centralized, common data warehouse and shared datamarts. | Management tools and technology are beginning to be integrated and operated throughout the organization. Enterprise architecture framework and standards well defined, aligned and communicated to IT and business. Processes managed and measured. Architecture is unified. On the way to cloud service. Enterprise data warehouse. | Management tools and technology completely integrated throughout the organization. Unified architecture under an ecosystem approach. Continuously improved processes. Cloud services are widely used and usually under a hybrid scheme. Analytics environment is integrated and extended to suppliers and other external actors. |
| | Governance | *Ad hoc.* Unaware of data governance practices. Few or no policies, standards or ownership. Data and information are not available when needed. | The value of data has been recognized. Data and its ownership begin to be defined and managed. Data and information are not easily available when needed, and it is unclear who to ask for it. | Department-focused data strategy and management. Policies and procedures are documented. Standard established regarding where and how data and information are made available but usually easy to find when required. | Organization's data governance program is in place. Well-defined data strategy and management. Processes availability are managed and measured. Clear responsibilities. Data and information are readily and consistently available when needed. | Integral data governance program and strategies well established. Well-governed and flexible data access. Continuously improving the processes that affect data and information availability. |
| | Properties | Only structured data from historical records. Low volumes of data isolated in spreadsheets or hard copy. Users cannot access any metadata. | Identified and collected internal structured data at the departmental level. Gradually increasing in volume but still mainly spreadsheets disconnected in silos. Metadata reports may be produced and distributed periodically. Realize the usefulness of unified and shared data resources. | Generally structured internal data. Volume increasing and centralized. Some spreadsheets and data siloed. Awareness of the need to access multiple data sources and types. There are several metadata repositories accessible to users. Data sharing as a collaborative activity. | Internal and external data in multiple forms: structured, unstructured and geospatial data. New sources of data absorbed as they emerge. A large amount of data-sharing across the company. Siloed data is minimized. There is a central updated metadata repository accessible for users. | Continually searching for and integrating new data sources of all types, including real-time data, both internal and external to the company. Huge and growing amounts of data handled and shared throughout the company and extended to suppliers and other external actors. Users can easily access updated, relevant and integrated metadata. |

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | ***Uninitiated*** | ***Awareness*** | ***Proactive adopting*** | ***Integral embracement*** | ***Completely embedded*** |
| ***Data Quality (DQ)*** | Quality & standardization | Poor quality and consistency. Files in different formats or similar data represented in different structures, without a naming standard or metadata. Problems with collecting data. Useful data not collected. No data management strategy in place. | DQ problems begin to be addressed reactively, discovering errors rather than eradicating the causes of defects. Different file formats with little to no standard naming or metadata. Reference data sets identified along with data element definitions for commonly used business terms. Guidelines for identifying information and standardized exchange formats. | There are still some problems but have established processes for identifying, quantifying and prioritizing DQ issues as well as the adoption of profiling and development of DQ standards. Data with standard naming or metadata at the departmental level. Structure and format standards for all data elements. Exchange schemas defined. | There are few DQ issues that are being resolved proactively. Integral DQ assurance program in place. Metadata attributes defined at division or company level. Master reference data sets identified. Exchange standards managed. Oversight of ongoing maintenance and compliance with internal and external data standards. | The DQ management process is continuously improved and evaluated. Metadata attributes defined in an updated, relevant and integrated way across the company. Master data concepts managed within a master data environment. Taxonomies for data standards are defined. Conformance with the standards is integrated into the company. |
| | Technology & methods | SQL and Excel or equivalent, in isolation. *Ad hoc* routines. Data values are corrected without coordination with business processes. Root causes are not identified. Same errors corrected multiple times. | Basic data profiling tools are adopted and available anywhere in the system development lifecycle using different types of basic descriptive statistics. DQ technology and tools used to locate, match, link and assess data. Data parsing, standardization and cleansing are available to track down errors due to incompleteness and invalid syntax/structure. Root causes analysis by simple DQ rules and data validation. | DQ assessment and measurement tools are implemented using methods of data profiling and other statistical and analytical techniques and DQ reporting. Business guidelines are employed for validation. Standardized technology components for implementing data validation, certification and reporting are in place. Dimensions, metrics and validity rules well-defined and mainly automated. Data flaws are manually inspected. Data contingency procedures and business impacts analysis in place. | Inspecting, monitoring and correcting DQ issues integrated into applications infrastructure. This may include routines of automated (checks during processing, data profiling, ETL tools) and manual processes (running queries or reports on data sources, data sampling). Automatic data correction guided by governance policies and defined business rules. Basic methods of remediation of DQ issues. Validation of exchange data in place. Auditable. Dashboard and reporting tools. | Tools for reporting, logging, tracking, remediation and improvement of DQ issues, both in databases as well as in ETL and messages between systems. Non-technical users can define and modify DQ rules and dimensions dynamically. Root cause analysis. Data cleansing. Data controls across the enterprise. Remediation methods and, consequently, a remediation plan is established, ranging from process re-engineering to simple data corrections. Transparent DQ management practices. |
| | Skills & expertise | Quality depends on individuals or IT department. Identified data problems are fixed manually. This identification is based on its usability for a specific business task. | A small group of people trained. Starting to conduct data profiling, assess DQ, establish a baseline, and identify improvements and investments in DQ. | The owner of the data is responsible for assessing and ensuring the quality of data within each department, specific business tasks or projects. | DQ experts are identified throughout the company and are engaged in all DQ improvement processes. | A DQ competency center (or equivalent) is funded and is in charge of continually assessing and improving DQ outside the system development lifecycle. |

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | *Uninitiated* | *Awareness* | *Proactive adopting* | *Integral embracement* | *Completely embedded* |
| ***Data analysis & Insight*** | Applications & tools | Spreadsheet programs with manual reporting for the data visualization. Baseline process metrics. | Low-cost investments are made in visualization and data analysis tools such as MIS, ERP, CRM, EPM, and tailored solutions for data management and reporting. Standard reports. | Unintegrated initiatives of BI, OLAP, data discovery, or analytics tools are in place. Dashboards and scorecards. | Analytics tools integrated within the business process. Predictive applications. Dynamic graphing and dashboards. | Analytical software fully integrated and embedded throughout the organization. Predictive and prescriptive applications. Customizable self-service dashboards. |
| | Techniques & analysis | Descriptive analytics of processes and measures for describing what has happened. Focus on data accuracy, consistency and timeliness. | Reactive reporting for decision-making. The analysis focuses on describing why something is happening. The data analysis seeks cost reduction. | Proactive reporting for decision-making. Analytical insight is used to predict the likelihood of what will happen to some current business processes. Self-service tools that allow slicing and dicing of data and data visualization. Trend Analysis and benchmarks. Analytics applications focus on compliance measurement at the tactical and operational level. | Predictive analytics is used to help the organization to solve business problems and make decisions, identifying actionable solutions to maximize business value through more complex statistical analysis and text mining. More strategic approaches and greater insights to predict gain and transform how they do business through their analytics applications. | Development of predictive and prescriptive models. Risk analysis and mitigation. It can easily link the new data with existing assets. Scenario modeling. Analytical insight is used to encourage innovation and enables decision-making to be guided to explore new business opportunities. Leverage innovation and search for new business opportunities. |
| | Skills & expertise | Understaffed. Analytical skills, usually confined to a department or line-business on a specific function, working in isolation. Best practices are not shared.<br>The culture is not data-driven. | Few isolated groups with analytical skills usually at departmental or line-business level. Beginning to gain greater awareness of data analysis potential and interest in training staff in this area. | Permeation of analysts in key business areas. Some specific expert groups in more advanced data analysis, such as risk analysis and predictive modeling, at the departmental or line-business level. There may be external consultancy support. | Analysts with higher levels of analytics skills, conforming centers of excellence or networks to support different parts of the organization. | The highest level of analytical skills. Centers of excellence (COE) are in place, with teams that innovate with analytics and that train other groups of beginners. |

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | *Uninitiated* | *Awareness* | *Proactive adopting* | *Integral embracement* | *Completely embedded* |
| ***Information use*** | Requirements & use | Information requirements are not defined. The users do not trust or use data/information available due to quality problems or the time and effort required to gather the needed information. Information is presented in static statistical reports that usually do not fully answer the questions or problems to be solved. Rely more on management experience than on the information provided by data analysis. | End users define the information requirements and the applications/tools are adapted to the specified needs. Users trust their own departments/groups' *ad-hoc* reports. The information is presented in standard statistical reports used reactively at operational levels. Awareness of the importance of the information provided by data analysis. | Information needs to be linked to business processes that support organizational goals. Users access updated information as actionable metrics and KPIs through dashboards and other tools used to improve processes and management at the tactical level. Users partially trust data/information, but reconcile it with other sources to ensure consistency. Becoming an information-driven organization. | The necessary information is integrated across the company and meets user requirements. Easily shareable dynamic graphs and dashboards are proactively used to support business strategy. Intelligence is leveraged to optimize future performance. Relevant and key information is used as a competitive tool. Users trust and use the data. | Enterprise information is embedded and is delivered or available when required. All reports are widely trusted and accepted. The user interacts with applications in real-time using customizable environments to visualize key updated information in an innovative and agile way. Information drives company strategy. The information-driven culture is embedded. |
| | Knowledge management (KM) | The organization lacks the consistency and the documented processes and practices for identifying, capturing, sharing, transferring and applying appropriately its core knowledge. | Value of KM recognized. KM strategies, processes and approaches are implemented and tested. | KM strategies and processes are standardized. KM roles are created, defined and filled. Capturing/sharing lessons learned and skills are aligned with business needs. | The foundations for KM are established and standardized. Consolidated knowledge-sharing culture. Organization-wide KM practices are implemented. The effectiveness of KM is measured. | Strategies, processes and approaches to KM are embedded in all organizational processes. Continuous improvement of KM processes and practices. |
| | Information governance (IG) | Information is not systematically managed, communicated or disseminated timely throughout the organization. IG is poorly controlled and reactive through email and documents (hard copy) and largely manual. May not effectively serve the business needs of the organization. Bureaucratic processes without central oversight or guidance. Not sufficient to meet regulatory requirements. There is no emphasis on transparency. | A defined governance structure and IG process begin to take place. Roles and responsibilities are established. Policies, processes and standards begin to be defined. Awareness of transparency in information dissemination. Email and information systems isolated. Some controls in place to ensure consistent information disclosure. Bureaucratic processes remain. Still vulnerable to scrutiny of its legal or regulatory requirements. May not meet the organization's business needs. | Organization-wide IG structures with executive sponsorship. All high-priority subject areas are represented. Policies and procedures standardized. Core information is managed, protected and beginning to be more centralized but is not yet fully integrated and disseminated across the organization. Transparency begins to take place and information is systematically available when needed. Governance targets and metrics defined. The company meets business legal requirements. | An integral IG program is in place throughout the organization's operations, with policies for continuously improving it. Governance is managed using KPIs. IG issues are integrated into the DMP. The degree of confidence in information is reflected in decision-making. The information is integrated across the company and monitored, shared and updated consistently to support business function and goals. Greater emphasis on transparency. The company easily meets its legal requirements. | Key information and IG are embedded within the organization's overall corporate infrastructure, with its culture and business processes being measured and reviewed. Governance is continuously improved through better understanding of internal requirements and research in best practices. A transparent information-sharing culture is consolidated. Compliance with legal responsibilities is routine across the organization. |

| Dim./Attr. | | Maturity stages | | | | |
|---|---|---|---|---|---|---|
| | | ***Uninitiated*** | ***Awareness*** | ***Proactive adopting*** | ***Integral embracement*** | ***Completely embedded*** |
| ***Decision-making*** | Goals & outcomes | Aims, objectives, policies and strategies are not consistently defined and the outcomes of decisions are not measured or evaluated. Data and metrics unexplored. | Aims, objectives, policies and strategies begin to be defined on the basis of internal data at the departmental or line-business level. Metrics begin to be explored and defined. | Aims, objectives, policies and strategies are periodically defined, revised and updated, taking into account data both internal and external to the organization but at the departmental or line-business level. Metrics are defined. Specific goals and metrics are established to measure the outcomes of decisions. | Aims, objectives, policies and strategies are continually reviewed on the basis of relevant internal and external data across the company. Metrics and goals are standardized, communicated and integrated to continually measure the outcomes of decisions across the organization. | Aims, objectives, policies and strategies have been implemented at the level of the entire company and are continually reviewed and improved in terms of relevant internal and external data. Metrics are continually measured, reviewed and improved. Successes and failures are identified, forming the basis to enhance and innovate. |
| | DMP | Decision-making is random or improvised rather than a deliberate, coordinated process. Decisions are made based on gut instinct or experience instead of facts. No considered potential risks, issues or consequences. | Decision-making is deliberate only in situations of crisis or high risks. There is no structured decision-making process. Aware of the need to become data-driven for decision-making. React reactively only to imminent risks. | Decision-making begins to take place under a systematic, coordinated and deliberate process on the basis of available data. Working to become more data-driven for decision-making. Beginning to consider risks and consequences. | Decision-making is done under a clearly articulated strategy throughout the organization and on the basis of objective, reliable and relevant data. Organization proactively considers and manages risks and potential consequences before decision-making. | The decision-making process is fully embedded into business strategy and objectives of the company. The information-driven decision-making culture is fully consolidated. Risk management is used as a differentiator for decision-making. |
| | Leadership & empowerment | There is no data-driven culture among leaders. Power is centralized within the top management level. Reluctance to delegate responsibilities or activities or to share information. | Leaders begin to recognize the importance and encourage the use of data for decision-making. The degree of autonomy and responsibility is unclear or limited to routine, common and simple activities to ensure functioning at the departmental or line-business level. | Work together across the organization in the use of data for decision-making. Leaders begin to strengthen analytical skills as well as delegate more activities and responsibilities to downstream levels of the organization. Differentiated degrees of autonomy and responsibility. | Engagement and collaboration for data-driven decision-making with clear prioritization and guidance, moving through the different levels of the organization. | Commitment, collaboration and strong promotion of information-driven decision-making delegated throughout the company with an approach strongly oriented at innovation, as well as identifying and exploring new business opportunities. |

# C

# CHROMA Model Assessment Tool

This appendix presents the assessment tool of the CHROMA model and its SHADE version. This assessment tool consists of two phases. Phase I allows the collection of information through face-to-face semi-structured interviews. Phase II covers the whole process of analysis and assessment of the organization with respect to the information collected according to its level of compliance in each of the aspects considered in the framework of the corresponding model.

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

# ANÁLISIS DEL USO DE INFORMACIÓN EN LA TOMA DE DECISIONES

## INFORMACIÓN PRELIMINAR

**Propósito**: Recolectar información de la organización que permita contextualizar su situación con respecto al proceso de toma de decisiones impulsado por la información e identificar oportunidades de mejora para promover la toma de decisiones bien informadas.

Para lograr este objetivo, se realizarán entrevistas a distintos tipos de perfiles que incluyen el coordinador del proyecto o responsable de las TIC y el Director General o persona en la que delegue, así como un breve cuestionario web a los tomadores de decisiones de los procesos claves y roles que sean relevantes para la organización que puedan aportar valor al estudio.

Este instrumento se utilizará para recoger la información obtenida a partir de las preguntas realizadas durante las diferentes entrevistas, y que sirva de base para valorar el funcionamiento de la organización, sus procesos y la manera en que se toman las decisiones así como la percepción de sus integrantes y su visión de mejora al respecto.

Las sesiones de trabajo se estiman de alrededor de 1 h 30 min con una duración máxima de 2 horas.

| Fecha | Hora: | Documento No. |
|---|---|---|

| | |
|---|---|
| Empresa: | Actividad económica: |
| Sector: | Orientación de la actividad económica: Productos ☐ Servicios ☐ |
| Nro. De trabajadores: | |

**Representantes de la empresa/sector contactados**

| Nombre | Cargo | Departamento |
|---|---|---|
| | | |
| | | |
| | | |

## FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION

**Objetivo**:

Introducción a la organización.

Entender los aspectos básicos de su funcionamiento.

Seleccionar las personas (Responsables de procesos/Departamentos) a las que se enviará el cuestionario Web y organizar su envío (mail).

Recolectar información que permita valorar el proceso de toma de decisiones impulsado por información en la organización con énfasis en los aspectos tecnológicos y de gestión asociados.

Recabar la documentación existente que pueda resultar de interés para el estudio (actas de reunión, formularios, informes, procedimientos…)

| Estructura Organizativa y funcionamiento general | Perfil prioritario |
|---|---|
| 1. El modelo de negocio, objetivos y visión de la organización | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 2. ¿Cómo está estructurada la organización?<br>¿Es ampliamente difundida y conocida por todos? | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

| FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION | |
|---|---|
| 3. ¿Cuáles son los roles claves? | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 4. ¿Cuenta la organización con alguien responsable de las TIC?<br>¿Cuál es la denominación de su cargo?<br>¿Cuáles son sus funciones y responsabilidades? | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 5. ¿Tienen identificados y definidos los procesos de la organización, su secuencia e interrelación?<br>Si ☐ No ☐ (Ir a la pregunta 11) | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 6. Procesos estratégicos<br>(Permiten definir y desplegar los objetivos y estrategias de la organización, vinculados a la estrategia adoptada y al ámbito de la responsabilidad de la Dirección) | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 7. Procesos claves<br>(Relacionados con los clientes externos. Añaden valor al cliente o inciden directamente en su satisfacción o insatisfacción, componen la cadena de valor de la organización pues están directamente ligados con la realización del producto y/o prestación del servicio) | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 8. Procesos de soporte<br>(Relacionados con los clientes internos. Dan soporte a los procesos clave, proveen los recursos necesarios para poder generar el valor añadido deseado por los clientes. Suelen referirse a procesos relacionados con recursos y mediciones) | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| **Toma de decisiones** | **Perfil prioritario** |
| 9. ¿Utilizan datos para soportar las decisiones? Sí ☐ No ☐<br>¿Son confiables y de buena calidad? Sí ☐ No ☐<br>¿Desde cuándo la organización utiliza datos para soportar sus decisiones? | 1ª DG ☐<br>2ª TIC ☐<br>3ª CP ☐<br>Otro: ☐ |
| 10. ¿Quién define las políticas, objetivos, planes y estrategias de la organización?<br>Dirección ☐ Mandos intermedios ☐ Mandos de primera línea ☐<br>Otros: ☐ ____________<br><br>¿Cómo y con qué frecuencia son diseñados?<br>Toda la organización ☐ Por áreas/departamentos ☐ Otro: ☐ ____________<br>Trimestral ☐ Semestral ☐ Anual ☐ Otro: ☐ ____________<br><br>¿Son difundidos a través de la organización? Sí ☐ No ☐<br><br>¿En qué se basan?<br>Datos internos relevantes: Sí ☐ No ☐ ¿Cuáles?<br>Rendimiento de procesos importantes ☐ Necesidades y expectativas de los grupos de interés ☐<br>Otros: ☐ ____________<br>Datos relevantes externos a la organización: Sí ☐ No ☐ ¿Cuáles?<br>Evolución de mercados ☐ Competencias ☐ Tecnologías ☐ Clientes ☐ Proveedores ☐ Leyes y normativas ☐ Otros: ☐ ____________ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

**FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION**

11. ¿Cómo abordan las diferentes decisiones?
Siguen un proceso estructurado y planificado ☐
Reuniones y comunicación (interacción) constante con las partes interesadas (decisiones conjuntas) ☐
Alineado con los objetivos y estrategias de la compañía ☐
Individual ☐ En equipo ☐ Deliberado ☐

¿Qué elementos intervienen y consideran previo a tomarlas?
Análisis e interpretación de los datos ☐
Informes técnicos ☐ Reportes estándar ☐ Estudios externos (Outsourcing) ☐
Análisis riguroso de los riesgos e impactos potenciales asociados ☐
Cursos de acción y alternativas ☐
Utilizan algún tipo de dinámica para generar nuevas ideas y/o innovar ☐

1ª DG ☐ 2ª TIC ☐ 3ª CP ☐ Otro: ☐

12. ¿Están claramente definidos y diferenciados los roles y responsables de tomar las decisiones?
Si ☐ No ☐
¿Quiénes participan en la toma de decisiones?
Dirección ☐ Mandos intermedios ☐ Mandos de primera línea ☐ Mandos operativos ☐
Personal de base ☐ Otros: ☐ ______________________

1ª CP ☐/ DG ☐ 2ª TIC ☐ Otro: ☐

13. ¿Qué tipo de decisiones se toman en las diferentes instancias de la organización?

| *Tipo de decisión* | *¿Quién las toma?* | *¿Con qué frecuencia son tomadas?* |
|---|---|---|
| *Estratégicas* | | |
| *Tácticas* | | |
| *Operativas* | | |
| *Rutinarias* | | |
| *No rutinarias* | | |

1ª DG ☐ 2ª CP ☐ 3ª TIC ☐ Otro: ☐

14. En orden de importancia ¿Cuáles consideras son las decisiones que resultan claves para la organización?

1ª DG ☐ 2ª CP ☐ 3ª TIC ☐ Otro: ☐

15. ¿Qué nivel de poder y autonomía tienen los gerentes, equipos y empleados para tomar decisiones con los recursos de información disponibles?
Suficiente/Extendida ☐ Proporcionada/priorizada ☐ Diferenciada ☐ Limitada ☐
Pocas consultas ☐ Todo es consultado ☐

1ª CP ☐ 2ª TIC ☐ 3ª DG ☐ Otro: ☐

16. ¿De qué manera se promueve en la organización la cultura de tomar decisiones basadas en datos?
Política institucional ☐ Formación periódica en el análisis de datos ☐
Mejora constante de las herramientas tecnológicas para facilitar el acceso y disponibilidad de datos ☐
Otros: ☐ ______________________

1ª CP ☐/ DG ☐ 2ª TIC ☐ Otro: ☐

17. Cuándo se presentan problemas en las diferentes instancias o procesos de la organización ¿Cómo son resueltos?

1ª CP ☐ 2ª TIC ☐ 3ª DG ☐ Otro: ☐

18. ¿Cómo se evalúa el resultado de las decisiones tomadas?
¿De qué manera identifican y evalúan los éxitos y fracasos de estas decisiones?

1ª CP ☐/ DG ☐ 2ª TIC ☐ Otro: ☐

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

## FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION

| Disponibilidad de datos | Perfil prioritario |
|---|---|
| 19. ¿La compañía cuenta con la infraestructura, arquitectura y los recursos informáticos suficientes y acordes para apoyar y optimizar el proceso de toma de decisiones sobre la base de datos? (Arquitectura de hardware y plataforma de software, incluyendo entornos de aplicaciones)<br>Sí ☐ No ☐<br><br>¿Están alineados con la estructura de la organización y los procesos de negocio, permitiendo integrarlos y darles un soporte adecuado? Sí ☐ No ☐ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 20. ¿Qué nivel de acceso dispone la arquitectura de datos de la organización para apoyar la toma de decisiones?<br>¿Se encuentra definida y documentada? ¿Se ajusta a los requerimientos empresariales y de IT? Mapa, Estructura (física y lógica), relaciones, requisitos estratégicos de los datos, localización, ciclo de vida, recorrido, componentes. ¿Los datos se pueden enlazar y conectar con los diferentes sistemas? | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 21. ¿Cuáles son los recursos con los que cuenta la infraestructura de datos en su organización?<br>Activos, conjunto de componentes de hardware, redes, servidores... | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 22. ¿Cómo los sistemas de información y bases de datos con que cuenta la organización soportan y se interrelacionan con los procesos de la organización?<br>Describe puntos fuertes y débiles de estos sistemas de información y/o bases de datos | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 23. ¿Han establecido y documentado una estrategia de gestión de datos con claras responsabilidades de uso y acceso a los datos? Sí ☐ No ☐<br><br>¿De qué manera son gestionados los datos de la organización?<br>Programa integral de gobernanza de datos ☐ Estrategia de datos bien establecida ☐<br>Responsabilidades claramente definidas ☐ Acceso a datos bien gobernados y flexibles ☐<br><br>¿Quién usa cada base de datos?<br>Dirección: ___________________________ Mandos intermedios: ______________________<br>Procesos/Departamentos: ______________________<br>Otros: ________________________________ | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 24. ¿Cómo y con qué frecuencia actualizan su plataforma TIC?<br>Ecosistema de aplicaciones, inventario<br>Trimestral ☐ Semestral ☐ Anual ☐ Otro: ☐ ___________________ | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 25. ¿Qué problemas se presentan frecuentemente (quejas de los usuarios) con respecto a los sistemas y bases de datos?<br>Problemas de acceso ☐ Rendimiento en sistemas ☐<br>Requerimientos de datos e información ☐ Falta de conocimiento ☐<br>Heterogeneidad de interfaces ☐ Otros: ☐ ________________________________ | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

| FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION | |
|---|---|
| 26. ¿Cuáles son las fuentes de las que provienen los datos y la información utilizados para soportar los procesos de toma de decisiones de la organización?<br>Internas ☐ Especifique cuáles:<br>Características: Estructurados ☐ No estructurados ☐ Geoespaciales ☐<br>Otros: ☐ ________<br><br>Externas ☐ Especifique cuáles:<br>Características: Estructurados ☐ No estructurados ☐ Geoespaciales ☐<br>Otros: ☐ ________<br><br>Metadatos ☐<br>Metadatos: datos que describen otros datos. Permiten describir el contenido y la estructura de los datos. Denominación estándar. Permiten una comprensión de datos más eficaz. | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 27. ¿Cuánto se tarda en incorporar una fuente de datos nueva y en ponerla a disposición de los analistas de negocio?<br>Días ☐ Semanas ☐ Meses ☐ Otro: ☐ ________ | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 28. ¿Qué datos que no se tienen consideras que serían de utilidad para tomar decisiones mejor informadas? | 1ª DG ☐<br>2ª TIC ☐<br>3ª CP ☐<br>Otro: ☐ |
| 29. ¿Cuáles son sus preocupaciones principales y qué mejoras querría realizar a nivel de IT para dar mejor atención a los usuarios? | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 30. ¿Cuál es el volumen de datos actual que maneja la empresa? (Total, Tasa de crecimiento)<br><br>¿Cómo caracterizas la cantidad de datos disponible para apoyar la toma de decisiones?<br>Enorme y creciente ☐ Gran cantidad ☐ Gradualmente creciente ☐ Poca cantidad ☐<br><br>Datos Estructurados<br>Demasiada ☐ Suficiente ☐ No suficiente ☐ No sabe ☐<br>Datos No estructurados<br>Demasiada ☐ Suficiente ☐ No suficiente ☐ No sabe | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 31. ¿Cuáles han sido los 3 principales impedimentos para usar (o aprovechar mejor) los datos en la toma de decisiones?<br>Falta de integración, acceso y disponibilidad de datos ☐<br>Escasez de personas calificadas para analizar los datos correctamente ☐<br>Tiempo que toma analizar grandes conjuntos de datos ☐<br>Contenido no estructurado es difícil de interpretar ☐<br>Su adopción no es vista como una prioridad ☐<br>Alto costo de almacenar y manipular grandes conjuntos de datos ☐<br>Resulta complejo recolectar, integrar y almacenar ☐<br>Otro: ☐ ________ | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 32. Los datos requeridos para apoyar la toma de decisiones<br>Están fácilmente disponibles de forma oportuna Sí ☐ No ☐<br>Ofrecen un acceso rápido y consistente Sí ☐ No ☐ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 33. Los datos requeridos para apoyar el desarrollo de las actividades habituales<br>Están fácilmente disponibles de forma oportuna Sí ☐ No ☐<br>Ofrecen un acceso rápido y consistente Sí ☐ No ☐ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH
Departament d'Estadística i Investigació Operativa

## FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION

| Calidad de datos | Perfil prioritario |
|---|---|
| 34. Los datos y la información son:<br>Útiles ☐ Confiables ☐ De buena calidad ☐ Consistentes ☐<br>Completos ☐ Actualizados ☐ Sin errores ☐ Relevantes ☐ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 35. ¿Los datos han presentado o presentan problemas de calidad como duplicidades, errores, inconsistencias, diferencias temporales, lagunas de información, etc.? Sí ☐ No ☐<br>¿Cuales?<br><br>¿Han sido resueltos? Sí ☐ No ☐ ¿Cómo? | 1ª TIC ☐<br>2ª CP ☐<br>3ª DG ☐<br>Otro: ☐ |
| 36. ¿Cuentan con alguna herramienta tecnológica para inspeccionar, conciliar, monitorear, evaluar y corregir los problemas de calidad de datos? Sí ☐ No ☐<br>¿Está integrada en la infraestructura de aplicaciones? Sí ☐ No ☐<br>¿Es acorde y suficiente para evaluar y mejorar la calidad de los datos? Sí ☐ No ☐<br>¿Cómo es implementado? Manual ☐ Automatizada ☐ | 1ª TIC ☐<br>2ª CP ☐<br>3ª DG ☐<br>Otro: ☐ |
| 37. ¿Qué hacen para asegurar el acceso y utilización de datos limpios, consistentes, confiables y armonizados para apoyar una mejor toma de decisiones?<br>¿Tienen procesos y métodos para evaluar y mejorar periódicamente la calidad de los datos?<br>Sí ☐ No ☐<br>¿Utilizan algún tipo de herramienta de extracción, transformación y carga (ETL) específico?<br>Sí ☐ No ☐<br>¿Se gestionan los riesgos de calidad de información? Sí ☐ No ☐<br>¿Cómo y cuándo comprueban la coherencia e integridad de los datos de los sistemas y bases de datos? | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 38. ¿Quiénes son los responsables de evaluar y asegurar la calidad de los datos?<br>¿Tienen la habilidad y experiencia para encargarse y comprometerse con los procesos de mejora de la calidad de los datos? Sí ☐ No ☐<br>¿Forman constantemente al personal para desarrollar y potenciar estas capacidades? Sí ☐ No ☐ | 1ª TIC ☐<br>2ª CP ☐<br>3ª DG ☐<br>Otro: ☐ |
| 39. ¿Cómo aseguran una definición e implementación estandarizada de los datos?<br>Programa integral de Calidad de Datos ☐<br>Taxonomía de datos ☐<br>Elementos de datos según términos de negocios e IT comúnmente usados (definiciones semánticas) ☐<br>Tipos y repositorios de datos ☐<br>Atributos de metadatos ☐ ¿Son actualizados, relevantes e integrados? Sí ☐ No ☐<br>Gestión de Datos Maestros ☐<br>Métricas utilizadas en la organización ☐ | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 40. ¿Qué problemas se les han presentado por falta de calidad de datos?<br>**Financieros:** Incremento del coste de operaciones ☐ Disminución de ingresos ☐<br>Pérdida de oportunidades ☐ Reducción/retrasos en el flujo de caja ☐<br>Otros: ☐ ________________________________<br>**Confianza/satisfacción:** Imagen corporativa ☐ Confianza del personal (datos) ☐<br>Previsiones (Fiabilidad) ☐ Reportes inconsistentes ☐ Decisiones a destiempo y/o imprecisas ☐ Otro: ☐ ____________________<br>**Productividad:** Cargas de trabajo ☐ Rendimiento ☐<br>Mayor tiempo de procesamiento ☐ Calidad del producto ☐<br>Otro: ☐ ________________________________________<br>**Riesgo:** Evaluaciones ☐ Inversiones ☐ Competencia ☐<br>Otros: ☐ ____________________ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

| FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION | |
|---|---|
| **Análisis de datos e insight** | **Perfil prioritario** |
| 41. ¿La compañía ha invertido en mejorar el proceso de toma de decisiones impulsado por datos a través de la adopción de aplicaciones y herramientas tecnológicas para apoyar su apropiado análisis y visualización y extraer el valor que en ellos reside?<br>Sí ☐ No ☐<br><br>¿Cuáles? MIS ☐ ERP ☐ CRM ☐ EPM ☐ BI ☐ OLAP ☐ Data mining ☐<br>Text mining ☐ Aplicaciones predictivas ☐ Aplicaciones prescriptivas ☐<br>Otros: ☐ ____<br><br>¿Están integradas y accesibles a toda la organización? Sí ☐ No ☐<br>¿Consideras que se encuentran acordes con las necesidades actuales requeridas por la organización en orden de ser más eficiente, ágil, innovadora y competitiva? Sí ☐ No ☐ | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 42. ¿Cómo se analizan los datos? ¿Cómo se transforman en información?<br>¿Qué técnicas de análisis utilizan y aplican a los datos?<br>Analíticos descriptivos ☐ Reportes estándar (Reactivos) ☐<br>Análisis de tendencia y benchmarks ☐ Cubos OLAP ☐ Analíticos predictivos ☐<br>Minería de datos y/o texto ☐ Analíticos prescriptivos ☐ Análisis de riesgos y mitigación ☐<br>Modelado de escenarios ☐ Otras: ☐ ____ | 1ª TIC ☐<br>2ª DG ☐<br>3ª CP ☐<br>Otro: ☐ |
| 43. ¿Han considerado explorar e implementar tecnologías emergentes como Big Data, Analytics entre otras que mejore las capacidades de la organización para extraer un mayor valor de sus datos? ¿Es un tema que les interese o les preocupe?<br>¿Han realizado cambios en los sistemas y formación de personal para adaptarse a estas tendencias?<br>Sí ☐ No ☐ | 1ª TIC ☐<br>2ª DG ☐<br>3ª CP ☐<br>Otro: ☐ |
| 44. ¿Cuentan con personal calificado en el análisis de datos en las diferentes áreas de la organización? Sí ☐ No ☐<br>¿Quiénes realizan análisis a los datos?<br>Dirección ☐ Mandos intermedios ☐ Mandos de primera línea ☐ Mandos operativos ☐<br>Personal de base ☐ Otros: ☐ ____<br>¿Realizan análisis avanzados a los datos para soportar las funciones de negocios y/o departamentos así como a la estrategia y objetivos de la organización? Sí ☐ No ☐<br>¿Esto se extiende para colaborar y contribuir a las diferentes partes de la organización? Sí ☐ No ☐ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 45. ¿Cómo catalogarías las capacidades analíticas del personal de la organización?<br>Excelente ☐ Bueno ☐ Regular ☐ Insuficiente ☐ Inexistente ☐<br>¿Tienen planes de formación profesional para desarrollarlas y/o potenciarlas? Sí ☐ No ☐ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 46. El análisis a los datos se enfoca en:<br>Describir que ha pasado ☐<br>Describir por qué ha pasado ☐<br>Predecir la probabilidad de lo que pasará en cuanto a la medición del cumplimiento a nivel táctico y operacional ☐<br>Resolver problemas de negocios, prediciendo lo que pasará desde una perspectiva más estratégica ☐<br>Predecir qué, cuándo y por qué pasará. Promover la innovación y permitir la toma de decisiones en orden de explorar nuevas oportunidades de negocio ☐ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 47. ¿Cómo se asegura la satisfacción del cliente?<br>¿Analizan la información proveniente de los clientes (contactos de vendedores, quejas, garantías, etc.) para anticiparse a sus necesidades actuales y futuras que permitan ofrecerles productos/servicios mejor ajustados? Sí ☐ No ☐ | 1ª CP ☐<br>2ª DG ☐<br>3ª TIC ☐<br>Otro: ☐ |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

| FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION | |
|---|---|
| 48. ¿Se logran proporcionar fácilmente y visualizar apropiadamente los datos requeridos por los miembros de la organización para apoyar la toma de decisiones? Sí ☐ No ☐<br>¿Cómo son visualizados los datos?<br>Interfaz gráfica (dashboards y scorecards) ☐<br>Hojas de cálculo independientes (creadas y mantenidas por el mismo personal) ☐<br>Hojas de cálculo a medida (personalizadas) e integradas ☐<br>Otros: ☐ ____________________ | 1ª TIC ☐<br>2ª CP ☐<br>3ª DG ☐<br>Otro: ☐ |
| **Uso de la información** | **Perfil prioritario** |
| 49. ¿Están satisfechos con el soporte tecnológico (TIC) en cuanto al uso de datos para tomar decisiones? | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 50. ¿Cuánto tiempo invierte en el tratamiento de requerimientos de IT y negocio?<br>Días ☐ Semanas ☐ Meses ☐ Otro ☐ | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 51. Explique brevemente cómo la información es importante para tu organización y soporta las decisiones | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 52. ¿De qué manera las herramientas tecnológicas con que cuenta la organización para proveer datos e información, soportan las funciones de negocios y los objetivos? | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 53. ¿Qué datos o información especial es frecuentemente requerida para apoyar las decisiones? | 1ª TIC ☐<br>2ª DG ☐<br>Otro: ☐ |
| 54. ¿Puede listar de forma estructurada/categorizada la información más relevante que se maneja en las bases de datos de la compañía? (Contable, personas, proceso productivo, proveedores, etc.) | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 55. ¿Tienen instaladas aplicaciones/herramientas de Business Intelligence y/o Business Analytics? ¿Cuáles?<br>¿Consideras que proporciona informes útiles, confiables y personalizables para los usuarios?<br>Sí ☐ No ☐<br>¿Los usuarios los usan en el desarrollo de sus actividades? Sí ☐ No ☐<br>¿Permiten el acceso a información actualizada como métricas accionables y KPI's? Sí ☐ No ☐ | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 56. ¿De qué manera es presentada la información a través de las herramientas y aplicaciones disponibles para gestionar y evaluar la estrategia analítica empresarial?<br>Interfaz gráfica (dashboards y scorecards) ☐ Gráficos dinámicos ☐ Informes/Reportes ☐<br>Hojas de cálculo ☐ Otros: ☐ ____________________ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |
| 57. ¿Periódicamente utilizan algún tipo de informe? Sí ☐ No ☐<br>¿Para qué los utilizan?<br>Apoyar la toma de decisiones ☐ Desarrollo de planes y estrategias ☐<br>Acciones de mejora ☐ Visión, análisis y perspectiva situacional ☐<br>Otro: ☐ ____________________<br>¿Qué tipo de información contienen? ¿Cómo se presentan los resultados que sustenten las decisiones a tomar? Listados ☐ Tablas ☐ Gráficos ☐ Medidas ☐<br>Indicadores ☐ Otros: ☐ ____________ | 1ª CP ☐/ DG ☐<br>2ª TIC ☐<br>Otro: ☐ |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

| FASE I. ENTREVISTAS - RECOLECCION DE INFORMACION | |
|---|---|
| 58. ¿Cómo hacen para identificar, mantener, proteger y aprovechar los conocimientos de la organización?<br>Programa de gestión del conocimiento ☐<br>Recolectan, mantienen, aprovechan y protegen los conocimientos tácitos y explícitos de la organización ☐<br>Promoción del aprendizaje y la transferencia de conocimiento ☐<br>El conocimiento es aprovechado para potenciar las capacidades como fuente para diferenciarse y mejorar ☐ | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 59. ¿De qué manera es realizada la gestión, uso, mejora y protección de la información organizacional?<br>Programa de gobernanza de la información ☐<br>Roles y responsabilidades claros de los datos e información ☐<br>Consideraciones de gobernanza integradas de forma rutinaria en los procesos de la organización ☐<br>Cumplen los requerimientos legales de seguridad y privacidad de la información ☐<br>Protección, mantenimiento y disposición de los registros e información (Privada, confidencial, privilegiada, secreta, clasificada, esencial o que requiere ser protegida y recuperada) ☐ | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |
| 60. ¿Cómo se comparte la información entre el personal de la organización?<br>Permisos ☐ Autorizaciones ☐ Otros: ☐ ____________________<br>¿Se comparte información con clientes y proveedores? Sí ☐ No ☐ | 1ª CP ☐<br>2ª TIC ☐<br>3ª DG ☐<br>Otro: ☐ |

| FASE II. VALORACIÓN | | | | | | |
|---|---|---|---|---|---|---|
| Elementos a considerar/ Atributos | Estatus/Puntuación | | | | | Preguntas relacionadas (Inputs) |
| | 0 | 1/4 | 1/2 | 3/4 | 1 | |
| **Estructura Organizativa** | | | | | | |
| 1. ¿Existe una estructura organizacional claramente definida y es conocida por todos los miembros de la organización? | | | | | | (2)<br>(5, 6, 7, 8) |
| 2. ¿La estructura jerárquica ofrece un esquema dinámico y flexible que promueva una comunicación efectiva en todas las instancias de la organización para tomar decisiones mejor informadas? | | | | | | (1, 2)<br>(5, 6, 7, 8) |
| 3. ¿Los roles, responsabilidades, interrelación y participación de todo el personal en el proceso de toma de decisiones están definidos de forma clara, transparente y documentada? | | | | | | (3, 12)<br>(4, 5, 6, 7, 8, 13) |
| 4. ¿Cuenta la organización con un Responsable TIC? ¿El cargo se encuentra formalmente dentro de la estructura organizativa de la compañía con sus responsabilidades claramente establecidas? | | | | | | (4) |
| **Disponibilidad de datos** | | | | | | |
| 5. ¿La arquitectura de datos con la que cuenta la compañía cumple con los requerimientos empresariales y de tecnología de información? | | | | | | (19, 20)<br>(16, 31) |
| 6. ¿Cuentan con la infraestructura para el debido almacenamiento y distribución de los datos? | | | | | | (19, 20, 21)<br>(31) |
| 7. ¿La arquitectura de datos se encuentra debidamente documentada, difundida y alineada con la estructura de la organización? | | | | | | (19, 20)<br>(21) |
| 8. ¿Los procesos de negocios se encuentran debidamente soportados tecnológicamente e integrados tanto a nivel | | | | | | (19, 22)<br>(16, 20) |

| FASE II. VALORACIÓN | | | | | | |
|---|---|---|---|---|---|---|
| Elementos a considerar/ Atributos | Estatus/Puntuación | | | | | Preguntas relacionadas (Inputs) |
| | 0 | 1/4 | 1/2 | 3/4 | 1 | |
| interdepartamental como de toda la organización? | | | | | | |
| 9. ¿Cuentan con un programa integral de gobernanza datos con estrategias y responsabilidades bien establecidas? | | | | | | (23)<br>(9) |
| 10. ¿Se tienen establecidos, documentados e implementados los procesos para recopilar datos fiables y útiles? | | | | | | (23)<br>(9, 31) |
| 11. ¿Cuentan con una política para mantener actualizada su plataforma TIC? | | | | | | (24)<br>(16) |
| 12. ¿Los datos y la información que maneja la organización provienen de múltiples fuentes que continuamente se van absorbiendo e integrando conforme van emergiendo? | | | | | | (26)<br>(25, 27, 31) |
| 13. ¿Los datos y la información de la organización se encuentran fácilmente disponibles y se comparten a través de toda la compañía así como a proveedores y otros actores externos? | | | | | | (32, 33, 60)<br>(23, 25, 28, 31) |
| 14. ¿La organización maneja y continuamente integra grandes y crecientes cantidades de datos de diferentes tipos y características? | | | | | | (26, 30)<br>(31) |
| 15. ¿Los usuarios pueden acceder a todos los datos que necesitan desde una sola interfaz de usuario? | | | | | | (25, 32, 33)<br>(22, 29, 31) |
| 16. ¿Los usuarios disponen de todos los datos que necesitan al momento de tomar decisiones? | | | | | | (32, 33)<br>(23, 25, 28, 29, 31) |
| 17. ¿Los usuarios pueden acceder fácilmente a metadatos integrados, actualizados y relevantes? | | | | | | (26, 39)<br>(23, 25) |
| **Calidad de datos** | | | | | | |
| 18. ¿Los datos son correctos, precisos, pertinentes, oportunos y confiables? | | | | | | (34)<br>(9, 35, 40) |
| 19. ¿Cuentan con herramientas tecnológicas acordes e integradas que permitan inspeccionar, conciliar, monitorear, evaluar y corregir los problemas de calidad de datos? | | | | | | (36)<br>(35) |
| 20. ¿Existen procesos y aplican métodos apropiados para evaluar y mejorar continuamente la gestión de calidad de datos? | | | | | | (37)<br>(35) |
| 21. ¿Se garantiza de forma continua, razonable y adecuada que la información generada y/o gestionada es auténtica, coherente y fiable (Integridad)? | | | | | | (37)<br>(36) |
| 22. ¿El personal cuenta con las habilidades y experiencia necesarias para evaluar y mejorar continuamente la gestión de calidad de los datos? | | | | | | (38) |
| 23. ¿Se encuentran definidos, documentados e implementados los métodos y herramientas para asegurar una definición e implementación estandarizada de los datos? | | | | | | (39) |
| **Análisis de datos e insight** | | | | | | |
| 24. ¿Tienen implementada una plataforma tecnológica de apoyo a las decisiones para impulsar la estrategia de la compañía? | | | | | | (41)<br>(55) |
| 25. ¿Explotan y aprovechan la tecnología existente para apoyar y mejorar la toma de decisiones impulsada por | | | | | | (41)<br>(42 55) |

| FASE II. VALORACIÓN | | | | | | |
|---|---|---|---|---|---|---|
| Elementos a considerar/ Atributos | Estatus/Puntuación | | | | | Preguntas relacionadas (Inputs) |
| | 0 | 1/4 | 1/2 | 3/4 | 1 | |
| los datos? | | | | | | |
| 26. ¿Apoyan la toma de decisiones con resultados derivados de la aplicación de herramientas y técnicas como analíticos predictivos y prescriptivos, OLAP, minería de datos y texto, machine learning, entre otros? | | | | | | (41, 42)<br>(55) |
| 27. ¿Analizan, comprenden y evalúan el impacto de tecnologías emergentes para su adopción que mejore las capacidades de la organización en el manejo eficaz de los datos? | | | | | | (43)<br>(41, 42, 55) |
| 28. ¿Adecúan los sistemas y forman al personal para adaptarse a los nuevos cambios y tendencias tecnológicas? | | | | | | (43)<br>(16, 45) |
| 29. ¿El personal posee habilidades, conocimientos y competencias en el manejo de diferentes herramientas informáticas, tecnologías TIC, distribución y análisis de datos que les conduzca a comprender y realizar sus actividades basadas en datos? | | | | | | (44, 45) |
| 30. ¿Disponen de personal con fuertes capacidades analíticas en las diferentes áreas de la organización contribuyendo y colaborando sinérgicamente a las funciones de negocio, estrategia y objetivos de toda la organización para tomar mejores decisiones impulsadas por datos? | | | | | | (44, 45) |
| 31. ¿Se tienen planes para desarrollar el perfil profesional del personal de la compañía y ampliar sus capacidades en los campos de las ciencias de la computación y aplicaciones, modelado, estadística, análisis cuantitativo y matemáticas para apoyar la labor de analizar y extraer valor de los datos disponibles que los oriente a alcanzar una ventaja competitiva sostenible frente a sus competidores? | | | | | | (45)<br>(16, 43) |
| 32. ¿Han adoptado y aplican técnicas y buenas prácticas analíticas para convertir los datos recopilados en la información necesaria y relevante para tomar decisiones mejor informadas? | | | | | | (42, 46)<br>(44, 47) |
| 33. ¿Las herramientas tecnológicas utilizadas para manejar y analizar los datos forman parte de la cultura organizacional y el personal las utiliza proactivamente para soportar sus actividades y la estrategia de la compañía? | | | | | | (16, 55)<br>(9, 44, 51) |
| 34. ¿Ofrecen la interfaz gráfica de usuarios con tableros de instrumentos (dashboards) y cuadros de mando (scorecards) necesarios, personalizables y actualizados para gestionar y evaluar la estrategia analítica empresarial? | | | | | | (48, 56)<br>(55) |
| **Uso de la información** | | | | | | |
| 35. ¿Los sistemas, aplicaciones y herramientas disponibles para proveer datos e información soportan las funciones de negocios y los objetivos? | | | | | | (51, 52, 53, 55)<br>(22, 54) |
| 36. ¿Satisfacen las necesidades de consulta del personal para el desarrollo de sus actividades permitiendo el acceso a información relevante, confiable, útil y | | | | | | (52, 53, 55)<br>(9, 16, 23, 25, 28, 29, 31, 32, 33, 34, 40, 41, 48, 49, 50, |

| FASE II. VALORACIÓN | | | | | | |
|---|---|---|---|---|---|---|
| Elementos a considerar/ Atributos | Estatus/Puntuación | | | | | Preguntas relacionadas (Inputs) |
| | 0 | 1/4 | 1/2 | 3/4 | 1 | |
| utilizable? | | | | | | 51, 56, 57) |
| 37. ¿Ofrecen entornos personalizables a los usuarios para visualizar la información clave de forma innovadora y ágil para gestionar y evaluar la estrategia analítica empresarial? | | | | | | (48, 55, 56) (41, 42, 57) |
| 38. ¿Proporcionan informes útiles y personalizables para los usuarios? | | | | | | (55, 56) |
| 39. ¿Son ampliamente utilizados por todo el personal para mejorar la eficiencia de sus actividades? | | | | | | (55, 56, 57) (48, 51, 52) |
| 40. ¿Los procesos disponen de información objetiva, actualizada, confiable e integrada que facilite la toma de decisiones en beneficio de la gestión, análisis y mejora del rendimiento organizacional? | | | | | | (51, 52, 55) (9, 22, 34, 41, 54, 56, 57) |
| 41. ¿Los tiempos de respuesta en los requerimientos de IT están acordes a la velocidad con que se toman decisiones? | | | | | | (49, 50) (25, 27, 29, 31, 41, 48, 51, 52, 53) |
| 42. ¿Se han establecido, documentado e implementado procesos para gestionar y aprovechar los conocimientos como recurso esencial de la organización? | | | | | | (58) |
| 43. ¿Se identifican, mantienen, aprovechan y protegen los conocimientos tácitos y explícitos de la organización? | | | | | | (58) |
| 44. ¿Se cuentan con políticas para crear un ambiente de trabajo que fomente el crecimiento personal, el aprendizaje, la transferencia de conocimiento y el trabajo en equipo? | | | | | | (58) |
| 45. ¿Tienen un programa integral de gobernanza de la información? | | | | | | (59) |
| 46. ¿Se encuentran claramente definidos los roles y responsabilidades con respecto a garantizar una adecuada gestión, uso, mejora y protección de la información organizacional? | | | | | | (59) |
| 47. ¿Las consideraciones de gobernanza de la información se encuentran integradas de forma rutinaria en las decisiones de negocios? | | | | | | (59) |
| 48. ¿Se cumple a cabalidad los requerimientos legales en cuanto a la seguridad y privacidad de la información asi como a las políticas de la organización? | | | | | | (59) |
| 49. ¿Se cuenta con mecanismos para asegurar un nivel razonable de protección y disposición de los registros e información privada, confidencial, privilegiada, secreta, clasificada, esencial para la continuidad del negocio, o que de alguna forma requiera protección? | | | | | | (59) |
| 50. ¿Los registros e información son mantenidos de cara a asegurar la oportunidad, eficiencia y recuperación exacta de las necesidades de información? | | | | | | (59) |
| 51. ¿Se promueve el manejo transparente de información relevante con todas las partes interesadas de la organización como medio para mejorar conjuntamente la toma de decisiones, el desempeño y los resultados? | | | | | | (60) |
| **Toma de decisiones** | | | | | | |
| 52. ¿Los planes y estrategias a cumplir se definen sobre la base de datos relevantes tanto internos como externos | | | | | | (9, 10) |

**FASE II. VALORACIÓN**

| Elementos a considerar/ Atributos | Estatus/Puntuación 0 | 1/4 | 1/2 | 3/4 | 1 | Preguntas relacionadas (Inputs) |
|---|---|---|---|---|---|---|
| alineados con las políticas y objetivos de la organización? | | | | | | |
| 53. ¿Se encuentran definidos y difundidos de forma clara, transparente y documentada las políticas y objetivos de la organización? | | | | | | (10) |
| 54. ¿Las decisiones son tomadas siguiendo un proceso estructurado, sistemático y planificado con pasos claramente definidos? | | | | | | (11) |
| 55. ¿Se llevan a cabo reuniones periódicas entre las diferentes instancias involucradas para analizar los datos que permitan definir y evaluar estrategias conjuntas enmarcadas en los objetivos de la organización? | | | | | | (11)<br>(12) |
| 56. ¿Se promueve una comunicación efectiva en todas las instancias de la organización para tomar decisiones mejor informadas? | | | | | | (11, 12)<br>(15, 44, 58, 59) |
| 57. ¿Utilizan algún tipo de dinámica para generar sinergia, nuevas ideas y/o innovar? | | | | | | (11) |
| 58. ¿Las diferentes opciones son analizadas tomando en cuenta: la interpretación de los datos, cursos de acción y alternativas? | | | | | | (11)<br>(42, 46, 47) |
| 59. ¿Son considerados y evaluados los riesgos, impactos, problemas y consecuencias potenciales que conlleva una elección antes de tomar la decisión? | | | | | | (11)<br>(17, 42) |
| 60. ¿Los resultados para soportar las decisiones se presentan de forma gráfica sobre la base de datos objetivos que permiten monitorear y evaluar periódicamente el cumplimiento y efectividad de los procesos con respecto a los planes y objetivos establecidos? | | | | | | (11, 57)<br>(41, 42, 48, 55, 56) |
| 61. ¿Se encuentran diferenciados y distribuidos los roles, responsabilidades y el alcance de las decisiones que se toman en las diferentes instancias de la organización? | | | | | | (12, 13) |
| 62. ¿Están discriminados los tipos de decisiones que se toman en cada nivel de la organización? | | | | | | (13) |
| 63. ¿Tienen identificadas las decisiones claves para la organización? | | | | | | (14) |
| 64. ¿Los gerentes, equipos y empleados de todos los niveles de la organización tienen el poder y autonomía para tomar decisiones en las diferentes instancias con los recursos de información disponibles? | | | | | | (15) |
| 65. ¿Se promueve en la organización la toma de decisiones basada en datos? | | | | | | (9, 16) |
| 66. ¿Se evalúa de forma objetiva la efectividad de las decisiones tomadas? | | | | | | (18)<br>(55) |

$$\text{Valoración} = \frac{\text{TOTAL}}{\text{N}} \times 100$$

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Departament d'Estadística i Investigació Operativa

| BALANCE GENERAL DE LA ORGANIZACIÓN | |
|---|---|
| *Puntos fuertes* | *Aspectos de mejora* |
| | |

*Evidencias/Observaciones:*

| *Estructura organizativa:* | *Disponibilidad de datos:* | *Calidad de datos:* | *Análisis de datos e insight:* | *Uso de la información* | *Toma de decisiones* | *Puntuación global:* |
|---|---|---|---|---|---|---|
| | | | | | | |

| ESQUEMA DE VALORACIÓN | |
|---|---|
| **Puntuación** | **Criterio** |
| 0 | No existe |
| 25 (¼) | Existe algo |
| 50 (½) | Existe en grado mínimo aceptable |
| 75 (¾) | Existe en grado Bueno |
| 100 (1) | Existe en grado Excelente |

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH
Departament d'Estadística i Investigació Operativa

**INSTRUCCIONES DE LLENADO**

A. **TÍTULO**: Análisis del uso de información en la toma de decisiones.
B. **OBJETIVO**: Recolectar y volcar la información obtenida a través de las entrevistas como base para llevar a cabo la valoración y evaluación del proceso de toma de decisiones impulsado por información de la organización bajo estudio.
C. **ACRÓNIMOS**:
   a. **CP** → Coordinador de proyecto. Es el enlace o persona de contacto entre la organización y el equipo asesor. Provee una perspectiva general e inicial de la organización y su funcionamiento. También ayuda a organizar el proceso de evaluación.
   b. **DG** → Director General, consejero o equivalente. Proporciona la perspectiva sobre qué tan bien la organización usa la información para tomar decisiones. La entrevista también permite alinear las expectativas de la alta dirección con el alcance del estudio y el resultado que será entregado.
   c. **TIC** → Responsable de las tecnologías de información y comunicaciones o equivalente. Provee información clave con respecto a la tecnología de gestión de datos usada, la disponibilidad de las bases de datos y la manera en se facilita a los usuarios el acceso a la información.
D. **CONSIDERACIONES**:
   a. El formulario está unificado para llevar a cabo las entrevistas según diferentes configuraciones que puedan adaptarse a las particularidades de cada empresa. Siendo el escenario ideal para causar la menor disrupción posible, la configuración de dos entrevistas a los perfiles: TIC (que a su vez deberá asumir las funciones de enlace entre la organización y los consultores), y el DG. Cuando no exista el perfil TIC, la organización deberá asignar a un CP que cubra esta función de enlace o vínculo.
   b. En ausencia del TIC, las preguntas asociadas a este perfil con un alto componente tecnológico serán respondidas por el DG. El resto serán distribuidas entre el CP y el DG de acuerdo con el orden de prioridad establecido.
   c. Para las diferentes preguntas en las que el DG se encuentre en prioridad 1, será suficiente con las respuestas que éste proporcione. En este caso no será necesario repetir estas preguntas al resto de los perfiles.
   d. Las preguntas en las que el CP y el DG se encuentren conjuntamente de 1º en prioridad, deberán ser formuladas a ambos perfiles, a menos que no se cuente con el perfil CP. En este caso solo se le preguntará al DG.
   e. Si el TIC está de 1º en prioridad y la empresa cuenta con este perfil, con su respuesta ya es suficiente no haciendo falta preguntar de nuevo al DG.
   f. Cuando un perfil (EJ.: DG) se encuentre de 2º en prioridad y el perfil inmediato superior no exista, este automáticamente pasará de 1º en prioridad.
   g. Al perfil que esté de 2º y 3º en prioridad no se requerirá volver a plantearle la misma pregunta si esta ya ha sido efectivamente respondida por el perfil previo.
E. **INSTRUCCIONES DE LLENADO**:
   a. **Fecha**: Coloque la fecha en que se realiza la entrevista.
   b. **Hora**: Coloque la hora en que se realiza la entrevista.
   c. **Documento No.**: Coloque el número correlativo correspondiente al número asignado a la empresa bajo estudio.
   d. **Empresa**: Coloque el nombre de la empresa bajo estudio.
   e. **Sector**: Coloque el sector económico al que pertenece la empresa bajo estudio.
   f. **Actividad económica**: Coloque el tipo de actividad económica al que pertenece la empresa bajo estudio.
   g. **Orientación de la actividad económica**: marque con una equis (x) si la actividad económica de la organización se orienta a ofrecer productos o servicios.
   h. **Representantes de la empresa/sector contactados**: Coloque el nombre, cargo y departamento de las personas que serán entrevistadas en representación de la empresa.

**FASE I. ENTREVISTAS – RECOLECCIÓN DE INFORMACIÓN**

i. Esta fase contempla seis bloques de preguntas semi-estructuradas que permitirán recolectar la información necesaria para completar la Fase II del formulario. Para agilizar el proceso de recolección de información, las entrevistas se han de grabar, notificando y solicitando el permiso correspondiente al entrevistado antes de comenzar.

j. Deberá prepararse previamente el formulario de acuerdo con los perfiles disponibles para facilitar y agilizar el proceso al momento de la entrevista.

k. Estas preguntas están formuladas, por una parte, de una forma abierta para permitir al entrevistado extenderse en la explicación al responder permitiendo recolectar información más completa. Y por otro lado, contiene información complementaria para ayudar al entrevistador a formular mejor las preguntas, ofreciendo una mayor comprensión al entrevistado sobre lo que se plantea que incremente la posibilidad de recolectar respuestas más precisas y enfocadas.

l. Adicionalmente, debajo de las preguntas están planteadas posibles respuestas en forma de opciones con casillas que permitirán ir rellenando al momento de la entrevista con la información recolectada para facilitar luego el proceso de análisis de la información.

m. Junto con las preguntas se encuentra una columna que indica el perfil al que le corresponde formularle cada pregunta de acuerdo con un orden de prioridad según las consideraciones establecidas en el literal D de estas instrucciones.

**FASE II. VALORACIÓN**

Esta fase del formulario representa el instrumento a través del cual se realizará la valoración de la organización en cuanto a su proceso de toma de decisiones impulsado por información, con base en la información recolectada. Está estructurada de la siguiente forma:

n. **Elementos a considerar/Atributos**: está estructurada en función de los mismos bloques temáticos en los que se subdivide la Fase I correspondiente a las entrevistas. Contiene las preguntas a través de las cuales se valorarán los aspectos/atributos considerados, los cuales tienen una clara y específica relación con las preguntas de la Fase I.

o. **Estatus/Puntuación**: contiene las casillas en las cuales se procederá a puntuar (valorar) de acuerdo a una escala que va desde 0 (el peor) a 100 (el mejor), el estatus de la organización para cada una de las preguntas (criterios) de los diferentes bloques temáticos con base en la información recolectada. Para esto se tomará en cuenta el esquema de valoración ubicado al final del formulario.

p. **Preguntas relacionadas (Inputs)**: Para facilitar el proceso de valoración, en esta parte del formulario se han resaltado los números de las preguntas de la Fase I que permiten dar respuesta a la pregunta asociada a cada celda. Al respecto, el (los) número(s) de la primera línea corresponde(n) a la(s) pregunta(s) de la Fase I más relacionada(s) con el ítem bajo ponderación. Los números de la segunda línea corresponden a las preguntas de la Fase I que ofrecen información complementaria para la valoración de ese ítem. Asimismo, en este espacio podrá apuntarse cualquier observación sobre la valoración que se considere importante resaltar.

**BALANCE GENERAL DE LA ORGANIZACIÓN**

Esta tabla del formulario permitirá al entrevistador realizar anotaciones libres acerca de los puntos fuertes y aspectos de mejora que pueda identificar al momento de la entrevista.

q. **Puntos fuertes**: son aquellos aspectos en los cuales la organización tiene un desempeño destacable, representan las fortalezas de la organización.

r. **Aspectos de mejora**: representan aquellas áreas de la organización, sus actividades e interrelaciones que no funcionan o funcionan de manera inefectiva por lo que requieren una especial atención para actuar en consecuencia.

s. **Evidencias/observaciones**: este espacio permitirá volcar cualquier observación o evidencia general que sea identificada al momento de la entrevista y requiera ser resaltada.

t. **Balance general de la evaluación**: en estas casillas se podrá colocar la puntuación total obtenida para cada bloque temático y de forma global.

# D

# Complementary web questionnaire (Survey) to the CHROMA Model Assessment Tool

This appendix presents the web questionnaire designed as a complementary tool to compare the results of the evaluation of maturity obtained from applying the CHROMA model with this self-assessment carried out by the company as a survey.

# Análisis del uso de información para la toma de decisiones

Como seguramente sabe, estamos realizando una evaluación del uso de la información para soportar los procesos de negocio y la toma de decisiones para su empresa. Para el éxito de la misma es importante conocer su opinión. Por ello le agradeceremos que responda una breve encuesta, que le tomará menos de 10 minutos de su tiempo. Las respuestas son anónimas y solo se usarán a nivel estadístico. De acuerdo a su percepción como responsable de un proceso/departamento clave de la empresa, califique los siguientes aspectos relacionados con la toma de decisiones conducidas por información:

1. **Disponibiliad de datos**

Grado en que se garantiza que los datos necesarios y pertinentes se encuentren disponibles y de fácil acceso a los usuarios en el momento en que este los necesita.
*Mark only one oval per row.*

| | Pobre | Insuficiente | Suficiente | Notable | Excelente |
|---|---|---|---|---|---|
| Recolección de datos provenientes de fuentes internas y externas | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Capacidades de las herramientas tecnológicas de gestión de datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Directrices de uso y acceso a los datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Manejo e integración de múltiples tipos de datos de diferente procedencia | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Facilidad para acceder a los datos requeridos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |

2. **Calidad de datos**

Grado en que se realizan acciones para garantizar que los datos de la empresa son correctos (no tienen errores) y pertinentes (los necesarios para una buena gestión).
*Mark only one oval per row.*

| | Pobre | Insuficiente | Suficiente | Notable | Excelente |
|---|---|---|---|---|---|
| Aseguramiento de datos útiles, relevantes, oportunos y confiables | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Herramientas tecnológicas para gestionar la calidad de los datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Métodos para la mejora continua de la calidad de los datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Competencia del personal para asegurar la calidad de los datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Estandarización de los datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |

3. **Análisis de datos**

Manera en que los datos se analizan y son utilizados en la organización para convertirlos en información útil y utilizable para apoyar la toma de decisiones.
*Mark only one oval per row.*

| | Pobre | Insuficiente | Suficiente | Notable | Excelente |
|---|---|---|---|---|---|
| Herramientas y aplicaciones tecnológicas para el análisis de datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Aplicación de técnicas para analizar los datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Capacidad analítica del personal | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Potencial de los análisis para extraer y aprovechar el valor de los datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Funcionalidad de las herramientas de visualización de datos | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |

4. **Uso de información**

Manera en que la información (Datos procesados que tienen un significado: relevancia, propósito y contexto) de la organización es utilizada para apoyar la toma de decisiones.
*Mark only one oval per row.*

| | Pobre | Insuficiente | Suficiente | Notable | Excelente |
|---|---|---|---|---|---|
| Capacidad de las herramientas de visualización y reporting de la información importante | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Manejo e intercambio transparente de la información con todas las partes interesadas | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Manejo e integración de la información requerida para soportar los objetivos de la organización | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Gestión y aprovechamiento del conocimiento de la organización | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Directrices para la gestión y protección de la información de la organización | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |

5. **Toma de decisiones impulsadas por información**

Sustentar las decisiones y acciones de la organización sobre la base de información objetiva, fiable, útil y utilizable.
*Mark only one oval per row.*

| | Pobre | Insuficiente | Suficiente | Notable | Excelente |
|---|---|---|---|---|---|
| Definición de objetivos y estrategias basado en datos relevantes | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Cultura para impulsar el proceso de toma de decisiones con base en la información | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Habilidad de los líderes para promover el uso de datos para apoyar la toma de decisiones | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Disposición a delegar responsabilidades y autonomía en la toma de decisiones | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |
| Medición objetiva de la efectividad de las decisiones tomadas | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ |

6. **En términos generales ¿Cómo percibe la competencia global de su organización para tomar decisiones conducidas por información?**

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Pobre | ◯ | ◯ | ◯ | ◯ | ◯ | Excelente |