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Assessing business intelligence & analytics maturity in Portuguese companies with TDWI model

Fernanda Coelho Borges

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NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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ASSESSING BUSINESS INTELLIGENCE & ANALYTICS MATURITY IN PORTUGUESE COMPANIES WITH TDWI MODEL

by

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Dissertation presented as a partial requirement of Master Degree in Information Management, with specialization in Knowledge Management and Business Intelligence

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STATEMENT OF INTEGRITY

I declare that I have conducted this academic work with integrity. I confirm that I have not engaged in plagiarism or any other form of improper use of information or falsification of results during the process of preparing this work. I also declare that I am aware of the Code of Conduct and the Code of Honor of NOVA Information Management School.

[Fernanda Coelho Borges]

[Lisboa, -07-2023]

DEDICATION

To Catarina and Rafael. There is no translation for “saudade”. And there are no words to describe the love that fills my heart since both of you were born.

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ABSTRACT

The adoption of Business Intelligence and Analytics solutions is becoming increasingly common among companies, because it has already been proven that they can efficiently support the decision-making process and ensure a data-driven culture. In Portugal, this Analytics solutions usage is widespread, especially in the Lisbon Metropolitan Area (AML), where the majority of the country's companies are located. However, it is perceived that certain companies may not be fully extracting the existing potential of these solutions because it is not enough to simply use these solutions, but rather to understand where they are leading the company. Thus, there is a need to assess the existing Analytics systems in these Portuguese companies and understand how advanced they are and where they can improve. Therefore, this study aims to evaluate the maturity level of Analytics systems in companies from different sectors, sizes, and revenue, all located in the AML. For this purpose, quantitative research was conducted using the Survey method. To assess the maturity level, the TDWI model was applied, which analyzes the companies' Business Intelligence systems from the perspective of 5 different dimensions based on the responses to a questionnaire consisting of 52 questions. According to the final score of the survey, companies are classified into five possible stages: Nascent, Early, Established, Mature, or Advanced/Visionary. The questionnaire received responses from 53 different companies, with the majority of them classified as "Established" in terms of maturity level. The dimension that performed the best was Organizational, while the Analytics dimension obtained the lowest result. The questionnaire results showed that, despite the systematic adoption of Analytics tools by most companies, there is a shortage of workforce and an urgent need for investments in training programs focused on this area, both at the academic and business levels. The Analytics dimension, although not yielding unfavorable results, clearly indicates areas for improvement, particularly in terms of taking greater advantage of Predictive and Prescriptive Analysis. The application of the TDWI model in a specific company or sector, the use of other maturity models applied in the same context as this research and the combination of the TDWI model with qualitative methods are suggestions for future academic work.

KEYWORDS

Business Intelligence; Analytics; Maturity Models; TDWI Maturity Model; Portuguese companies.

Sustainable Development Goals (SDGs):

INDEX

1. Introduction 10
1.1 Research Context 10
1.2 Research Framework and General Research Goal 11
1.3 Reasons and relevance of research...12
2. Literature review 13
2.1 Data, Information, Knowledge Management and Decision Making.........................13
2.2 Types of data Analytics..14
2.3 Business Intelligence and Analytics..14
2.4 Maturity Models...15
2.5 The Methodology of the TDWI Model 18
3. Research Metodology..21
3.1 Research Type: Descriptive 21
3.2 Research Approach: Quantitative 21
.3.3 Research Method: Survey 21
4. Methodological procedures 23
4.1 Operationalization of Research..23
4.2 Data Collection 24
4.3 Profile of the sample: Role of Respondents..25
4.4 Profile of the sample: Annual Revenue...26
4.5 Profile of the sample: Business Area...27
5. Data Analysis..27
5.1 Stages of maturity: General Result 27
5.2 Dimension analyses: Organization 30
5.2.1 Stages of Maturity: Organization Dimension Results x General Results.....30
5.2.2 Organization Dimension: Categories Performance 31
5.3 Dimension Analysis: Infrastructure Dimension 32
5.3.1 Stages of Maturity: Infrastructure Results x General Results 32
5.3.2 Infraestruture Dimension: Categories Performance 33
5.4 Dimension Analysis: Resource Dimension 35
5.4.1 Stages of Maturity: Resource Results x General Results.............................35
5.4.2 Resources Dimension: Categories Performance 36
5.5 Dimension Analysis: Analytics Dimension..37
5.5.1 Stages of Maturity: Analytics Resources x General Resources 37
5.5.2 Analytics Dimension: Categories Performance 39

5.6 Dimension Analysis: Governance Dimension..41
5.6.1 Stages of Maturity: Governance Results x General Results........................41
5.6.2 Governance Dimension: Categories Performance......................................42
6. Conclusions..44
6.1 Final considerations on the results...44
6.2 Research Contributions..45
6.2.1 Enhanced understanding of the level of maturity of BI/Analytics within the Portugal's context..45
6.2.2 A practical application of TDWI Maturity Model...46
6.2.3 Practical Guidance for Portuguese companies..46
6.3 Challenges and Research Limitations..46
6.4 Proposals for future research..47
References..48
Attachments..50
TDWI Survey (2020 Version)..50

FIGURES INDEX

Figure 1: Dimensions of the TDWI Analytics Maturity Model 19
Figure 2: Stages of Maturity in TDWI Analytics Maturity Model 20
Figure 3: Categories in Dimensions 23
Figure 4: Percentage ranges and stages of maturity 24
Figure 5: Message showed at the end of the survey 25
Figure 6: Role of the respondents 26
Figure 7: Annual Revenue 26
Figure 8: Business Area 27
Figure 9: General Results 28
Figure 10: Stages of Maturity x Annual Revenue 29
Figure 11: Stages of Maturity x Business Area 29
Figure 12: Stages of Maturity in Organization Dimension 30
Figure 13: General x Organization results 31
Figure 14: Performance by Category 32
Figure 15: Stages of Maturity in Infrastructure Dimension 33
Figure 16: General x Infrastructure results 33
Figure 17: Performance by Category 34
Figure 18: Stages of Maturity in Resource Dimension 35
Figure 19: General x Resources results 36
Figure 20: Performance by Category 37
Figure 21: Stages of Maturity in Analytics Dimension 38
Figure 22: General x Analytics results 38
Figure 23: Performance by Category 40
Figure 24: Stages of Maturity in Governance Dimension 41
Figure 25: General x Governance results 42
Figure 26: Performance by Category 43

TABLE INDEX

Table 1: Size of companies 27
Table 2: Organization Dimension: Number of questions per category 31
Table 3: Infrastructure Dimension: Number of questions per category 34
Table 4: Resources Dimension: Number of questions per category....................................... 37
Table 5: Analytics Dimension: Number of questions per category.. 39
Table 6: Governance Dimension: Number of questions per category..................................... 42

LIST OF ABBREVIATIONS

AML	Área Metropolitana de Lisboa
BI	Business Intelligence
GDP	Gross Domestic Product
TDWI	The Data Warehousing Institute
APMM	Analytics Process Maturity Model
DAMM	Data Analytics Maturity Models for Assessment
OAMM	Online Analytics Maturity Model
WAMM	Web Analytics Maturity Model
INE	Instituto Nacional de Estatítica
EUROSTAT	European Statistical Office
DVS	Diversity, Volume and Speed
RGPD	General Data Protection Regulation
UE	European Union
IT	Information Technology

1. INTRODUCTION

1.1 RESEARCH CONTEXT

The world is generating an extraordinary volume of data each day, whether via instant message applications, commercial transactions, interactions on social networks, and other huge possibilities that technological evolution has allowed. In 2020, the total amount of data consumed globally reached 64.2 zettabytes. The growth was higher than previously expected caused by the increased demand due to the COVID-19 pandemic, as more people worked and learned from home and used home entertainment options more often Up to 2025, global data creation was projected to increase more than 180 zettabytes. (Taylor, 2022).

In a corporative context, among academics and researchers on this subject, there is a consensus that data should be used largely on enterprises, especially since it is possible to obtain real-time information regarding customers markets, and other relevant data, which provides to these companies more agile and assertive decision-making process (Brandão et al., 2016). In fact, companies have significantly invested in Big Data and AI projects, with a high pace of investment and substantial funding. However, despite these efforts, they continue to struggle in deriving value from these investments and becoming data-driven organizations. In 2021, the 1000 largest companies in United States (according to Fortune Magazine), experienced a decline in key metrics measuring the success of their data and AI investments. They face difficulties in managing data as a business asset, fostering a data culture, competing with data and Analytics and using data for innovation. Few have achieved transformative business outcomes or developed well-defined data strategies. Only 24% of them considered their organization to be truly data-driven (Bean, 2021).

Nevertheless, data by themselves probably will be irrelevant, especially within a business context. According to Ponchirolli & Fialho, (2005) , data have no value without a context. To be useful as information, data must be acted upon and correlated to other data to provide meaningful and relevant information. Thus, according to Bellinger et al., (2003), by crossing data in a relational database, they finally starts to have meaning and can be used as information. Therefore, according to Drucker (quoted by Ponchirolli and Fialho (2005)), information is data that has relevance and purpose, to which, after being collected, organized, and ordered, meanings and context are assigned. After that, companies must interpret and use it as a support in decision-making processes.

In a context of high competitiveness between companies, in increasingly results-oriented management and where a simple mistake can lead to financial losses besides immaterial ones, managers are being pushed to have faster and more accurate decisions. Business Intelligence (BI) can support this objective, as it is a tool capable of supporting these managers both at a management and strategic level.

Regarding the concept of Analytics, according to Sharda et al., (2014), it is the process of developing decisions or recommending actions based on insights that are the result of processing and analyzing historical data. Still, according to these authors, the word "analytics" has replaced the definition for the various decision support programs that were previously labeled with different names and definitions and, with that, many authors and practitioners in the BI area started to use the word Analytics as a synonym of the the term BI.

The Gartner Group, from the emergence of new technologies, defines a broader term that includes, besides BI, other solutions that arise with technological advancements, such as Machine Learning, for example. This term is Analytics which can be defined along with BI as "an umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance." (Gartner, 2022) . This research is based on the definitions advocated by Sharda et al. (2014) and Gartner Group (2022), as it will consider the Terms BI and Analytics as synonyms in the following pages.

According to Pereira et al., (2000), BI/Analytics systems became more relevant in the 90s, with the emergence of the information age, where the analytical capacity of a company became increasingly valued. Thus, it was no longer enough for systems to store a large amount of data; it was necessary to be able to perform analyses from different points of view. According to the definition by Musskopf, (2017), BI/Analytics tools exist intending to provide a global view of the business, optimizing how data is distributed, aiming "transform large amounts of data into quality information for decision-making" to get quality information from large amounts of data in order to support decision-making processes.

1.2 Research Framework and General Research Goal

According to Davenport & Prusak. 1998, (quoted in Medeiros & Silva (2018)), an organization will only take advantage of information systems if they are used efficiently, in other words, the information provided by these systems must be filtered as companies should only focus on those which are relevant in the process management. With this, using BI/Analytics systems pragmatically and consciously is essential within this process. Besides that, understanding their function and how they are being used is vital to make conscious and truly profitable use of the resources they supply.

In this way, it is important to know how companies are managing the process of choosing these programs and implementing these systems; how data infrastructure, architecture, data flow, data governance, and data security are evolving. Also, how the human resources that work directly with these systems, and even the resources who are working in other sectors are aware of the importance of having a data-driven culture; and finally, how they are up to date with Analytics trends (Halper, 2020).

In a Portuguese context, a 2022 study by Gartner Digital Markets states that Portugal is one of the countries that most invested in adopting BI/Analytics tools in the last 2 years, with 54% of companies asserting that they are investing massively in these solutions, which makes Portugal one of the main countries that are investing in this market (Gartner, 2022). A good part of this phenomenon is taking place in the Lisbon Metropolitan Area (AML in Portuguese), which corresponds to 38% of Portuguese GDP (Regionais et al., 2020). In addition, AML serves as a center for cutting-edge technology and R&D companies, housing approximately 354,406 companies. It exhibits a greater concentration of international workforce and high-tech industries, surpassing the national average. Lisbon entices foreign investments and stands out as a favored destination for multinational corporations, particularly in shared service centers, presenting excellent opportunities for nearshoring services. Prominent sectors within the region encompass IT (software and internet) along with healthcare services (Lisboa: A economia em números, 2020).

Concerning the adoption of digital technologies by companies in Portugal, it is observed that there is a higher level of investment in Social Media and Digital Marketing, Big Data and Analytics, Cloud Computing, and IoT (Internet of Things). However, only 35% of the participants indicate having achieved an advanced level of implementation in these areas (NovaSBE Center for Digital Business & EY, 2018).

Based on the information described so far, it is relevant to investigate the maturity level of the BI/Analytics ecosystems, represented by its different tools and process, in AML's companies. Thus, the main question that will guide the development of this research is:

- **What is the maturity level of the Business Intelligence/Analytics ecosystems used in companies in the AML?**

The answer to the question above will clarify the main objective of this dissertation, which is to understand the context of BI tools usage, the maturity level of the BI/Analytics ecosystems in the studied companies, using the TDWI methodology.

According to Halper (2020) , a BI/Analytics ecosystem means having technologies deployed and organizational components, resources, management and data governance within a company. Nevertheless, implementing a BI/Analytics tool does not guarantee that organizations will receive a financial or operational return that justify the efforts and investments to build a BI/Analytics infrastructure. Therefore, models such as the one proposed by TDWI are important for companies to evaluate each step taken during the implementation of these tools and how they are evolving.

1.3 Reasons and relevance of research

Portugal has been a leading investor in BI/Analytics tools, with 54% of companies indicating significant investments in these solutions, making it a major player in the market (Gartner, 2022). The Lisbon Metropolitan

Area (AML) is a focal point for this trend, accounting for 38% of Portuguese GDP, with a concentration of technology companies and multinational corporations (Regionais et al., 2020). As a result, the AML has become a key hub for nearshoring services, including technology consulting and sectors such as health and industry. In addition, it provides an overview of this market in a local context and extracts patterns and particularities from these data with more trustful analyses (Lisboa: A economia em números, 2020). For example, reports such as the Gartner Group, although recognized for their methodology and relevance, often do not allow a framework within the reality of each country, and few studies characterize the use of BI in Portugal (Colaço, 2013).

Thus, research that characterizes this reality is quite interesting, as it can serve as a closer reference to the context and needs of companies and professionals in the country; a study on the maturity of Analytics would enhance the theory and practice of analyzing business data. By identifying emerging trends, solutions, and methodologies, the research findings could be readily applied in a business context. A BI maturity study could help companies in the Lisbon region identify weaknesses in their Analytics strategies and make improvements to increase the efficiency of internal processes and business decisions. As the demand for optimal data analysis continues to grow, particularly in areas such as artificial intelligence and machine learning, companies with higher levels of maturity in Analytics will be better equipped to adapt to market trends and customer needs. From a theoretical point of view, a study of this kind could identify gaps in knowledge, enabling researchers to investigate more thoroughly relevant topics related to Analytics in companies and identifying knowledge gaps, allowing researchers to further investigate relevant topics related to BI and Analytics in companies. Besides, universities will be able to base themselves on this kind of research to prepare their academic program, considering the local reality. Thus, this study can generate practical insights and contribute to theoretical development in data analysis.

2. LITERATURE REVIEW

2.1 Data, Information, Knowledge Management and Decision Making

According to Ponchirolli and Fialho (2005), data are records about a particular event, but they lack meaning when presented outside of a context. Setzer (2015)defines data as formalized and structured representations that can be quantified, processed, and stored in a computer. Information, on the other hand, is derived from manipulated, organized, and consolidated data, as stated by Sordi (2008) (cited by Musskopf, 2017).

According to various authors, information is the result of organizing, analyzing and interpreting data, giving it meaning and context. Ponchirolli & Fialho (2005) emphasize the importance of identifying relevant information to generate the necessary knowledge to support the decision-making process within organizations. For Rossetti & Morales (2007), knowledge is one of the main resources for organizational strategy.

2.2 TYPES OF DATA ANALYTICS

According to Huisman (2015), Data Analytics can be subdivided into three approaches: Descriptive, Predictive and Prescriptive Analytics. Descriptive analytics can be defined as the process of summarizing and altering data into relevant information which supports decision making process. It also enables detailed investigation to address specific questions or concerns. For Delen and Dermikan (2013), Predictive Analytics has the existence of data modelling as prerequisite which results in business simulation and forecasting to make authoritative predictions about the future. Currently, the most parts of the efforts and use of Analytics are in Descriptive and Predictive solutions (Delen and Dermikan,2013).

While Descriptive Analytics answers questions like “What has happened?” and Predictive Analytics seeks to answer questions as “What will happen?”, Prescriptive Analysis answers “What should I do” (Lepenioti et al, 2019). According to these authors, Prescriptive Analytics wants to find the best way to act in the future and “is often considered as the next step towards increasing data analytics maturity and leading to optimized decision making ahead of time for business performance improvement”.

2.3 BUSINESS INTELLIGENCE AND ANALYTICS

The concepts of BI and Analytics are often confused and converge towards the same goal, which is the intelligent and efficient use of data. In a generalist definition, Business Intelligence and Analytics is an umbrella term encompassing concepts and technologies that are implemented together and allow executives, managers, and analysts to make more assertive decisions in less time (Gartner, 2022) .

From a conceptual perspective used in the TDWI model, Analytics would be the range of all techniques that go from the simplest spreadsheets and dashboards to more advanced techniques such as self-service BI and Machine Learning. The use of these techniques can undoubtedly generate increased productivity and improvement in customer support services, optimization in operational processes, among other benefits that result in cost savings for companies (Halper, 2020).

According to Sharda et al., (2014) , although many authors see the definition of Analytics slightly differently, it can be said that it is the process of developing decisions or recommending actions based on insights that result from the processing and analysis of historical data. Furthermore, these authors state that the term "analytics" replaced the definition for various decision support programs that were previously labeled with different names and definitions, and as a result, many authors and professionals in the BI field began using the term Analytics instead of BI. This case study relies on the definitions of Sharda et al. (2014) and Gartner (2022) and considers the terms BI and Analytics to be synonymous.

Rezende (2002), points out that despite the visible advantages that can arise from the implementation of a BI/Analytics system, there are still bottlenecks that are difficult to overcome, such as choosing the right tool and using it in a way that brings the greatest benefits to the organization. Regarding the financial return on investment (ROI), Vanmare (2006), in a report on the implementation of BI solutions in the banking industry in South Africa highlights the difficulty of measuring this indicator, which makes difficult to know what the financial gain (if any) after the implementation of Analytics solutions in a company.

According to Caseiro & Coelho (2018), BI/Analytics can be viewed in two ways: as a process and as a product. The process consists of methodologies that companies use to obtain useful information that can help organizations remain competitive and grow. The product, on the other hand, can be considered as information that will enable organizations to predict the behavior of their "competitors, suppliers, customers, technologies, acquisitions, markets, products and services, and the general business environment" with satisfactory accuracy that will allow for reliable forecasting.

Despite the challenges and the need for both intellectual and financial capital, (Cunha et al., 2015) recognize the ability of these systems to effectively manage the data generated by companies and their valuable contribution to decision-making.

2.4 Maturity Models

BI/Analytics has been occupying prominent positions in companies of all sizes and segments, being used in different ways, from the simplest managerial reports to performance management, in most cases, with a direct impact on the decision-making of these organizations. These different forms and perspectives of BI applications "differentiate not only the models and tools but also the value generated for each business." (Pastori, 2012). To differentiate the various forms and perspectives of BI/Analytics applications, it is necessary to define the concept of maturity models. According to Becker, Knackestedt, and Pöppelbuβ (2009), cited by Dinter (2012), a maturity model is a delimited sequence of object levels that represent different stages of maturity, starting from a fairly incipient level of application of this system, up to a high stage of evolution and functionality of the same system. Maturity models are based on the understanding that things change over time and can be predicted and regulated. Literature reviews indicate that models in various domains evolve, improve, and are influenced by past experiences of other authors (Rajterič, 2010).

These models are used by companies as a way to signal where they want to go with the implementation of a BI/Analytics solution and what guidelines, tasks, and methodologies must be followed to achieve this goal. When applied frequently, they assist in fulfilling these guidelines, but with attention to certain requirements. An example of these requirements is that the models should cover all relevant aspects for the implementation of BI/Analytics in addition to the availability of data, which will allow comparison by other companies (Dinter, 2012). According to the

TDWI Model Assessment Guide , the more mature an organization is in terms of data analysis, the greater its ability to measure its positive and/or negative impacts, which is part of a virtuous circle where companies increasingly realize the importance of being data-driven and the greater their ability to build a path of success within the competitive market (Halper, 2020).Król & Zdonek (2020), describes 11 types ofanalytics maturity models which are:

1. **Analytics Processes Maturity Model (APMM**): This model evaluates an organization's analytic maturity using concepts such as analytic models, infrastructure, and operations. It is based on the Capability Maturity Model and encompasses six key process areas: building models, deploying models, managing infrastructure, protecting assets, governance, and identifying opportunities.
2. **Analytics Maturity Quotient Framework:** The Analytics Maturity Quotient assesses an organization's maturity based on data quality (DQ), data-driven leadership (L), people with analytics skills (P), data-driven decision-making process (D), and agile infrastructure (I).
3. **Blast Analytics Maturity Assessment Framework**: Evaluates an organization's maturity in six key process areas and success factor dimensions: strategy, governance, data management, insights, evolution, and resources. Each dimension is rated on a scale of 1 to 6 points, allowing the organization to be categorized into a specific development stage.
4. **Data Analytics Maturity Models for Assessment (DAMM):** To address the demand for analytics maturity assessment in associations and non-profit organizations, the DAMM model (DAMM for Associations) was developed as a tool by Association Analytics (A2), a provider of association management tools. The DAMM model evaluates four key elements of data analytics: organization and culture, architecture/technology, data governance and strategic alignment.
5. **DELTA Plus Model:** Analytics Maturity Assessment (AMA) is a tool that evaluates an organization's ability to apply corporate analytics using the DELTA Plus model and five analytics maturity stages. AMA assesses analytics capacities, analytics culture, and the use of analytics tools to determine an organization's placement on the analytics development path. The DELTA model consists of five components relevant to assessing analytics maturity: Data (availability of high-quality data), Enterprise (orientation towards analytics management), Leadership (analytics leadership), Targets (strategic targets), and Analysts (analytics skills). The model has been extended to include Technology (infrastructure and tools) and Analytics techniques (methods and techniques).
6. **Gartner's Maturity Model for Data and Analytics:** According to Gartner's Maturity Model for Data and Analytics, organizations are categorized into five analytics maturity stages with distinct attributes: Level 1: Basic—limited data utilization, fragmented management, ad hoc analysis, spreadsheet reliance. Level 2: Opportunistic—inconsistent information availability, organizational barriers, lack of leadership, data quality challenges. Level 3: Systematic—emerging strategy, integrated data sources, business executives

as champions. Level 4: Differentiating—executive champions, business-driven approach, Chief Data Officer (CDO) involvement, data-driven performance and innovation. Level 5: Transformational—data-centric business strategy, influential data value, strategic alignment, CDO in board-level role.

7. **Logi Analytics Maturity Model:** The Logi Analytics Maturity Model (LAMM) proposes that the more advanced data analysis opportunities are incorporated into everyday applications, the greater the adoption of analytics in daily work. LAMM consists of five stages of analytics maturity, ranging from Standalone Analytics (level 0) to Genius Analytics (level 4). Logi also offers a self-assessment tool. At each level, the model describes the level of integration and functionality.
8. **Online Analytics Maturity Model (OAMM):** OAMM serves as a self-reflection tool for organizations to gain insights into their identity and capabilities. It provides an impartial and user-friendly representation of an organization's analytics infrastructure and initiatives. OAMM offers a benchmarking feature, including a free self-assessment survey, that compares the organization to industry peers using extensive databases. The model evaluates the organization across six dimensions: management, governance, and adoption; objective definition; scoping; analytics team and expertise; continuous improvement process and analysis methodology; and tools, technology, and data integration.
9. **SAS Analytics Maturiy Scorecard:** The SAS Analytics Maturity Scorecard evaluates an organization in four dimensions: Culture, Internal Process Readiness, Analytical Capabilities, and Data Environment. Based on this scorecard, the organization can be categorized into one of five analytics maturity stages. Level 1 is Analytically Unaware, Level 2 is Analytically Aware, Level 3 is Analytically Astute, Level 4 is Empowered, and Level 5 is Explorative. Each level represents the organization's approach to analytics and decision-making, ranging from lacking analytics skills to leveraging advanced analytics for business growth.
10. **TDWI Analytics Maturity Model:** The TDWI (Transforming Data with Intelligence) Model measures and monitors analytics implementation, guiding the development of analytics culture. It analyzes organizational maturity using 52 questions across five areas: Organization, Resources, Data Infrastructure, Analytics and Governance. The model comprises five stages: nascent, initial, established, mature and advanced/visionary.
11. **Web Analytics Maturity Model (WAMM):** The Web Analytics Maturity Model (WAMM) enables an assessment of an organization's usage of web analytics. WAMM includes scoring in six dimensions, placing the organization in a specific stage of analytics development: management, objectives, scoping, analytics team, continuous improvement, and tools.

With the exception of the Analytics Maturity Quotient Frameworks model, which establishes a maturity quotient, the models presented above have in common the fact that they analyze the level of maturity under different dimensions and classify companies in different stages of maturity. However, the application of these models is different from each other, with different levels of complexity when applying them.

In selecting the appropriate maturity model for this research, some factors were considered. First, the model's ability to assess various aspects that influence the success of an Analytics solution. Second, the model's provision of a methodology guide for implementation. Lastly, the model's compatibility with the evolving landscape of Business Intelligence solutions, ensuring updated versions are available. Additionally, the availability of a readily accessible questionnaire for applying the model was also a crucial factor.

Thus, based on these considerations, this research analyses the maturity of companies in AML based on 2020’s year version of TDWI Maturity Model due to its comprehensive methodology, which encompasses various factors that influence the maturity of Analytics systems within an organization and also the relative ease of implementing it. By employing this model, a holistic perspective can be obtained regarding the processes that contribute to the development of these systems, as at this methodology, it is analyzed deeply cultural, organizational and technical aspects regarding the application of Analytics solutions. Furthermore, the availability of a well-structured guide and a questionnaire provided by the TDWI Institute played a crucial role in selecting this model when comparing these same aspects of other methodologies.

2.5 THE METHODOLOGY OF THE TDWI MODEL

The TDWI Maturity Model emerges within this context of objectively and systematically evaluating and validating BI systems. The TDWI is an evaluation tool that provides organizations with an understanding of the maturity level of their solutions, as well as serves as a benchmark for comparison with other companies operating in the same industry (Halper & Stodder, 2014). "The TDWI model objectively measures the maturity of BI, representing on a horizontal scale where companies move according to the evolution of their BI process domain" (Pastori, 2012).

The TDWI Model evaluation methodology involves distributing 52 questions across five categories or dimensions: Organization, Resources, Data Infrastructure, Analytics, and Governance. The "Organization" dimension assesses how committed the organization is to obtain a data-driven culture, the degree of data usage when making decisions, whether there is reliability in the generated data and information, a willingness to try new things, and a unified strategy.

The "Resources" dimension will analyze resources from both a financial and intellectual capital perspective, as well as self-sufficiency capacity, both financially and in relation to human resources and infrastructure made available for this purpose.

The "Data Infrastructure" dimension will analyze data in terms of volume, frequency, integrity, accessibility, whether data cloud services are used, and whether the data meets user needs.

The "Analytics" dimension checks what types of tools and methodologies are used (Machine Learning, real-time analysis, Big Data), also checks the level of accessibility of Analytics tools within the Organization, what percentage of users are able to do their own data analysis and what level of innovation in Analytics the company has.

Finally, the "Governance" dimension evaluates the coherence of the data governance strategy with the Analytics program. In addition, it measures the level of collaboration between the IT and Business areas. If the organization is able to ensure appropriate access to data usage, in addition to measuring the level of tracking developments in Production and whether there is security and privacy regarding personal data.

Figure 1: Dimensions of the TDWI Analytics Maturity Model - Source: TDWI Analytics Maturity Model Assessment Guide (Halper, 2020)

After answering the questionnaire, organizations will be classified into 5 different stages: Nascent, Beginning, Established, Mature, and Advanced/Visionary. Between the "Established" and "Mature" stages, there is an intermediate state called the "Chasm." Below is a brief definition of each stage:

Nascent: Organizations are in an earlier stage before adopting a data-driven culture. They may be limited to using Excel spreadsheets for analysis and decision-making is often based on instinct and intuition rather than reliable data. Although there may be employees interested in advancing a data culture, there is no general predisposition or direction towards it.

Early: There is a consensus and awakening that the organization needs to build a data-driven culture. Key employees may have started taking courses, attending lectures, and training to better understand Analytics concepts. The organization may have acquired tools like Self-Service BI, and there is the use of a data warehouse. This leads to employees recognizing the importance and power of making data-driven decisions.

Established: At this stage, it means that data analysis tools and methodologies are already implemented and in operation. The organization systematically uses a data warehouse to feed dashboards and data visualizations. However, in this stage, the IT department still "owns" the data, and the Business department is responsible for the analyses. The tendency is for both areas to start working together.

The Chasm: Between the Established and Mature stages, there is a gap that represents the challenges that companies must overcome to reach the level of maturity. These challenges may involve a lack of personnel or tools, as well as political obstacles. As the need to meet quality and governance standards arises, departments may "compete" for control of these tasks, or there may be a reluctance on the part of some sectors to commit to achieving this level of standard and quality. According to the TDWI Model Assessment Guide, 2014, many companies "fall into the chasm" and fail to advance their BI systems, remaining in this position or even gradually ceasing to use the tools until they are completely forgotten.

Mature: In this stage, maturity has been achieved regarding a data-driven culture. Users have realized the capacity and power of data and are willing to base their routines and decisions on reliable information. There is trust in these systems, and a greater availability to use semi-structured data in analyses.

Advanced/Visionary: The Advanced/Visionary stage represents a minority of companies that reach a high level of maturity in their data culture. In this stage, organizations have a holistic and strategic vision of data usage, with the ability to integrate advanced analyses such as machine learning and artificial intelligence into their operations. The company has the ability to make real-time decisions based on real-time data and is highly data-driven in all areas of the business, from strategic planning to operational decision-making.

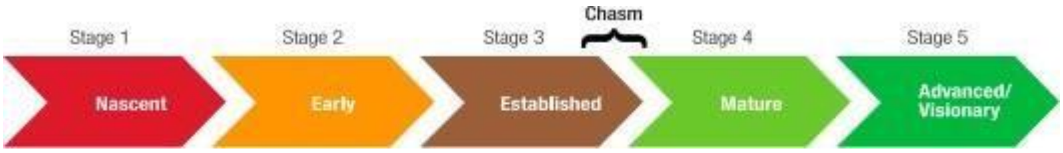

Figure 2: TDWI Analytics Maturity Model Stages - Source: TDWI Analytics Maturity Model Assessment Guide (Halper, 2020)

3. RESEARCH METODOLOGY

3.1 RESEARCH TYPE: DESCRIPTIVE

As the type of research, this dissertation can be classified as descriptive, after all, it is intended to demonstrate the characteristics of the experimented sample, as well as the results found, and it tries to find connections between the distinct variables of these results. According to Fontenelles et al. (2009), the objective of this type of research approach is only to observe, document and portray the characteristics of a certain phenomenon that occurred in a sample or population, without evaluating its substance.

(Musskopf, 2017) states that descriptive research aims to describe the features of a given population or phenomenon and establish connections between variables.

3.2 RESEARCH APPROACH: QUANTITATIVE

The research can be categorized as quantitative. According to Hayes et al. (2013) (quoted by Halcomb & Hickman (2015)), quantitative research at its most basic level, involves the collection and analysis of numerical data, while qualitative research focuses on experiential or narrative data.

According to Serapioni (2000), the main characteristics of a quantitative research are:

• Focus on investigating the scale and causes of social phenomena, disregarding the subjective aspect, and employ controlled methods;

• Objectivity and a distant perspective from the data (external, as an outsider), emphasizing verification and following a hypothetico-deductive approach:

• Fixed or unchanging reality;

• Prioritize achieving results, being able to be replicated and generalized.

In addition, Côrte-Real (2011) states that a study which aims to establish causal relationships and measure the maturity of BI using a questionnaire follows a quantitative approach. This research measures the maturity of BI systems in the companies studied using the final score from the questionnaire. The companies are classified into five possible levels or into an intermediate state, called “Chasm”. Despite being exclusively based on the score provided, the study also attempts to infer the reasons for the result and the main factors influencing it, mainly through a performance analysis of the categories of each dimension.

3.3 RESEARCH METHOD: SURVEY

The methodology used is Survey Research. According to Glasow (2005), , survey research employs independent and dependent variables to determine the scope of the study, however, the researcher cannot exercise explicit control over them. The objective of this method is to gather data or information on the characteristics or opinions of a specific group of individuals that represent a target population, typically employing a questionnaire as the primary research tool Fonseca (2002), cited by Gerhardt Engel (2009), . A survey, unlike survey research, is merely a data collection tool utilized for conducting survey research. The term "survey instrument" is frequently used to differentiate the survey tool from the survey research it is intended to support. In this work, it will be applied the questionnaire developed in 2020 by the TDWI Institute.

4. METHODOLOGICAL PROCEDURES

4.1 OPERATIONALIZATION OF RESEARCH

About the application of the survey (Annex 1), it was chosen to use the assessment model proposed by TDWI Research Institute, since it is validated by the leading authority in the application of this model, and the platform chosen to host the questionnaire was Qualtrics. The choice of the platform was based on the premium license obtained by Universidade Nova Lisboa, as well as the various resources that the tool provides, such as customization of responses at the end of the survey, the possibility of distributing questions into categories, and the quick and efficient support of the tool.

The survey consists of 52 multiple-choice questions, which are distributed across 5 dimensions: Organization, Resources, Data Infrastructure, Analytics and Governance. Besides that, the questions in each dimension are distributed in different categories.

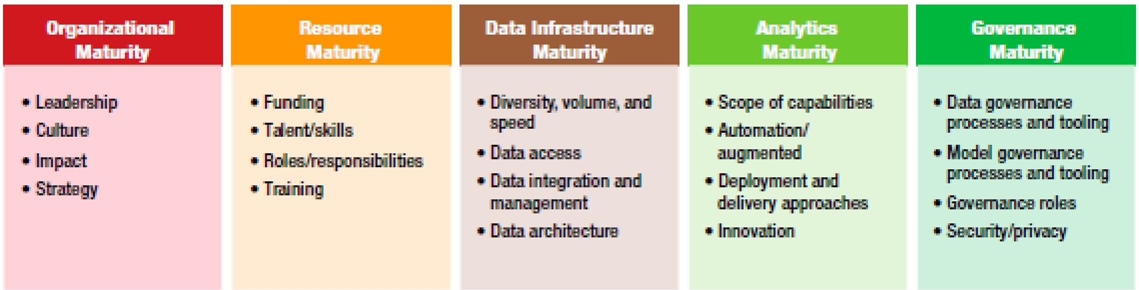

Figure 3: Categories in Dimensions. Source: (Halper, 2020)

As stated in the TDWI Model Assessment Guide, the decision about the score for each question is up to the person/team who is applying the survey. However, each category must add up to exactly 20 points. Thus, for the research method, the distribution of these scores was based on the level of objectivity on the alternatives.

For example, questions with answer choices ranging from "Strongly Disagree" to "Strongly Agree" were weighted with a lower value, considering the subjective nature of these different alternatives. Questions with more objective answer choices received higher value and, consequently, more weight within each category. As a result, each dimension should total a maximum of 20 points, and the sum of the five dimensions should be 100 points. According to the final score of the survey, the company was categorized in one of the 5 possible stages of maturity, besides the chasm intermediate stage, as it showed in the figure below.

Intervals	Stages of Maturity
Less than 29,99%	Nascent
30% to 59.99%	Early
60% to 79%	Established
79,1% to 79,99%	Chasm
80% to 94,99%	Mature
More than 95%	Advanced

Figure 4: Percentage ranges and stages of maturity. Source: (Halper, 2020 - adapted)

4.2 DATA COLLECTION

The data collection took place between February and April 2023. According to the research framework, the questionnaire was completed anonymously by employees of companies whose activities are in the Lisbon Metropolitan Area. These employees were initially contacted through the author's network via emails, phone calls and contacts via Linked in. It was provided an explanation of research objectives and key information about the survey, such as the anonymous nature, number of questions, average response time and other relevant information. Once the research is applied in a Portuguese reality, the survey was in Portuguese.

Before answering the questions, the respondent was required to answer questions about their job position within the organization, the business area and the company's revenue. Additionally, the respondent had to indicate whether they considered themselves to have sufficient knowledge to answer questions about the company's BI and Analytics systems. It is worth noting that the survey was sent to individuals with positions related to the company's Analytics/BI areas. However, this question at the beginning of the questionnaire was a way to ensure that the respondents declared themselves capable of doing so confidently regarding their answers.

At the end of the survey, the respondent received a percentage which represented the company's maturity stage. Due to the limitation of finding a free survey application tool that would allow providing, in addition to the overall score, the score for each of the 5 dimensions, the respondent would end up receiving only the overall percentage. However, it should be noted that even if the company was classified in a percentage representing a maturity state as "Established", for example, it was possible that in a specific dimension, the company would be classified with an "Advanced" level of maturity. Aware of this limitation, the link to the application guide of the model was made available to the respondent who wished to delve deeper into the theory of this methodology and understand which aspects could be improved in the company in order to achieve a higher level of maturity.

Inquérito de Avaliação da Maturidade dos Sistemas de BI em Empresas Portuguesas

O Resultado Final do nível de maturidade da empresa foi: **50.4%.** Abaixo está uma breve interpretação e explicação de cada intervalo da Metodologia TDWI:

Menor ou igual 29,99% - Indica que a empresa está no estágio **"Nascente"**. Este estágio representa um ambiente anterior à utilização de uma cultura de análise de dados, por exemplo, nesse contexto as empresas se limitam a fazer análises em planilhas de Excel. Embora possam haver funcionários interessados em avançar dentro de uma cultura de dados, não há uma predisposição geral e muito menos da direção em tornar a empresa voltada para dados e as tomadas de decisão acontecem muito mais baseadas no instinto e intuição do que em fatos e dados confiáveis.

Entre 30% e 59,99% - Indica que a empresa está no estágio **"Inicial"**.Neste estágio há o consenso e o despertar de que a empresa precisa avançar de forma a construir uma cultura voltada à análise de dados. Funcionários com posições chaves podem ter iniciado cursos e frequentado palestras de forma a perceber melhor os conceitos de Analytics e a empresa pode ter feito aquisições de ferramentas como soluções de Self Service BI, há a utilização de um data warehouse e com isso os próprios funcionários já começam a notar a importância e o poder de tomar decisões baseadas em dados.

Entre 60% e 79% - Indica que a empresa encontra-se no estágio **"Estabelecido"**. Esta fase significa que as ferramentas e metodologias de análise de dados já estão implementadas e em funcionamento. A organização já utiliza sistematicamente um data warehouse para alimentar dashboards e visualizações de dados. No entanto, neste estágio a área de IT ainda é "dona" dos dados e a área de Business, responsável pelo Analytics. A tendência é que as duas áreas passem a trabalhar de forma conjunta.

Figure 5: Message showed at the end of the survey. Source: The author.

A total of 58 responses were collected, however, 3 of them were incomplete. In addition, 2 individuals answered that they did not consider themselves capable of responding to the survey, thus, these 5 collects were considered invalid and the analysis was performed on the basis of 53 valid responses.

4.3 Profile of the sample: Role of Respondents

To ensure that the questionnaire was answered by individuals who hold leadership positions and actively participate in the decision-making process of their companies or teams, invitations were prioritized for such individuals as it can be considered they are more capable of providing responses that accurately reflect the reality of their respective organizations. However, the survey also received and accepted responses from data analysts with more than 2 years of experience in their companies.

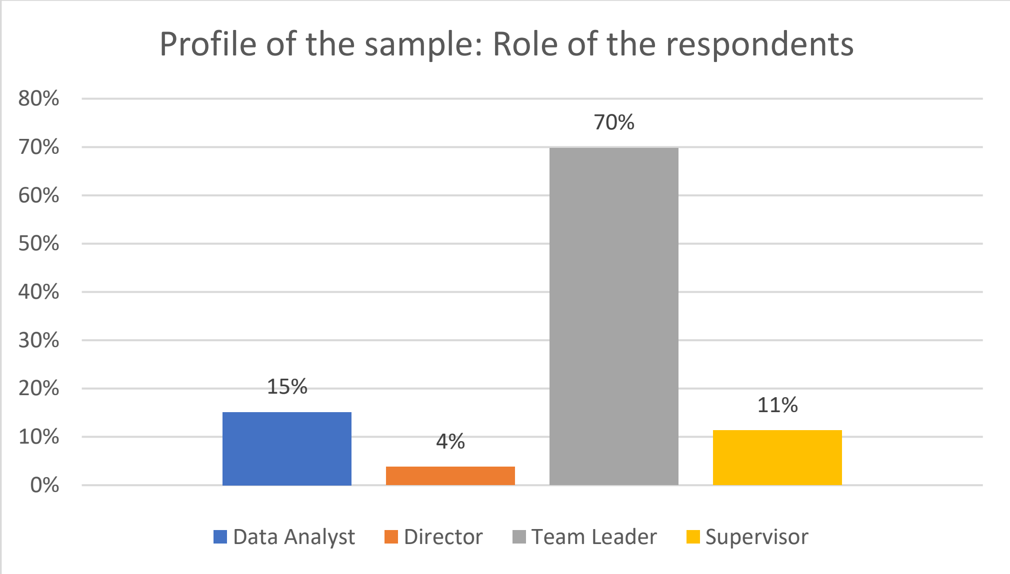

Figure 6: Role of the respondents. Source: The Author.

4.4 Profile of the sample: Annual Revenue

Among the 53 responses received, 23% of the participants were unable to provide information about their company's annual revenue. This same percentage (23%) corresponds to the proportion of companies with a turnover between 500 million and 999 million euros. Additionally, 19% of the companies reported having no more than 50 million euros in annual revenue.

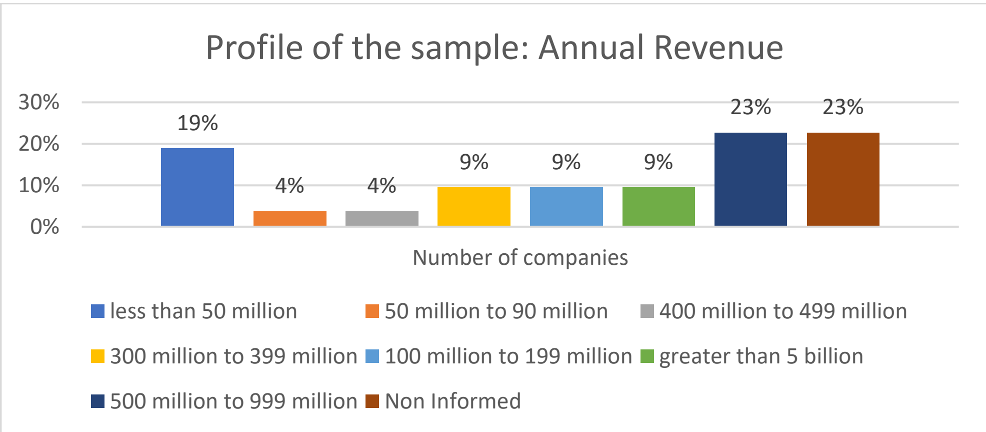

Figure 7: Annual Revenue. Source: The author.

By excluding the 23% of respondents who did not provide their company's annual revenue, the results can be categorized according to the size of the company, as per the classification of the *Instituto Nacional de Estatística* (INE). Out of the remaining responses, 24% were from small or medium-sized companies with an annual revenue of up to 50 million euros, while the remaining 76% were from large companies with a turnover exceeding 50 million euros per year.

Table 1: Size of the companies. Source: The author

Size accordding the annual revenue in euros (INE classification)	Total
Small or médium	24%
Large	76%

4.5 Profile of the sample: Business Area

Most part of the respondents works in the bank sector, followed by those who work in companies categorized as “Industrial (informatics)”. “Consulting”, “Food Beverage”, “Telecom”, “Insurance” and “Industrial (non-informatics)” corresponded to 45% of the respondents. The sample is completed with companies from “the Retail” sector and “Other business area”.

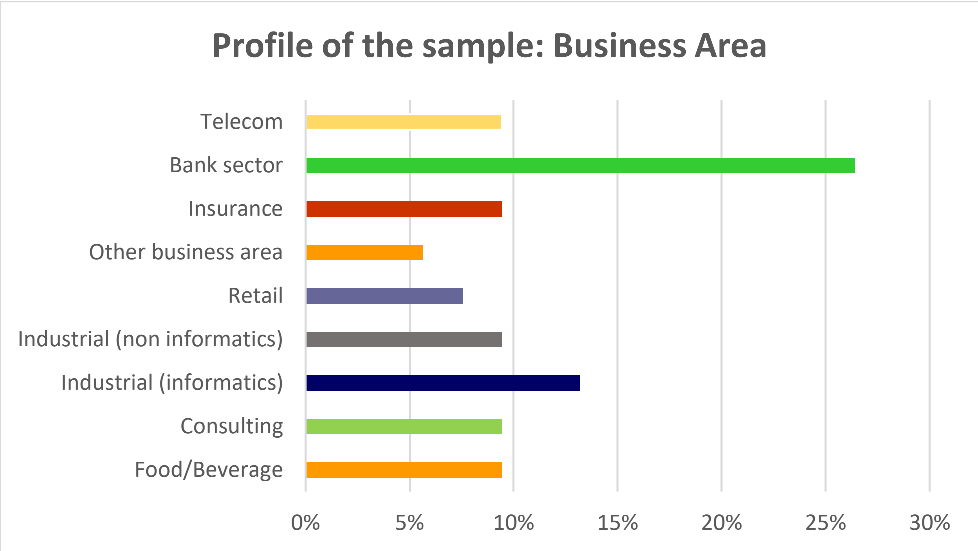

Figure 8: Business Area. Source: The Author.

5. DATA ANALYSIS

In this section, 2 types of analysis were done: the first one is called “General Analysis", based on the final score of the survey. Another one is referred to as “Dimension Analysis”, where the analysis is grouped by the results in each dimension and their respective categories.

5.1 Stages of maturity: General Result

Once the profile of the sample has been presented, the results can be analyzed based on the maturity level of the BI/Analytics systems implemented by companies located in the AML. The general result corresponds to the overall score that is provided in the final of the survey. According to the data, the majority of the companies (43%) have attained the "Established Stage" of Maturity. The next highest percentage of companies (26%) are in the "Early Stage", followed by those in the "Mature Stage" (23%). Only 4% of companies are in the "Nascent Stage", with an equal percentage of companies in the highest stage of maturity, which is the "Advanced Stage". None of the companies analyzed in the sample were in the intermediate level between the Established and Mature Stages, referred to as "Chasm".

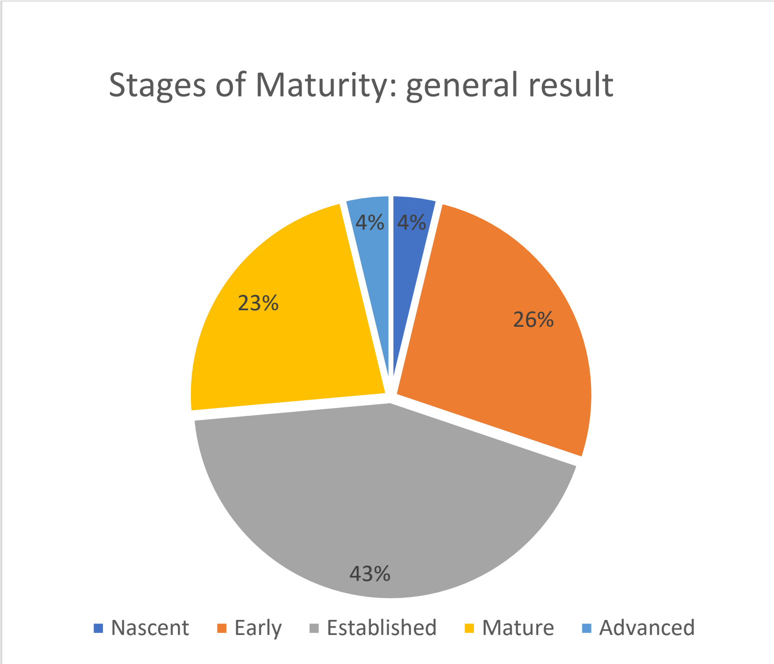

Figure 9: General Results. Source: The Author.

Also, it is possible to group these stages according to the revenue and the business area, thus it can be visualized how these different variables are linked to the results.

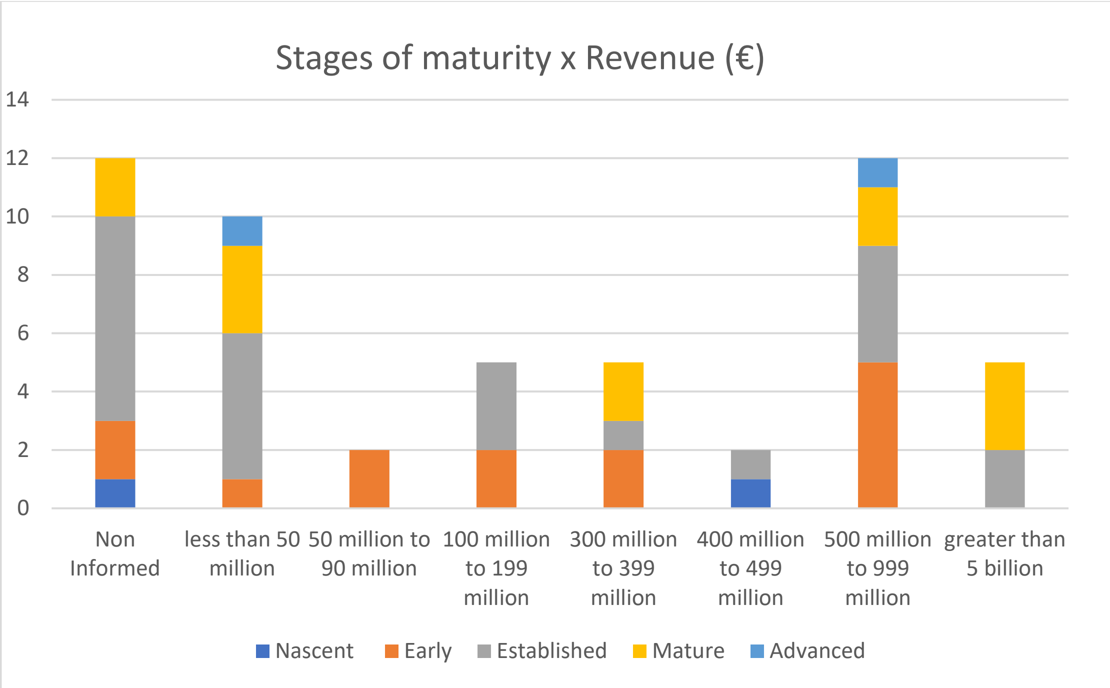

Figure 10: Stages of Maturity x Annual Revenue. Source: The Author.

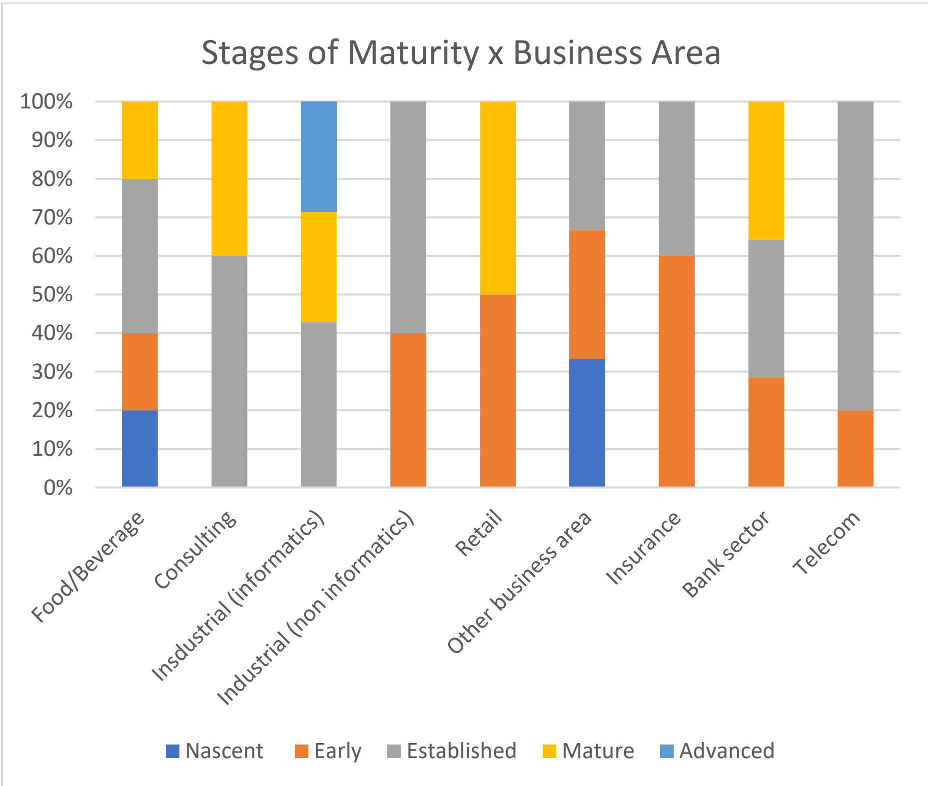

Figure 11: Stages of Maturity x Business Area. Source: The Author.

Based solely on this data, it is not observed a relationship between maturity and annual income. The charts show that in almost every income range with a higher number of responses, the results were quite mixed.

When grouped by business area, the areas related to Consulting and Industrial (IT) have, at least, established Analytics systems, indicating that these sectors are more advanced in their systems. On the other hand, all other business areas presented more initial levels of their BI systems ("Nascent" or "Early").

5.2 Dimension analyses: Organization

5.2.1 Stages of Maturity: Organization Dimension Results x General Results

A notable deviation from the general analysis is observed upon analyzing the Maturity Stage based solely on the Organizational Dimension. Most part of companies are classified as being in the Mature stage, followed by the Early stage. It is worth noting that while the Established stage corresponds to the largest proportion of companies in the general analysis (43%), it represents only 9% in the Organizational Dimension. Conversely, the Advanced Stage represents 9% (compared to 4% in the general analysis). The Nascent stage accounts for 5% of companies and is slightly higher than the 4% found in the general analysis.

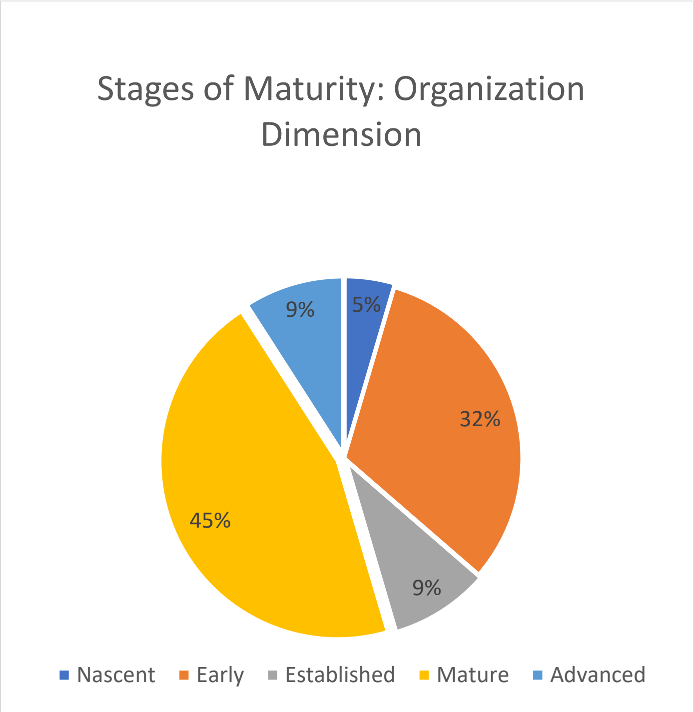

Figure 12: Stages of Maturity in Organization Dimension. Source: The Author.

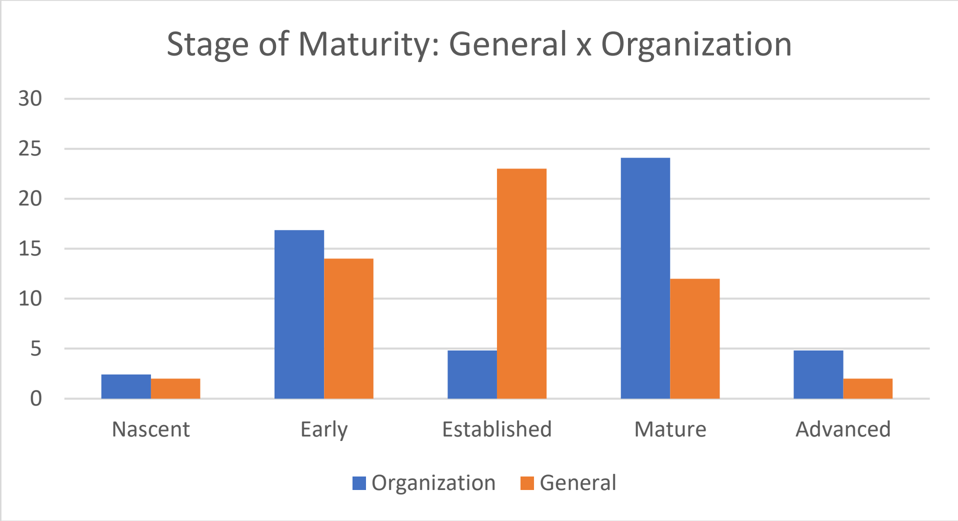

Figure 13: General x Organization results. Source: The Author

5.2.2 Organization Dimension: Categories Performance

Out of the 52 questions present in the survey, 11 questions are related to Organization Dimension which is subdivided according to the following categories: Leadership, Strategy, Impact and Culture. The first three categories have 2 questions each, while the Culture category corresponds to 5 questions. The questions related to the strategy category has a better performance, with 80% of the maximum possible score, while Leadership, Impact, and Culture categories scored similarly with 72%, 70%, and 69%, respectively. Although these scores have not a bad performance, they may indicate that companies, despite having well-defined strategies on paper, may be struggling to implement them and measure the impacts when some of these strategies are implemented.

Table 2: Number of questions per category. Source: The author

Categories	Number of questions
Leadership	2
Strategy	2
Impact	2
Culture	5

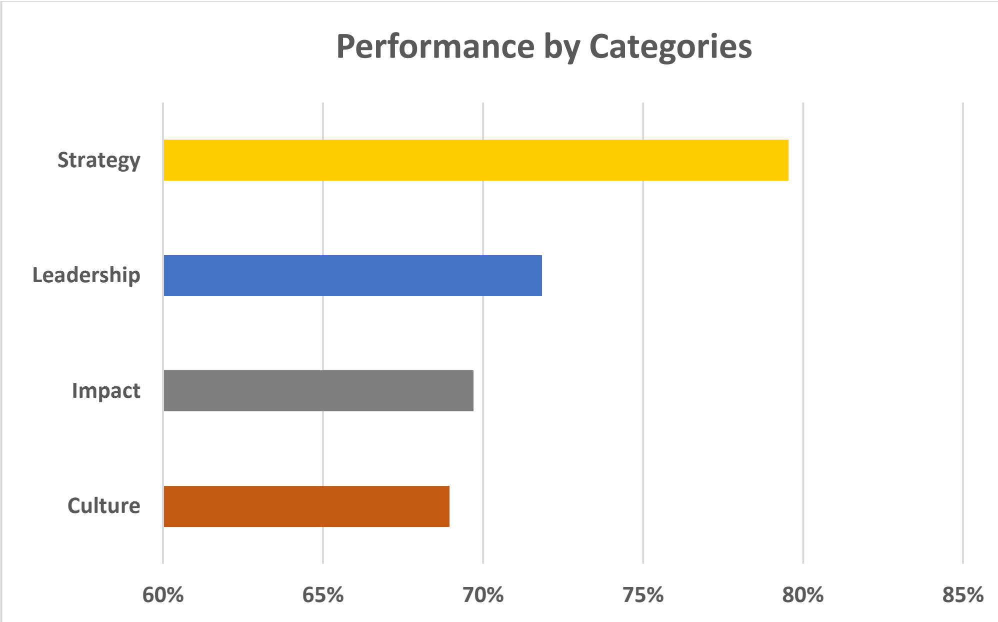

Figure 14: Performance by Category. Source: The author.

5.3 Dimension Analysis: Infrastructure Dimension

5.3.1 Stages of Maturity: Infrastructure Results x General Results

When analyzing the results presented by the Infrastructure Dimension, a notable difference is also noticed in relation to the global result, with the predominance of the “Mature Stage”, with 41% of the companies composing this range. The “Early Stage” corresponds to 27% of the sample, followed by the “Established Stage”, with 18%. With the same trend shown by the Organization Dimension, the “Established Stage” presents a result much lower than that shown in the “General Analysis”.

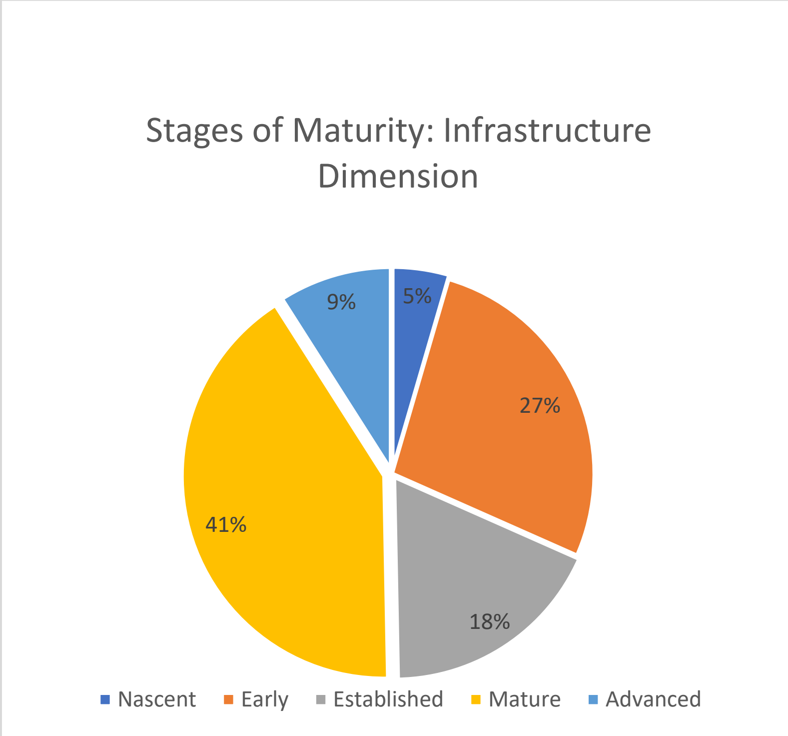

Figure 15: Stages of Maturity in Infrastructure Dimension. Source: The Author.

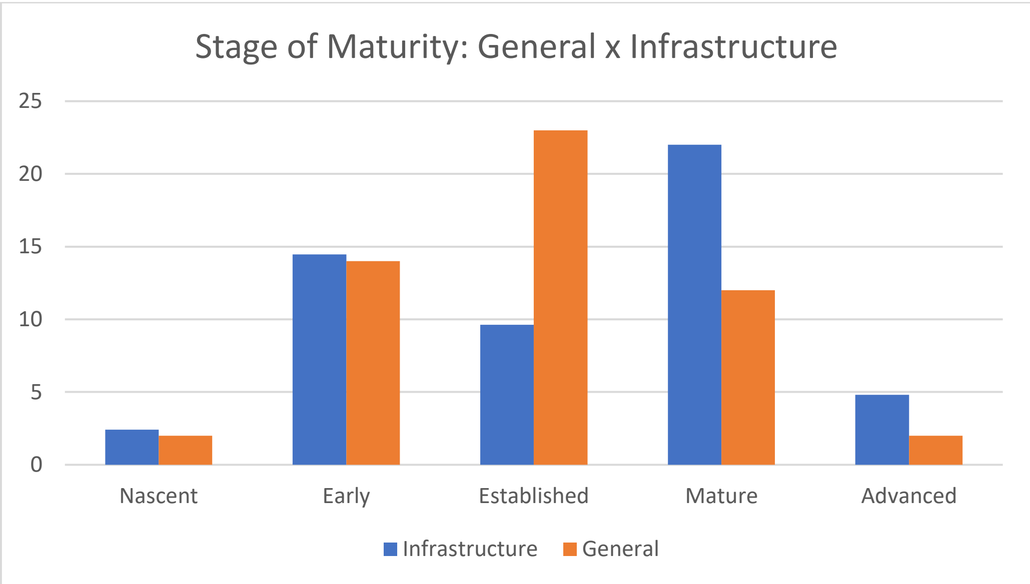

Figure 16: General x Infrastructure results. Source: The Author

5.3.2 Infraestruture Dimension: Categories Performance

The Infrastructure Dimension has 10 questions which are subdivided according to the following categories: Diversity, Volume and Speed - DVS, Data Access, Data Integration/Management and Data Architecture. The questions related to the "DVS" category presented the best performance, with 79% of the maximum possible score. This category has only one question which is about the types of data which are collected and managed about the company, if they are structured and/or semi-structured, or if the company takes advantage of text, videos, clickstreams and so on. “Data Access” also has one question which was about the access of data, if there is a strong dependency on the IT area, or if the employees can access these data through a consolidated platform with a good governance process. This category had a performance of 72%. “Data architecture” had the same performance, 72%. Four questions made up “Data Architecture” category and these were about how the architecture is designed, if it is capable to support increasing demand, whether it can answer users’ needs and the capacity to integrate distinct sources and types of data. The “Data Integration/Management” category had a performance of 70%. With 4 questions in this category, the survey covered subjects related to the user’s confidence in the data foundation for analytics, how the companies manage their volume of data and if they are capable of orchestrating/monitoring multiple data pipelines.

Table 3: Number of questions per category. Source: The author.

Categories	Number of questions
DVS	1
Data Access	1
Int/Manag	4
Architecture	4

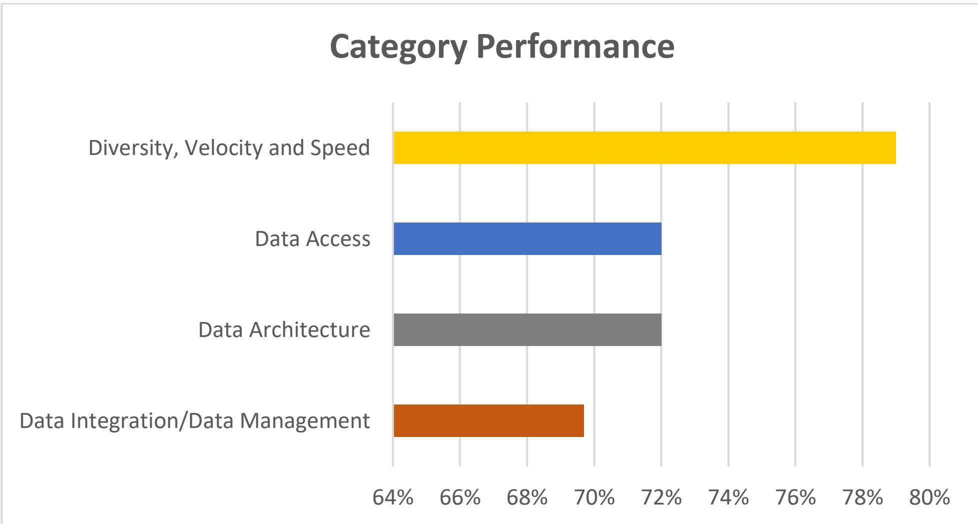

Figure 17: Performance by Category. Source: The author.

In general, companies exhibited favorable outcomes in their data infrastructures. However, the superior performance of the "DVS" category suggests that companies, despite dealing with diverse data types and technologies, are not effectively leveraging the potential of this broader variety and availability. This may indicate the companies have some lack of data-focused management, as reflected by the underperforming category "Data Access." Furthermore, the results of the "Data Architecture" and "Data Integration/Management" categories reveal areas for improvement in terms of the structuring, integration, and management of data.

5.4 Dimension Analysis: Resource Dimension

5.4.1 Stages of Maturity: Resource Results x General Results

The Resource Dimension also had the “Mature Stage” as the predominant (32%), although the results were more balanced than for the first two dimensions. The “Established Stage” corresponds to 27% of the sample, followed by the “Early Stage”, with 23%. “Nascent Stage” and “Advanced Stage” has both 9%.

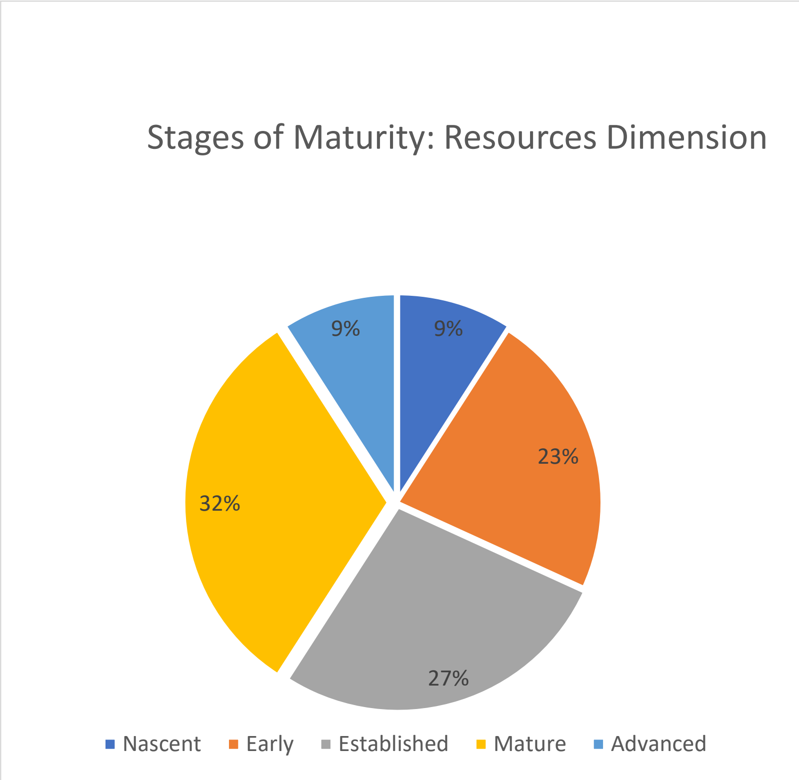

Figure 18: Stages of Maturity in Resource Dimension. Source: The Author.

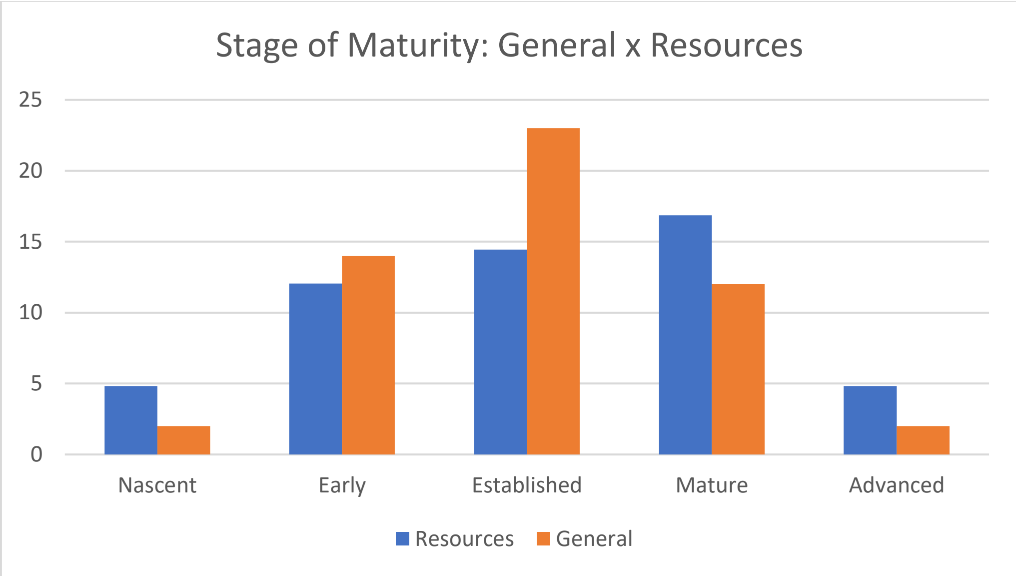

Figure 19: General x Resources results. Source: The Author.

5.4.2 Resources Dimension: Categories Performance

The 10 questions of this dimension are distributed across 4 categories, which are: funding; talent/skills; roles/responsibilities and training. The "Funding" category has 3 questions that refer to the funding process for technology and analytics, also want to know if Analytics is independent of other areas and whether the level of investment in changing management initiatives are oriented to data. This category presented a performance of 70%. "Role/responsibilities" performed 74% of positive answers. It is composed of 3 questions that are focused on figuring out if the company is struggling to support its analytics, whether it has capable professionals to deal with the Analytics life cycle and its different needs and particularities. The next category is "Training" with 72% of the maximum possible score. It has one question which asks if the companies are investing constantly in training and workshops to their collaborators. Another category is "Talent/Skills" with 4 questions about data literacy across the organization, as well as the level of the professionals in dealing with Analytics. That represented the worst category performance so far, with 58% of positive answers.

This result validates the findings of a 2018 study conducted in collaboration between NOVA SBE Business School and Ernst Young Consulting, which focused on digital transformation in Portuguese companies. Of the study participants, only 38% expressed confidence in the presence of competent personnel within their respective companies possessing the requisite knowledge and qualifications to effectively navigate into digital transformation processes. As a consequence, organizations will need to allocate substantial resources towards both recruitment efforts and the cultivation of technical expertise (NovaSBE Center for Digital Business & EY, 2018).

Table 4: Number of questions per category. Source: The author.

Categories	Number of questions
Funding	3
Talent/skills	4
Roles/Responsabilities	3
Training	1

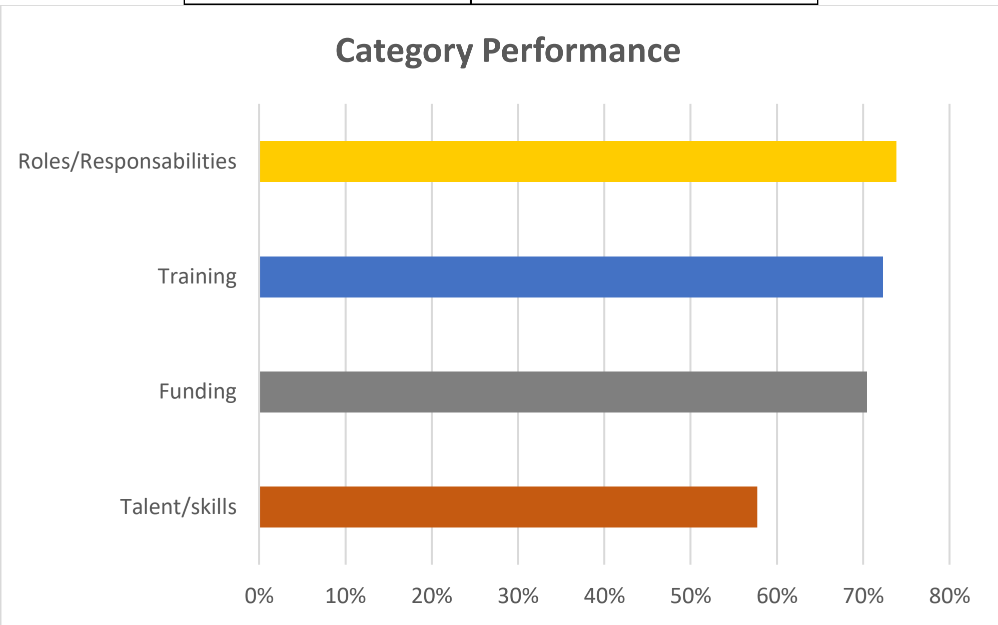

Figure 20: Performance by Category. Source: The author.

Finally, these results can highlight that although companies are willing to invest in an Analytics Culture, the workforce is not enough to boost these initiatives, even if nowadays Portugal is being an attractive hub for these professionals, both for the local and foreign workforce. Moreover, it can be inferred that in some companies exists a reluctance among certain employees to make their decisions and routines more data-driven, which hinders their ability to effectively carry out Analytics initiatives.

5.5 Dimension Analysis: Analytics Dimension

5.5.1 Stages of Maturity: Analytics Resources x General Resources

While the previous dimensions showed results higher when compared to "General Results", the "Analytics Dimension" was the opposite: the results indicate that overall performance is better than when analyzing performance solely within this dimension. 41% of the companies are in the "Early" stage of maturity. "Established" and "Mature" presented the same percentage, 27%. The "Nascent" stage corresponds to 5% of the companies. It doesn't have any company in the "Advanced" level.

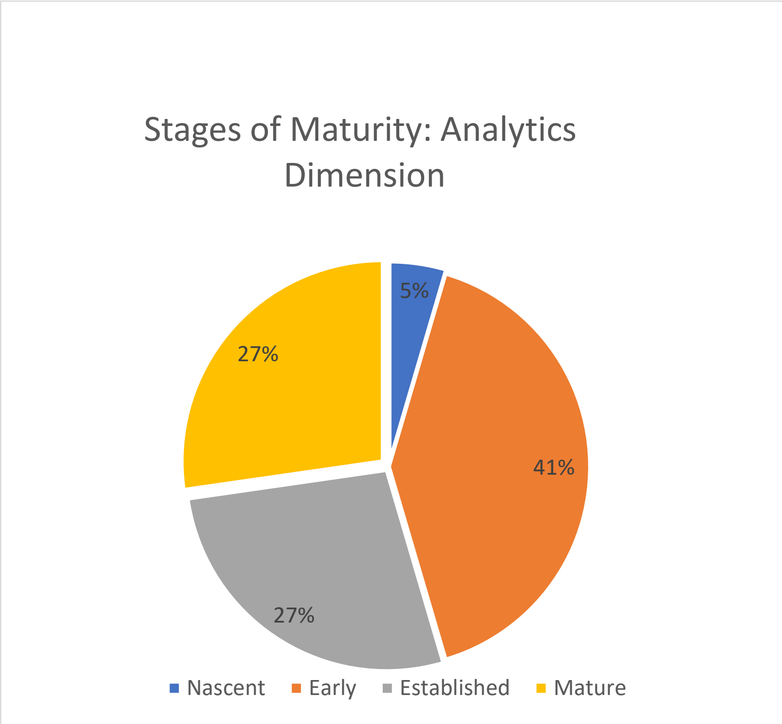

Figure 21: Stages of Maturity in Analytics Dimension. Source: The Author.

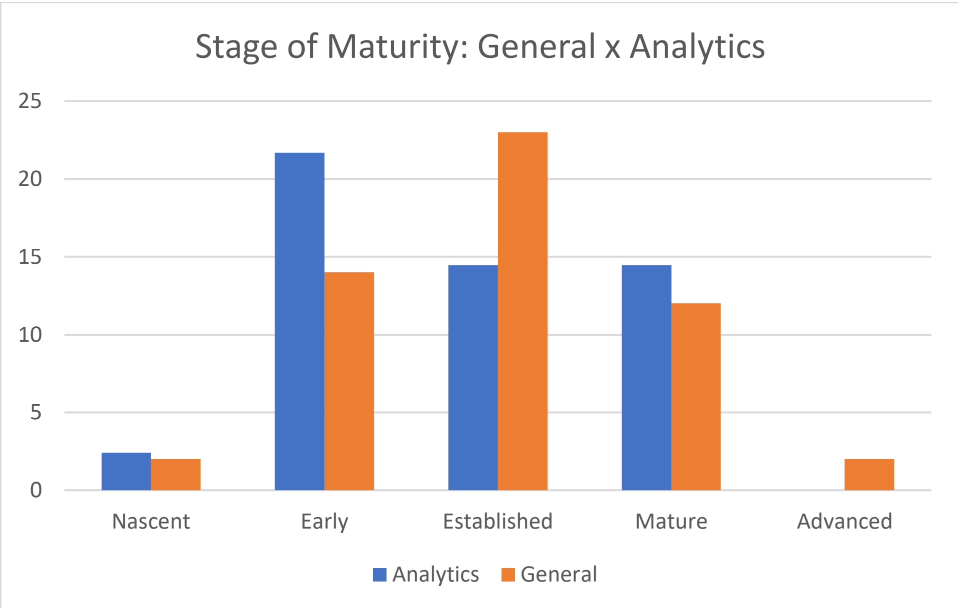

Figure 22: General x Analytics results. Source: The Author.

5.5.2 Analytics Dimension: Categories Performance

The “Analytics Dimensions” has a total of 12 questions distributed along 5 categories, which are: Platform/Techniques, Use Cases, Deployment/Delivery Methods, Scope and Model Management. “Scope of Capabilities” category, which has 54% of performance, is composed by 4 questions with the goal to understand how the Analytics, in general, is structured at the companies: what kind of technologies are used, if there are the use of Machine Learning models or whether the BI/Analytics solutions are spread across all the company. In “Use Cases” categories, with 2 questions, it asked how the company is taking advantage of its BI/Analytics solutions, this category reached 65%. The next category is “Platform/Techniques” with 3 questions. This category addresses how personalized the Analytics solutions are, with a suitable user interface (UI) according to each role, what is the level of automatization of these platforms and whether it uses open sources technologies. This category reached the better performance in dimension, with 77% of positive responses. The next category is “Deployment/Delivery Methods”, with has a performed with 58%. It has 2 questions regarding the development and the features of deployment process through the pipeline. The last category is “Model Management”, with the worst performance of the entire questionnaire, with only 23%. It has 1 question about the usage of decay techniques on the models.

Table 5: Number of questions per category. Source: The author.

Categories	Number of questions
Scope of capabilities	4
Use Cases	2
Deployment and Delivery Methods	3
Platform/Techniques	2
Model Management	1

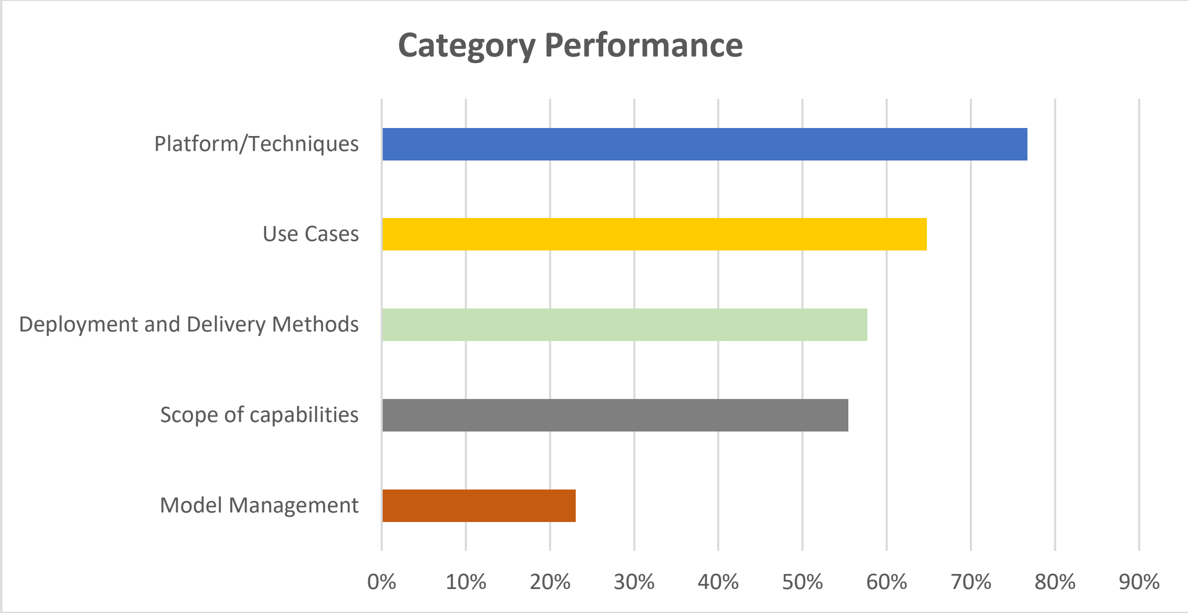

Figure 23: Performance by Category. Source: The author.

The results allow us to infer that the categories with questions regarding the usage of the most cutting-edge features of Analytics (Machine Learning, Techniques for decay and so on) had the worst performance observed so far. Although the companies are using and taking advantage of Analytics, Predictive/Descriptive Analyses seem to be still predominantly, and for now, the companies are not focused or even are not capable of using Prescriptive Analytics properly.

According to a 2021 study conducted by the European Statistical Office (Eurostat), which is affiliated with the European Union, only 9% of Portuguese companies are reported to employ AI applications. These applications encompass various uses, including machine learning for large-scale data analysis, chatbot services, service robots, and internal big data analysis supported by natural language processing, natural language generation, or voice recognition (Eurostat (European Static Office), 2021). In 2018, a study conducted on a sample of companies located in Portugal revealed a modest adoption rate of just over 20% for AI techniques, and the projected investments in these technologies for subsequent years were estimated to be less than 30% (NovaSBE Center for Digital Business & EY, 2018). These findings corroborate the observations made in the present study, highlighting that the implementation of more advanced Analytics technologies in companies within the Lisbon Metropolitan Area (AML) and, consequently, in Portugal, is still at an early stage, with considerable aspects yet to be implemented and/or enhanced.

5.6 Dimension Analysis: Governance Dimension

5.6.1 Stages of Maturity: Governance Results x General Results

In the "Governance Dimension", the "Early Stage" was the predominant, with 41% of the companies with an initial stage on their governance process. The next stage with the highest incidence within the "Governance Dimension" was the "Mature Stage", representing 36% of the companies. 14% of the organizations are in "Established Stage". 5% of the companies seem to have consolidate policies regarding their governance processes and are composing the "Advanced Stage". On the other hand, 4% of the enterprises have governance policies almost inexistent or even do not implement any practice.

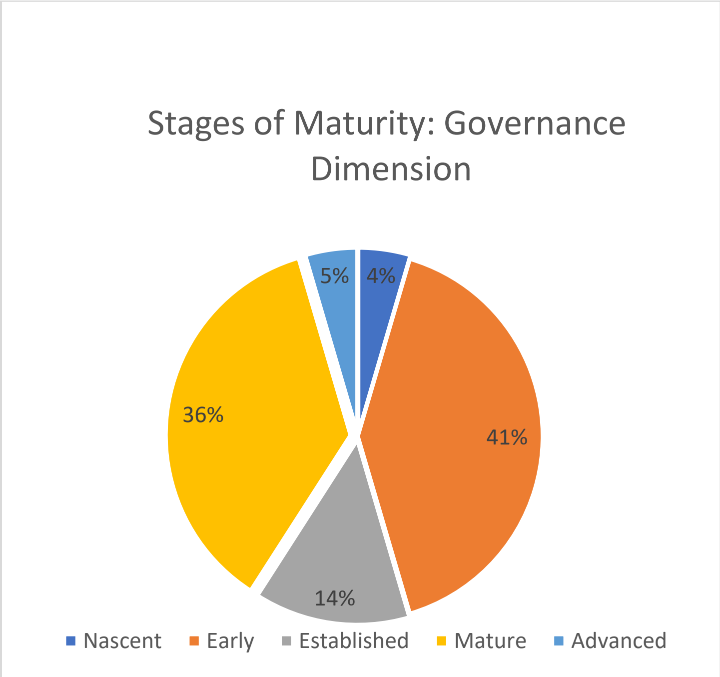

Figure 24: Stages of Maturity in Governance Dimension. Source: The Author.

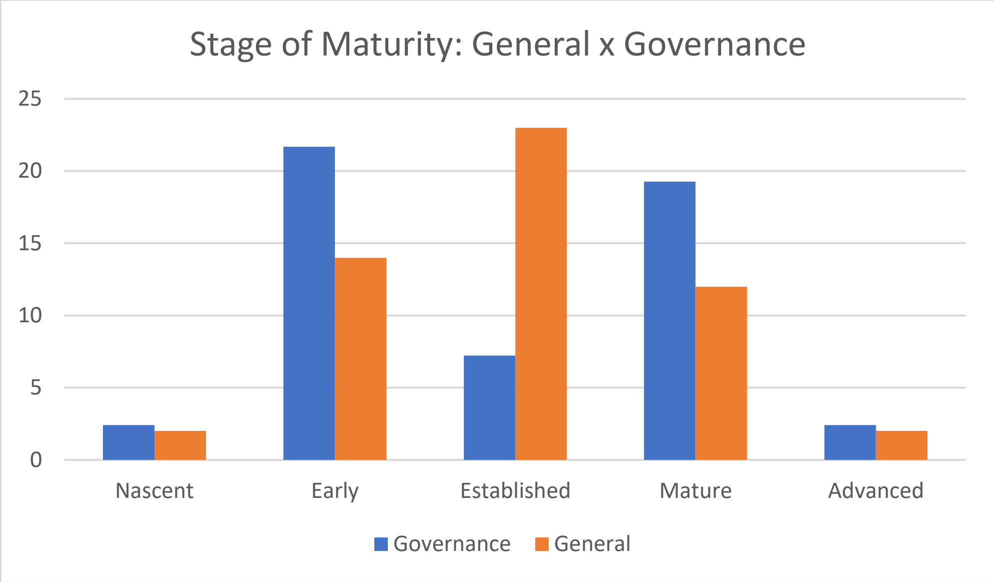

Figure 25: General x Governance results. Source: The Author.

5.6.2 Governance Dimension: Categories Performance

The "Governance Dimension" is composed of 10 questions distributed in four categories: Data Governance, Model Governance, Governance Roles and Security and Privacy. The best results were for "Data governance", with a performance of 78%. In this category are placed 4 questions regarding data governance process, such as how confident the DW and data silos are, whether they have key policies for that and the user's acceptance of these policies and practices. "Model Governance" has 2 questions about controlling incorrect or unethical models or if there is version controlling on the models or metadata captures for them. This category had the worst for the dimension, with 58%. The next category is the "Governance Roles" which performed with 60% of positive responses. It has 2 questions, one of them is about the existence of a data steward and, in case of a positive response, whether this role has responsibilities very well defined. Another question asked whether there is a data and analytics governance team, with representatives from across the company. The last category is "Security and Privacy" with a performance of 67%. It has one question about security policies, if all sources, data lakes and, especially, sensitive data.

Table 6: Number of questions per category. Source: The author.

Categories	Number of questions
Data Governance	4
Governance Roles	2
Model governance	2
Security	1

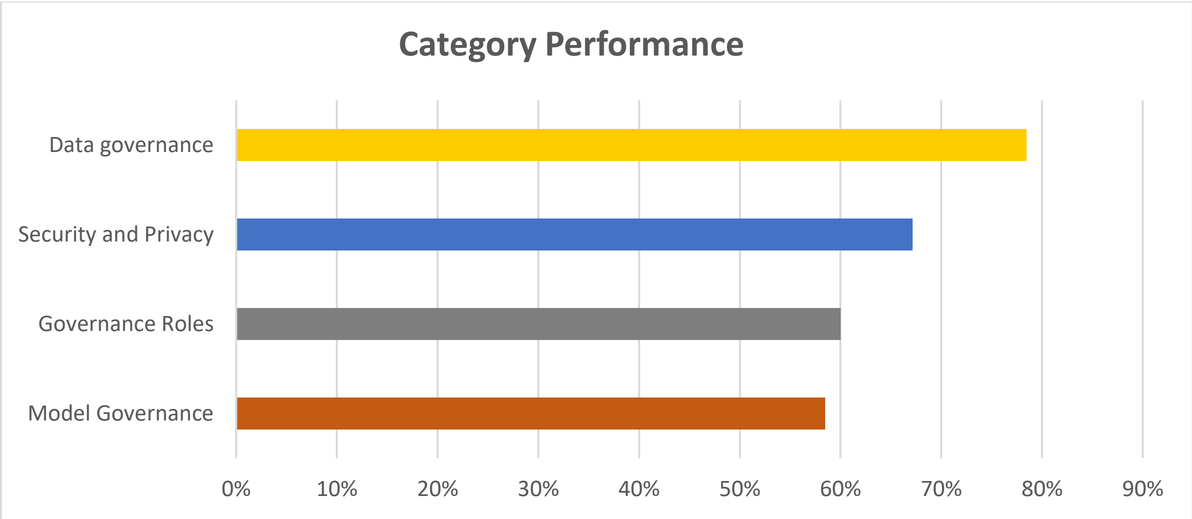

Figure 26: Performance by Category. Source: The author.

The results indicate that although there is confidence in the data and recognition about the importance of data privacy, maybe encouraged by the RGPD guidelines, which are mandatory in UE since 2018 (Institui & Oficial, 2021), there is room for improvement in governance policies within companies. Enhancements can be made by ensuring broader representation of key stakeholders across the organization, rather than relying solely on the involvement of the IT department. On the other hand, it seems that the companies have a lack of version control features to make sure their models represent trustful and ethical information. The exponential growth in data access, facilitated by advancements in technology, has prompted the publication of laws and the development of ethical codes. These regulations are designed to safeguard privacy, protect personal data, ensure proportionate data usage, and prevent discrimination. However, despite their existence, these norms alone are inadequate in addressing the complex ethical challenges associated with data generation and management (Correia, 2016).

6. CONCLUSIONS

6.1 FINAL CONSIDERATIONS ON THE RESULTS

Through the application of the TDWI Methodology, the research allowed us to know and understand better about the structure of BI/Analytics in companies in the AML, which serves as the economic and productive hub of Portugal and houses most of the country's prominent enterprises. Considering this context, this type of study can be quite interesting to carry out. A total of 53 employees representing companies of diverse sizes and business sectors participated in the questionnaire. These individuals have holistic views about processes involving BI/Analytics into their respective organizations. The findings revealed that the majority of participating companies are situated in the "Established Stage”, which means that most of these companies already use Analytics and that these tools collaborate in the decision-making processes. The best performance occurred in the dimensions of Organization, Infrastructure and Resources, respectively. These outcomes mean an existing inclination towards a data-driven culture within these companies, alongside the availability of well-established BI/Analytics solutions. Concerning the workforce, it was observed that while these organizations have trained professionals in the field, there is still a scarcity of such expertise, preventing the progress of these systems and their optimal utilization. While each company has its unique reality and context, there is an evident demand for skilled workforce within the sector to effectively leverage the advantages of a data-driven culture and overcome the challenges it presents. A collaborative endeavor is required, involving academia to provide an expanded range of courses and training tailored to this domain, as well as companies themselves, which rely on such talent pool for their operations. It is anticipated that companies will be required to make significant investments in recruitment and talent development, given the relatively underdeveloped nature of this area for most organizations. Consequently, an escalation of the "war for talent" phenomenon in the digital era tends to keep existing (NovaSBE Center for Digital Business & EY, 2018).

The Analytics dimension, although not yielding unfavorable results, clearly indicates areas for improvement, particularly in terms of taking more advantage of Predictive and Prescriptive Analysis. As tools like ChatGPT are gaining popularity, it is expected that companies will increasingly invest in such types of analyses, despite Portugal's relatively modest level of investment in these initiatives compared to other European Union countries such as Ireland, Malta, and Finland (Eurostat (European Static Office), 2021). Portuguese companies are hesitant to embrace a leading role in adopting advanced Analytics technologies, despite the potentially disruptive nature of these solutions, the findings suggest that companies lean towards a cautious approach, opting to observe and await the maturity of these technologies and the validation of their adoption by other entities and competitors (NovaSBE Center for Digital Business & EY, 2018). Therefore, although caution is necessary, it is important to note that companies willing to take this risk will be ahead of their competitors by making greater investments in these technologies. Additionally, the findings regarding the shortage of skilled workforce cannot be disregarded, as it may be correlated with the challenges of implementing more advanced Analytics models. Thus, investing in training and qualified personnel is also essential to achieve this goal.

For Governance dimension, even with the widespread adoption of these tools, it is really necessary a heightened focus on ethical considerations, demanding well-aligned, structured, and defined governance policies involving the entire organization. This will enable responsiveness to the demands of an increasingly digital world while remaining vigilant and committed to steering these technologies in a responsible direction. It is essential to invest in people through awareness, education, training, and the organization of meetings and seminars. Ethical codes, even when accompanied by training programs, are not sufficient on their own. It is necessary to have an integrated governance and management structure, where information security resources, such as computer security products and internal intrusion tests, are crucial. With current technology, which allows us to access personal data, it is necessary to establish alerts to prevent silent invasions of people's privacy and ensure respect and integrity for these individuals (Correia, 2016). This will enable responsiveness to the demands of an increasingly digital world while remaining vigilant and committed to steering these technologies in a responsible direction.

6.2 Research Contributions

6.2.1 Enhanced understanding of the level of maturity of BI/Analytics within the Portugal's context

The study yielded data that holds relevance for both academic and industrial sectors. The findings of this research provide valuable insights for these stakeholders, highlighting areas of strength and areas in need of improvement in the field of Analytics. Academic institutions can leverage these findings to enhance their curriculum and attract more students, thereby contributing to the local workforce and fostering a greater pool of professionals capable of driving BI advancements in Portugal. For researchers, this study can be used as an important reference to future research, besides encouraging further academic investigations on this field.

Moreover, the data generated from this serve as a valuable resource for companies in the AML region, offering guidance for decision-making processes aimed at enhancing their Analytics solutions. Additionally, it sheds light on often overlooked aspects that play a crucial role in the progression of Analytics maturity within these organizations.

6.2.2 A practical application of TDWI Maturity Model

This research serves as a practical illustration of the importance of employing a maturity model such as TDWI for companies. The participants of the questionnaire had the chance to familiarize themselves with this methodology, and it is plausible that some of these individuals developed an interest in further exploring the methodology and implementing it within their respective companies. This aspect contributes to the development of a culture where organizations not only adopt Analytics solutions but also actively track the outcomes and implications of these endeavors.

6.2.3 Practical Guidance for Portuguese companies

The findings of this study, combined with the insights derived from the application of the TDWI model, besides highlights weakness and strengths of the companies which participated in this research, provide valuable guidance for Portuguese companies seeking a systematic understanding of their Analytics solutions performance and the benefits they yield. Moreover, this survey serves as a benchmark for these companies to assess their competitive positioning. As previously noted, Portuguese companies tend to closely monitor the adoption of these technologies by other entities, fostering confidence in their investment choices concerning emerging technologies and trends.

6.3 Challenges and Research Limitations

The primary challenge encountered in this study was related to the sample, encompassing both its quantity and the diversity of respondents' profiles. It was not feasible to guarantee that research participants possessed the comprehensive knowledge required to respond confidently to the questionnaire, given the range of topics covered. Initially, a preference was given to individuals holding higher strategic positions in companies who possessed knowledge of Analytics; however, due to difficulties in recruiting participants, responses were accepted from individuals in other roles, such as Team Leaders and Data Analysts with more than 2 years in their companies. Furthermore, participants highlighted the exhaustive nature of the questionnaire, consisting of 52 questions with multiple alternatives, which proved to be a challenge for some.

It is important to note that the presented results are grounded solely in the perspective of the TDWI methodology, without the presence of contrasting methodologies that would validate their accuracy. Additionally, the application of an anonymous questionnaire alone does not guarantee a direct reflection of reality, as it does not involve a deep exploration of each company's specific context.

Hence, even if this research provides valuable insights, it is necessary to recognize and consider these limitations. Future studies should aim to address these aspects and enhance the understanding about the Maturity Models for Analytics.

6.4 PROPOSALS FOR FUTURE RESEARCH

Here are some suggestions for future research endeavors that aim to address the current limitations and enhance academic studies on BI/Analytics maturity models, particularly within the context of Portugal:

- Apply the TDWI Model to a specific company or specific sectors to gain more targeted insights;
- Perform a multi-country BI maturity assessment to understand the differences between countries in the usage of this type of tools;
- Conduct similar studies that explore the application of alternative maturity models, in addition to the TDWI Model;
- Combine the application of the TDWI Model with qualitative interviews to gain a deeper understanding of the findings.

REFERENCES

Bean, R. (2021). Why Is It So Hard to Become a Data-Driven Company? *Harvard Business Review.* https://hbr.org/2021/02/why-is-it-so-hard-to-become-a-data-driven-company

Bellinger, G., Castro, D., & Mills, A. (2003). Data , Information , Knowledge , and Wisdom. 5–7.

Brandão, A., Pereira, E., Esteves, M., Portela, F., Santos, M. F., Abelha, A., & Machado, J. (2016). A benchmarking analysis of open-source business intelligence tools in healthcare environments. *Information (Switzerland)*, *7*(4), 1–16. https://doi.org/10.3390/info7040057

Caseiro, N., & Coelho, A. (2018). *Business intelligence and competitiveness: the mediating role of entrepreneurial orientation*. Competitiveness Review, *28*(2), 213–226. *https://doi.org/10.1108/CR-09-2016-0054*

Colaço, O. J. C. R. (2013). Caracterização Do Data Warehouse / Business Intelligence (Dw/Bi) Em Portugal – Um Estudo Sobre Os Dw/Bi Das Maiores Empresas Portuguesas.

CORREIA, P. et al. (2016). Comparação de normas de conduta dos trabalhadores da administração pública portuguesa: a tensão entre o tratamento de dados pessoais e os deveres éticos. *Ciências e Políticas Públicas / Public Sciences & Policies*, *2*(1), 51–74. https://doi.org/10.33167/2184-0644.cpp2016.viin1/pp.51-74

Côrte-real, N. (2011). *Avaliação da maturidade da business intelligence nas organizações*. 104.

Cunha, I. B. de A., Pereira, F. C. M., & Neves, J. T. de R. (2015). Analysis of Informational flow present in a company of Value Added Services segment (VAS). *Perspectivas Em Ciencia Da Informacao*, *20*(4), 107–128.

Dinter, B. (2012). The maturing of a business intelligence maturity model. *18th Americas Conference on Information Systems 2012, AMCIS 2012*, *5*, 3948–3957.

Eurostat (European Static Office). (2021, April 13). *Artificial intelligence in EU enterprises - Products Eurostat News - Eurostat*. Https://Ec.Europa.Eu/Eurostat/Web/Products-Eurostat-News/-/Ddn-20210413-1.

Fontenelles, M. J., Simões, M. G., Farias, S. H., & Fontenelles, R. G. S. (2009). Metodologia da Pesquisa Científica: diretrizes para elaboração de um protocolo de pesquisa. *Metodologia Da Pesquisa Científica: Diretrizes Para Elaboração de Um Protocolo de Pesquisa*, 8.

Gartner. (2022). *Software Market Insights: Business Intelligence (BI) and Data Analytics*.

Gerhardt Engel, T. & D. T. S. (2009). *Métodos de Pesquisa*.

Glasow, P. A. (2005). *Fundamentals of Survey Research Methodology* (pp. 1–27).

Halcomb, E. J., & Hickman, L. (2015). Mixed methods research. *Nursing Standard: Promoting Excellence in Nursing Care*, *29*(32), 41–47.

Halper, F. (2020). TDWI Analytics Maturity Model. *TDWI Research*, 22.

Halper, F., & Stodder, D. (2014). TDWI Analytics Maturity Model Guide. *TDWI Research*, 22.

Institui, A., & Oficial, J. (2021). *Celex_02016R0679-20160504_Pt_Txt*. *2*, 1–78.

Król, K., & Zdonek, D. (2020). Analytics maturity models: An overview. *Information (Switzerland)*, *11*(3), 1–19. https://doi.org/10.3390/info11030142

Lisboa: A economia em números. (2020). Lisboa: A economia em números 2020. *Câmara Municipal de Lisboa*, 60.

Medeiros, L. de C., & Silva, M. A. L. da. (2018). Business Intelligence (BI): Análise comparativa entre as ferramentas líderes no mercado. *Revista Eletrônica Da Reunião Anual de Ciência*, *8*(1), 1–13.

Musskopf, G. W. (2017). *ANÁLISE DAS FERRAMENTAS DE BUSINESS INTELLIGENCE UTILIZADAS POR EMPRESAS BRASILEIRAS*.

NovaSBE Center for Digital Business, & EY. (2018). *Estudo da Maturidade Digital das empresas portuguesas*. 1–18.

Pastori, E. (2012). *Nível de Maturidade em Business Intelligence*. 1–50.

Pereira, R., Rezende, D., & Abreu, A. (2000). Gestão do conhecimento com apoio dos recursos de sistemas de informação e tecnologias emergentes. *Encontro Nacional De …*, *January*. http://189.73.88.26/petry/arquivos/Artigo_gestao_conhecimento_01.pdf

Ponchirolli, O., & Fialho, F. (2005). Gestão estratégica do conhecimento como parte da estratégia empresarial. *Revista FAE, Curitiba*, 127–138. http://www.fae.edu/publicacoes/pdf/revista_da_fae/rev_fae_v8_n1/rev_fae_v8_n1_11.pdf

Rajterič, I. H. (2010). OVERVIEW OF BUSINESS INTELLIGENCE MATURITY MODELS. *Managment*, *15*, 47–67. https://doi.org/10.1109/ROMAN.2005.1513741

Regionais, C., Norte, N., Ii, N., Regionais, C., Anuais, C. N., & Simplificada, E. (2020). *Contas Regionais – Base 2016 2018 e 2019 Provisório Em 2019 , a atividade turística impulsionou um crescimento na Área Metropolitana de Lisboa , no Algarve e na Região Autónoma dos Açores superior à média nacional*. *Base 2016*, 1–15.

Rezende, Y. (2002). Informação para negócios: os novos agentes do conhecimento e a gestão do capital intelectual. *Ciência Da Informação*, *31*(2), 120–128. https://doi.org/10.1590/s0100-19652002000200013

Rossetti, A. G., & Morales, A. B. T. (2007). O papel da tecnologia da informação na gestão do conhecimento The role of information technology in knowledge management. *Ci. Inf., Brasília*, *v. 36*(n. 1, jan./abr.), 124-135,. http://www.scielo.br/pdf/ci/v36n1/a09v36n1

Serapioni, M. (2000). Métodos qualitativos e quantitativos na pesquisa social em saúde: algumas estratégias para a integração. *Ciência & Saúde Coletiva*, *5*(1), 187–192. https://doi.org/10.1590/s1413-81232000000100016

Setzer, V. W. (2015). Dado, Informação, Conhecimento e Competência. *Instituto de Matemática e Estatística Da Universidade de São Paulo*, 1–14. https://www.ime.usp.br/~vwsetzer/dado-info.html

Sharda, R., Delen, D., & Turban, E. (2014). *Business Intelligence and Analytics: Systems for Decision Support, Global Edition*.

Taylor, P. (2022). *Total data volume worldwide 2010-2025*. Statista. https://www.statista.com/statistics/871513/worldwide-data-created/

Vanmare, J. (2006). the Benefits of Implementing Business Intelligence Solutions in a South African. November.

ATTACHMENTS

TDWI Survey (2020 Version)

Organization

Leadership

1. Your leadership supports and evangelizes analytics across the company.

1. Not at all
2. They seem ambivalent about analytics and they don't really evangelize it
3. They support analytics efforts and are starting to evangelize it. That includes using analytics to make decisions
4. They firmly support analytics efforts, they use analytics to make decisions, and they evangelize it across the company

2. Your company has a Chief Analytics Officer (CAO) who is in charge of analytics efforts.

1. We don't have anyone in charge of analytics at my company
2. Analytics is controlled by IT in my company
3. We have one or more VPs or Directors of Analytics in my company, who are in charge of analytics
4. We have a Chief Analytics Officer

Strategy

3. Your company has a strong strategy in place to support its data and analytics efforts.

1. No, and we have no plans to do so
2. No, but we plan to do so in the next year
3. Yes, we are in the process of putting a strategy together
4. Yes, we have a solid strategy in place for analytics

4. Analytics is an important part of your company's digital transformation strategy.

1. No, we do not have a digital transformation strategy
2. Yes, we are in the process of uniting our digital transformation strategy with our analytics strategy

3. Yes, analytics is an important part of my company's digital transformation strategy

Impact

5. % of business units in your company use analytics for day to day decision making.

1. Less than 25%
2. 26-40%
3. 41-55%
4. 56-70%
5. Greater than 70%

6. Your organization has measured an impact with its analytics.

1. No, we have not measured any impact
2. No, we have not measured any impact, but we believe we have gained value
3. Yes, we have measured a top-or bottom-line impact

Culture

7. Your organization uses analytics to take action.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

8. There is a culture of trust in analytics across your company.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

9. There is strong collaboration on analytics in your organization.

1. No, we don't perform analytics

2. No, we don't collaborate on analytics - IT is in charge
3. Not yet, but we are moving in that direction
4. Yes, business and IT regularly work together as they need to
5. Yes, business, IT, and others work together because they want to and see their collaboration as helpful for success

10. There is a culture of innovation in your company that extends to analytics.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely disagree

11. There is a strong ethical foundation in your organization that extends to analytics.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

Data Infrastructure

Diversity, Volume, and Speed

12. Your organization currently collects and manages what types of data as part of its analytics efforts?

1. None
2. Structured data (e.g., tables records) from internal sources only
3. Structured data plus at least one of the following: semi structured data (e.g., JSON, XML), text data, machine generated data, geospatial data, real-time event data, audio, video, weblogs, clickstreams
4. Structured data plus at least three of the following: semi structured data (e.g., JSON, XML), text data, machine generated data, geospatial data, real-time event data, audio, video, clickstream

Data access

13. Employees can access data as needed, including structured and unstructured data, through a well-defined unified access platform and governance process.

1. Not at all
2. Only if they go through IT
3. Yes, mostly business analysts and data scientists can access and make use of the data, although sometimes it is a struggle
4. Yes, we use technology such as data sharing options to help organize and access data

Data integration/management

14. Your organization often makes use of multiple data sources for analytics.

1. No
2. Yes, with structured data
3. Yes, with different kinds of data including semi-structured data and other non traditional data sources
4. Yes, with different kinds of data and we do a good job integrating it
5. Yes, with structured, semi structured and unstructured data from internal and external sources-- it's all just data to us and essential that we get a full picture

15. Your organization has a trusted data foundation for analytics.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

16. Your organization is utilizing the following kinds of technology for data management:

1. We use flat files or spreadsheets only
2. We have a data warehouse or data mart
3. We use our data warehouse together with a data lake, but they are siloed
4. We utilize a range of technologies including our data warehouse, data lake, cloud, or other type and are architecting them together as an ecosystem
5. We utilize a range of approaches that form a well-architected data platform for data access

17. Your organization is able to orchestrate and monitor multiple data pipelines.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

Data architecture

18. Your organization has a company-wide data architecture in place for analytics that can handle user growth.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

19. Your organization has designed its architecture to integrate diverse data from disparate sources for access and analysis.

1. Not yet
2. We use multiple sources, but all the integrated analytics utilize structured data
3. Yes, and we integrate both structured and semi structured data because it's all data needed to give us the most complete picture and make the best decisions or automate the best actions

20. Your data architecture is designed for scale.

1. Not really
2. Not yet, but we are moving to a more flexible and scalable architecture
3. Yes, we are confident in the company's ability to scale by use case, including seasonal fluctuations

21. Your architecture is designed to scale on demand, to fit user's needs.

1. No
2. We are moving in that direction
3. Yes

Resources

Funding

22. Your organization has a well-established funding process for both technology and analytics. It is both business - and IT - driven.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Strongly agree

23. Your organization's analytics strategy includes an organizational component that allows your organization to execute its analytics. This might include funding a center of excellence, innovation teams, and the like.

1. No, and I'm not sure we know what that is
2. Not yet, but we know this is important and some people want this
3. Yes, we are in the process of organizing to execute
4. Yes, we have groups/teams like this in place and we are working to expand it
5. Yes, we have a significant investment in this kind of thing which includes training and support for analytics initiatives

24. Your company invests in change management initiatives

1. No, and we have no plans to do so
2. No, but we plan to do so in the next year
3. Yes, we are in the process of doing this now
4. Yes, we have that in place to provide change management training, but it is only for executives
5. Yes, we have put that in place across the organization

Roles and Responsibilities

25. Your team is struggling to maintain its data infrastructure to support analytics.

1. Yes, it is a struggle; there are too few resources
2. We are trying to work smarter and use technology to help boost productivity, along with hiring more people
3. We are working smarter and have the resources we need

26. Your company has hired data scientists as part of its analytics efforts.

1. No, and we have no plans to do so
2. No, but we are planning to do this within the next year
3. Yes, we have hired a few data scientists
4. Yes, our data scientists are part of the analytics team
5. Yes, our data scientists are part of the analytics team and they collaborate with the business

27. Aside from data scientists, your organization employs a range of staff to deal with different aspects of the analytics life cycle. This includes data engineers and operations teams for example, to deal with analytics in production.

1. No, and I'm not sure we are thinking about data engineers or DevOps
2. No, but we realize that this is important and we may be trying to work on it in an ad hoc manner with existing staff
3. We are putting a dedicated group/staff in place for this

4. Yes, we have dedicated team members in place with a specific mandate and skills for this

Talent and skills

28. Your organization has a talented team in place to execute against data management for analytics.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

29. Your organization has a talented team in place to execute its analytics.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

30. Your company believes it can upskill its business analysts to become data scientists.

1. No, we are not at the point where we need data scientists
2. Yes, but they will need help from others
3. Yes, they can build models, especially with the easy-to-use tools on the market
4. We have all the data scientists we need

31. Your organization is data literate. Business users as well as business analysts can use data to derive insights.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

Training

32. Your organization invests in training for analytics.

1. No, and we have no plans to do so
2. No, but we suggest staff read and educate themselves

3. Yes, we fund internal training only
4. Yes, we regularly schedule funded training and encourage-- if not mandate-- employees to attend to ensure that we are well equipped and trained

Analytics

Scope

33. Which of the following technologies does your organization use to analyze its data?

1. We use spreadsheets
2. We use spreadsheets along with reports, dashboards, and visual discovery
3. We use the above along with self-service data discovery; we are also starting to use predictive analytics
4. We use the above along with predictive analytics/machine learning against multiple data types
5. We use the above along with other techniques such as NLP, deep learning and other facets of AI

34. Your organization manages large volumes of data for analytics (e.g., more than 10 TB)

1. No
2. Not yet, but we are moving in that direction
3. Yes, we utilize analytics against large volumes of data

35. How many predictive analytics/machine learning models does your company have in production?

1. None
2. 1
3. 2-10
4. Dozens
5. Hundreds

36. What percent of people in your company have access to analytics?

1. Less than 25%
2. 26-40%
3. 41-55%
4. 56-70%
6. 5. Greater than 70%

Use cases

37. Your organization is successful at articulating business problems that require analytics. It understands when to use specific techniques to solve different problems.

1. We are not at all successful at doing this
2. We are not very successful at doing this
3. We are neither successful nor unsuccessful at doing this
4. We are successful at doing this
5. We are very successful at doing this

38. Analytics is used by teams across the organization, where needed.

1. No, it is mostly used in finance, operations, or IT
2. Not currently, but more organizations are taking interest in it
3. Yes, we use analytics across the organization

Platforms/Techniques

39. Your analytics solutions are persona driven to provide the best UI to the right person (e.g., business analysts, business users, data scientists, data engineers, etc.). For instance, data scientists might use data science notebooks while business analysts might prefer drag, drop, and drill GUIs, and general business users might just want to consume dashboards and reports or utilize automated actions suggested by your models.

1. No, we just have one tool and everyone complains about it as it's not a good fit for anyone
2. We're thinking about or planning to install tools that can be used by different personas
3. Yes, we make use of multiple tools so each of our personas has the appropriate environment
4. Yes, we make use of a data platform so every persona has an environment that maximizes efficiency, and there are clear processes to push work between them
5. Same as (4) and also our platform makes data sharing between environments as seamless as possible

40. Your organization utilizes automated analytics (e.g., systems that suggest insights or build models)

1. No
2. No, but we are exploring these solutions
3. We use them to democratize analytics and boost productivity
4. Yes, we use a data platform to help boost productivity and we put controls in place around these tools to make sure that they are working properly

41. Your organization utilizes open source technologies for analytics.

1. Yes, we use open source only
2. Yes, we use open source in conjunction with commercial products; we support whatever the

data scientist/analyst needs

3. No, we only use commercial products

Delivery methods

42. Analytics are operationalized/deployed in a business system(s) or an application(s) in your organization.

1. No, and we have no plans to do so
2. No, but we are planning to do this in the next year
3. Yes, we are trying to do this now in dashboards
4. Yes, we do this routinely in dashboard applications
5. Yes, we routinely operationalize our analytics, including dashboards as well as predictive models into production

43. The output of models built using augmented intelligence have explanation features to increase transparency for experts and non-experts alike.

1. Not applicable, we are not using these tools
2. No, not that we've seen
3. Yes, we only use packages that have these features

Model Management

44. Your organization monitors predictive analytics/machine learning models for decay.

1. Not applicable, we have no models in production
2. No, and we have no plans to do so
3. Not yet, but we are thinking about it
4. Yes, we are trying to do this now
5. Yes, we do this regularly
6. Yes, we routinely do this with automated checks and allot the necessary time for our staff to address this

Governance

Data governance

45. Data is trusted and governed across platforms in your organization

1. No, we have many data silos that are not governed
2. We trust the data that we use for reporting that comes from our DW, but not much else
3. We are starting to put processes in place for data governance beyond just the DW or other sources of data that need to be compliant (e.g., HIPAA) so we can trust other key data sources

4. We have a solid data governance plan that outlines key policies and processes; these are followed in the organization

46. Your organization understands the source(s) of its data and has the right policies in place to deal with different kinds of data.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

47. Users accept and adhere to data governance policies.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

48. Your organization uses tools such as data catalogs to help users access trusted data.

1. No, and we have no plans to install a data catalog
2. No, but we are thinking about it
3. We are in the process of selecting a catalog vendor now
4. Yes, we have a data catalog and people have bought into using it
5. Yes, we have a data catalog, but not everyone uses it

Model governance

49. Predictive analytics/machine learning model deployment processes are in place in your organization. For example, models must be checked so as not to be incorrect or unethical (e.g., have racial bias) before they are put into production.

1. Not applicable, we don't have models in production in my company
2. We have models deployed, but we don't check to see if they are correct. We trust our data scientists
3. We are in the process of implementing controls over models in production
4. We have a strong model control process

50. Model management policies are in place in your organization. Models must be version controlled and metadata captured for each model put into production.

1. Not applicable -- we don't have models in production

Governance roles

51. Your company has a data and analytics governance team with representatives from across the company including key business stakeholders. Roles and responsibilities are clearly defined.

1. Completely disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Completely agree

52. The role of data steward(s) is in place and that person's (or team's) roles and responsibilities are clearly identified.

1. No
2. We are in the process of identifying data stewards
3. Data stewards are in place in my company

Security and privacy

53. Security policies are established and enforced for all forms of data in your company.

1. No
2. Data in the warehouse is secured and governed, but not necessarily in external sources or in data lakes, etc
3. Yes, security policies exist for all kinds of sensitive data
4. Yes, we have carefully thought through how we deal with different kinds of data on our governance team
5. Yes, we have carefully thought through and operationalized how we deal with different kinds of data using our data platform on our governance team

About your company

Demographics

Please provide us with answers to these two questions. Then you can receive your score by industry and by company size.

1. Which best describes your industry?

1. Financial Services

2. Insurance
3. Consulting
4. Software/Internet
5. Telecommunications
6. Manufacturing (non computers)
7. Manufacturing (computers)
8. Retail/Wholesale
9. Government
10. Education
11. Pharmaceuticals
12. Media/Advertisting
13. Utilities
14. Hospitality/Travel
15. Transportation
16. Food/Beverage
17. Online retail
18. Other

2. What size is your company?

1. Less than $10M
2. $10-$50M
3. $50M-$100M
4. $100M-$500M
5. $500M-$1B
6. $1B-$5B
7. $5B-$10B
8. Greater than $10B
9. Don't know