An Application of the Analytic Hierarchy Process to the Evaluation of Companies' Data Maturity

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Abstract: The study reports the data maturity evaluation on a sample of Italian firms of different sectors and sizes, retrieved through an online assessment made by 261 professionals and entrepreneurs operating in the data domain. The paper's objective is to derive the relative importance of the critical factors to impact successful big data initiatives, according to organization reality and manager perspective. The questionnaire was distributed among IT professionals and decision-makers in Italy using the LinkedIn platform. The assessment was divided into two sections: the 1st one contained the assessment of 8 critical success factors for big data, whereas the 2nd section assessed weights based on an application of the analytic hierarchy process. The result of this process is a scoring system that includes the characteristics a company "must-have" to become data-oriented and make data-driven decisions. The application of the weights allows giving more importance to the domains that managers think are more important in a data-driven company. Respondents agreed to the importance of integrated architecture, data-friendly corporate culture, and integrated organization domains. Once the results consider the weights from the AHP, data friendliness becomes the most sought-after characteristic. The findings provide direction for further development of the assessment system.

1 INTRODUCTION

Data science is the set of statistical techniques and methods necessary for the extraction, analysis, and interpretation of data. In the era of "Big Data" where a huge amount of information is available to companies, data-driven choices are essential for defining a company's medium and long-term strategy and can turn into a huge competitive advantage success (Grover et al., 2018; Kubina et al., 2015). The major internet and manufacturing companies like Google, Facebook, and Apple hire the best data science talents to work in their vast data science departments. Being a successful company today means making data-driven decisions (Ghasemaghaei, 2019; Wamba et al., 2017). Companies that have overlooked the potential of data science have observed their competitors seize market share and enlarge their customer base over the past years. Pioneers like Facebook, Amazon, and Google instead developed dominant market positions. Nowadays, basically, companies of all sizes are investing heavily in data and AI initiatives to narrow the gap with the tech giants(Davenport & Bean, 2019). Although the value that data analytics brings to companies has been recognized (Grover et al., 2018; Günther et al., 2017; Mikalef et al., 2019), there is still confusion on how to properly integrate big data initiatives within the organization for long-term planning (McShea et al., 2016; White, 2019). This is today the main reason for the actual failures of more than half of big data programs worldwide. Being a data mature organization means being able to spot new data-driven opportunities in advance while they are still invisible to the competitors, using analytic insights to deliver business outcomes.

In this study, we analyze the data maturity of a representative sample of Italian companies of different sectors and sizes. To score what the ripeness level of the enterprises is, we relied on an eight-

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dimensional assessment system derived from the literature (De Mauro et al., 2021) - the CBDAS - consensual with the existing big data maturity models. The CBDAS applies the analytic hierarchy process to assign weights to the critical success factors for big data initiatives. We analyze how respondents (Senior Manager and IT Decision-makers) agreed or disagreed with questions that underlined the importance of each success factor proposed. As a result, the paper derives insights on the importance that the managers give on data-driven choices and on the validity of the CBDAS to apply to companies of different sizes and industry sectors.

2 BIG DATA MATURITY MODELS

In the digital era, data analytics becomes a central point of achieving corporate objectives (Khanra et al., 2020). The ability of a company to take advantage of the usage of big data (degree of corporate data maturity) determines the degree of success or failure of a data-driven initiative (Constantiou & Kallinikos, 2015; Santos-Neto & Costa, 2019; Sharma et al., 2014).

The big data maturity models represent robust frameworks that support the evaluation of old and new big data initiatives among specific aspects or domains to rule whether they can generate new knowledge for a company (Grover et al., 2018; Olszak & Mach-Król, 2018; Santos-Neto & Costa, 2019; van Hillegersberg J., 2019).

By leveraging a maturity model, data maturity can be evaluated at the sub-domain level when it refers to micro-level factors such as routines and organizational requirements, at the domain level when it refers to the macro-level factors to assess the needed conditions to reach maturity stages. While macrolevels generally assess strategic factors of big data initiatives' success, microlevels make clear the actions to be taken to guide maturity within organizations (Comuzzi & Patel, 2016; Halper & Krishnan, 2014; Nott, C. and Betteridge, 2014).

The aspects investigated through the maturity models can be many, such as IT management, business intelligence ecosystem, and data warehouse adoption, among others. In general, big data maturity models give the company the maximum value when used to analyze how business processes and strategies integrate with big data initiatives, providing management with the needed information to support strategic and operational decisions (Al-Sai et al., 2019).

Data models help to outline the optimal choices for a path of improvement of the business management system. The absence of specific procedures regarding the assessment and operation of maturity models may represent a limitation for the use of the model as an organizational and diagnostic-prescriptive management system.

So far, only a few of the big data maturity models present in the literature contain details on the development, validation, and evaluation processes of the model itself, constituting a limit to the validity and usefulness of many proposals (Pöppelbuß & Röglinger, 2011; Santos-Neto & Costa, 2019).

We rely on the Consensual Big Data Assessment System (CBDAS) proposal (De Mauro et al., 2021), which starts from a holistic and conceptual integration of existing models. It encompasses the key elements of success that are coherent with big data's essential components and consensual with the most prominent existing models. The CBDAS offers a robust conceptual model complemented by a practical assessment and recommendation system to grant usefulness and applicability for industries.

3 METHODOLOGY

3.1 Sample Collection

In this work, we submitted a Likert-scale (1-strongly disagree to 5-strongly agree) questionnaire to 261 Italian companies' employees, where the participants were asked to answer questions that measure a company data maturity. The participants were mostly company managers and IT experts. We used the LinkedIn platform to draw a representative sample of professionals worldwide to conduct the online assessment. Although the LinkedIn community is not encompassing the population of industry representatives exhaustively, it might be considered suitable for targeting professionals in scope. The process of sample selection leverage publicly available information about the respondents provided by LinkedIn users, which increases the credibility of the sample and permits control over its composition.

The inclusion criteria were related to (a) the seniority of the respondents (Senior Managers and Directors), (b) the position covered in their organization (IT Director, IT Responsible, IT Specialist, Senior Data Specialist, Senior Data Scientist, Senior Business Analyst, IT Consultant), (c) their confirmed experiences and skills in the area of Data Analytics, Big Data, and IT Management. With the inclusion criteria identified, we had a potential audience of more than 320.000 unique respondents, targeted with LinkedIn campaigns launched from October to December 2021. Exclusion criteria have been applied to filter (a) uncomplete assessments and (b) companies operating outside Italy since the study focus on the Italian territory.

3.2 Assessment Structure

The CBDAS assessment was structured in two parts: the first part is composed of 40 questions divided into 8 domains and allows the evaluation of data maturity on critical success factors for big data initiatives; the second part is made of 15 questions that focus on the pairwise comparison of data maturity characteristics of the company, which represent a multifactorial combination of the 8 critical success factors.

Table 1: Assessment submitted to the participants.

Domain	Questions
DATA STRATEGY	1) The company has a solid data analysis strategy. 2) The company uses data analysis to make strategic decisions. 3) Data analysis is not an important part of the company's transformation strategy. 4) The Corporate Data Strategy has been documented, approved, and communicated by Top Management to the entire organization. 5) Leadership promotes the use of data analytics throughout the company. 6) There is a list of key analytical projects or analysis priorities whose progress is regularly tracked. 7) The legal procedures on data usage and management are documented and communicated to the entire organization. 8) There are regular audit processes on data usage and management within the organization
DATA-PROCESS INTEGRATION	9) Business processes are guided by numerical evidence, which directly impacts the way the company operates. 10) The Key Performance Indicators related to data processes are stored and could be analyzed in real-time. 11) The organization uses automated analyses (e.g., systems that suggest in-depth analysis or build models, alert systems based on control levels, reports that automated data processing and output delivery). 12) Your company has organizations (internal or external) that focus on data engineering, software development, data quality to ensure proper support to analytical processes. 13) Managers and process owners know what data are available in the company to support their business decisions.
TECH INFRASTRUCTURE	14) The data infrastructure is adequate to the size of the organization, and the organization is using the following types of data management technology where needed: Cloud Systems, Big Data Architectures. 15) The organization is able to monitor more data pipelines. Therefore, the organization is able to manage multiple analytical projects in parallel. 16) The organization has designed its data architecture to integrate multiple sources and facilitate data access and analysis. 17) The computational power and the size of the available memory are adapted to the current information injections. 18) Systems comply with high-security standards and are subject to periodic intrusion tests. 19) How many of the following technologies use your organization to analyze your data? (Spreadsheets, reports, dashboard, predictive analysis/machine learning, deep learning, and other aspects of the AI). 20) Only a few managers in the company have access to the analysis results.
INTEGRATED ARCHITECTURE	21) The organization collects and manages structured (i.e., sales data in tabular format) and unstructured (i.e., Video and Audio) data types for its analysis activities. 22) Employees can access data as needed, including structured and unstructured data, through a well-defined governance process. 23) The data formats are standardized and documented. 24) There is a single data model to which all the business units refer.

Table 1: Assessment submitted to the participants (cont.).

Domain	Questions
DATA INTERFACE	25) Analysis solutions are designed to provide the best user interface to the right person (for example, corporate analysts, business users, data scientists, data engineers, et al.). 26) Employees do not receive guides on how to access the data. 27) It is easy to get data in a format not covered by existing interfaces; the technical support needed is minimal, and the request is standardized. 28) Corporate data are accessible through a business intelligence interface that allows users to combine different data sources, create graphs and tables with a high degree of customization, and allows users to share the most interesting views with other stakeholders. 29) Data Scientists and Business Analysts are able to connect any application developed with the latest data available at the needed level of detail.
ANALYTICAL SKILLS	30) The knowledge of data science techniques is widespread in the organization, even outside the business units dedicated to data analysis. 31) The analysts use tested and documented tools and methodologies to respond to the business questions of the organization, which requires analytical support. 32) There is a career model for Business Analysts and Data Scientists. 33) The company has a clear recruitment strategy for data professionals. 34) There is a broad and modular program for analytical skills development open to all employees and modulated according to career aspirations and personal interests. 35) The organization invests in the training of data analysts.
INTEGRATED ORGANISATION	36) Business Analysts and Data Scientists operate in an integrated manner with the rest of the organization. 37) Analysts are in contact with corporate opportunities and challenges; they can directly impact decisions and influence the corporate strategy. 38) Analysts' priorities are defined according to urgencies and are not linked to the company's opportunities.
DATA FRIENDLY APPROACH	39) The entire organization is pervaded by widespread knowledge and live interest in data, and the role of analytics is recognized in guiding the company to success. 40) Top Managers are consistently leveraging the recommendations generated by data and algorithms.

We leveraged the Analytic Hierarchy Process (AHP) (Thomas L. Saaty, 1990) to obtain appropriate weights for the questionnaire answers. The result of this process is a scoring system that evaluates the data maturity of a company and includes the principal characteristics that a company must have to become data-oriented and make data-driven strategic decisions. Moreover, this assessment gives more importance to the domains that managers think are more important in a data-driven company.

3.3 The Analytic Hierarchy Process

The AHP process is a quantitative method for making decisions based on the relative importance that people arbitrarily assign to certain factors. This process requires answering pairwise comparison questions structured in the following way:

(A) is X times more important than (B)

Or

(A) is as important as (B)

Or

(B) is X times more important than A

Weights for the single criteria are then computed in the following way.

$$V_1 = \sqrt[3]{x_{11} * x_{12} * x_{13}}$$

Which is the criterion 1 geometric mean. Then each geometric criterion mean is divided by the sum of all criteria:

$$W_1 = \frac{V_1}{V_1 + V_2 + V_3}$$

The 15 questions in the second section of the CBDAS require the respondent to choose between a pairwise comparison of data maturity characteristics and how much it counts on a specific aspect versus one other to improve big data management, according to the organization's reality.

In our specific case, the AHP process was used to evaluate the following company characteristics, derived from the conceptual CBDAS:

1. The proliferation of a data culture across the entire organization.
2. Availability of IT services.
3. Managers' support in data-driven projects.
4. Care of analytical talents within the company.
5. Satisfaction of technological needs.
6. Business sponsorship to facilitate data-driven decision-making.

The respondents were allowed to rank one of the options from equally important to 3 times more important, according to the respondent's perspective on its organization reality. It is crucial to figure out that not all the domains could always be relevant to a particular context (Walls & Barnard, 2019). For the same reason, certain factors may be more important than others in specific sectors. To respond and collect all those situations, we included the respondents' possibility to assign different weights to each organizational need in this section of the assessment. The resulting AHP matrix is shown in Table 2.

Table 2: AHP Matrix results based on the interview of 261 Italian managers and entrepreneurs.

	Proliferation of a data culture across the entire organization	Availability of IT services	Managers' support in data-driven projects	Care of analytical talents within the company	Satisfaction of technological needs	Business sponsorship to facilitate data-driven decision making
Proliferation of a data culture across the entire organization	1.0000	1.6061	0.9394	1.0000	1.6902	0.5926
Availability of IT services	0.6226	1.0000	0.5000	0.5000	1.2677	0.5505
Managers' support in data-driven projects	1.0645	2.0000	1.0000	0.8451	0.8923	0.8165
Care of analytical talents within the company	1.0000	2.0000	1.1833	1.0000	0.9646	0.6246
Satisfaction of technological needs	0.5916	0.7888	1.1208	1.0366	1.0000	0.6768
Business sponsorship to facilitate data-driven decision making	1.6875	1.8165	1.2247	1.6011	1.4776	1.0000

The associated weights are depicted in Figure 1:

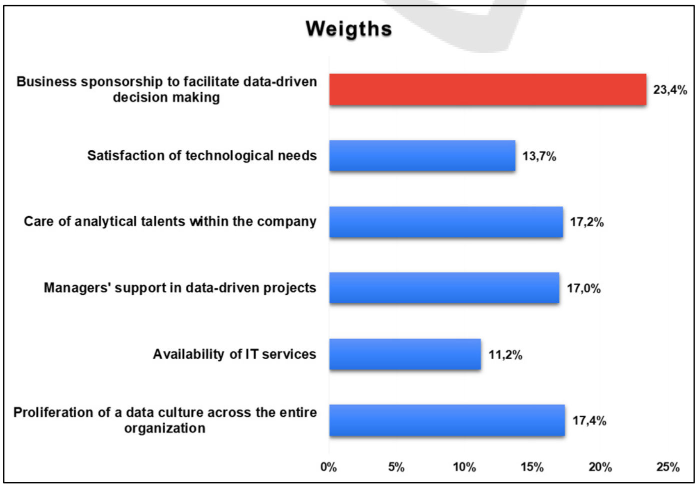

Figure 1: AHP weights for each of the dimensions chosen in this study. According to more than 261 managers interviewed, the key factors for a company's data maturity are that the business facilitates data-driven decisions and the proliferation of data culture across the entire organization.

4 ASSESSMENT RESULTS

The questionnaire results are synthesized in Figure 2, where the respondent proportion for each question is represented as vertical bars of distinct colours. As shown in the bar chart, more than half of the respondents agreed or strongly agreed to the importance of "Integrated architecture", "Data Friendly" and "Integrated organization" domains. This can also be seen in Figure 3, where the unweighted score shows how the domain in which the interviewed agreed more are the same mentioned before. The situation changes dramatically if one considers not only how strongly each person agreed to a certain question but, most importantly, how much importance relative to the other domains each person would give (i.e., by applying the AHP weights to the unweighted scores). This can be seen in Figure 4.

In Figure 4, one can see that once one considers the weights from the AHP, data friendliness in the organization becomes the most sought-after characteristic. Followed by "Integrated Organization" and "Analytical Skills."

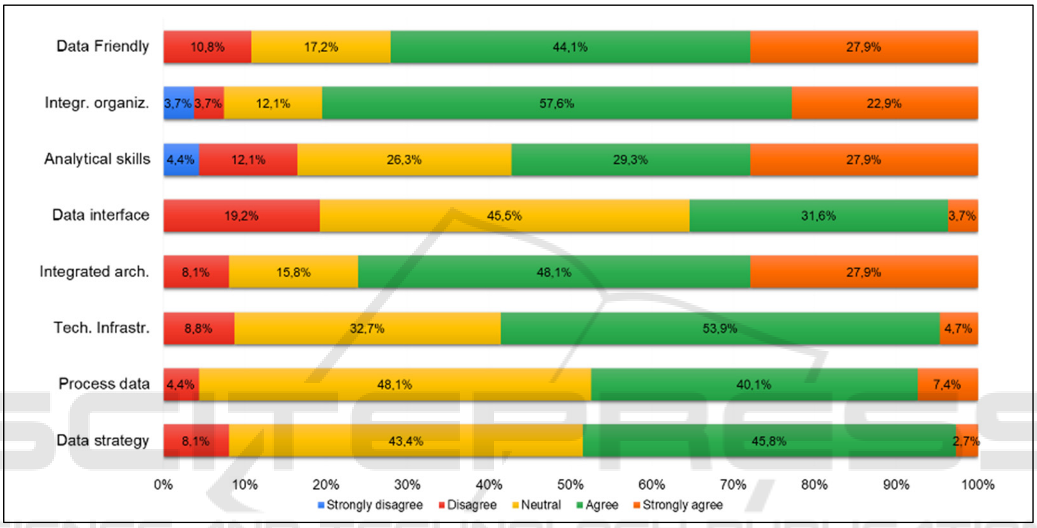

Figure 2: Relative percentage of answers for each domain.

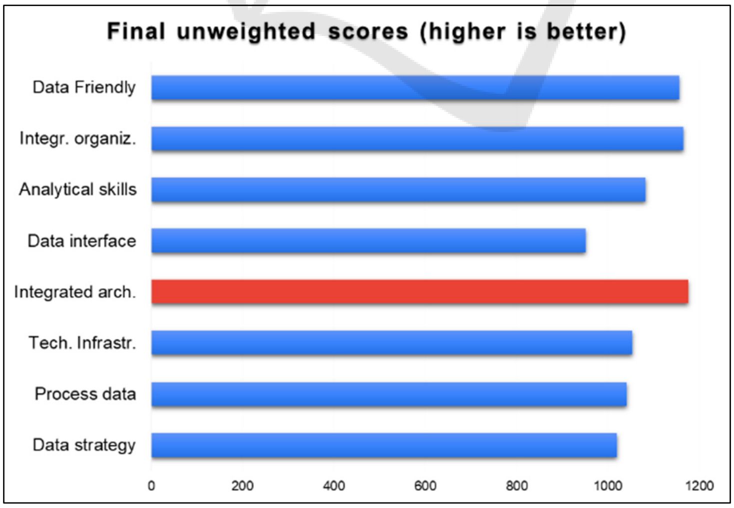

Figure 3: Unweighted final scores. This graph compares the sum of the Likert scores given by each of the 261 people interviewed.

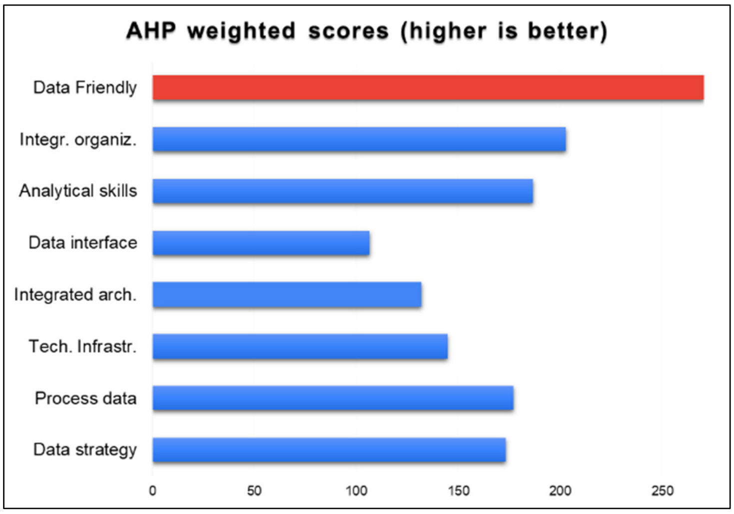

Figure 4: Final scores weighted using the AHP process. The results now look quite different since the domain "data-friendly" was considered the most important (higher weights) in the AHP process.

4.1 Correlation among Parameters

As one may expect, there may be correlations among domains due to their nature or to the similarity of questions. To investigate that, we calculated a correlation coefficient between every domain listed in Table 1. To do that, we used a Spearman correlation coefficient (Spearman rank correlation) (Spearman, 1904) that has the advantage of not being limited to continuous numerical variables but can also be applied to discrete ordinal variables. Moreover, this method of calculation can spot strictly non-linear correlations and can assess how much two variables are correlated by a monotonic function (Zar, 1972). For linear relationships, the two methods give similar answers. The value of Spearman's R is always between -1 (indicating a perfect negative correlation) and +1 (indicating a perfect positive correlation). Weak correlations have R values $0 < |R| < 0.2$, moderate correlations $0.2 < |R| < 0.6$ and strong correlations $0.6 < |R| < 1$ We have created a correlation Matrix using the software R 4.1.2 and the command *rcorr*. The results are shown below in Figure 5.

It was to be expected that only positive correlations had to be found since all questions in the Likert scale go in the same direction. The strongest correlations happen to be between data process integration and data-friendly approach, where a R=0.78 indicates a strong correlation. It also appears a strong correlation between the domain integrated architecture and data interface with a Spearman's R=0.72.

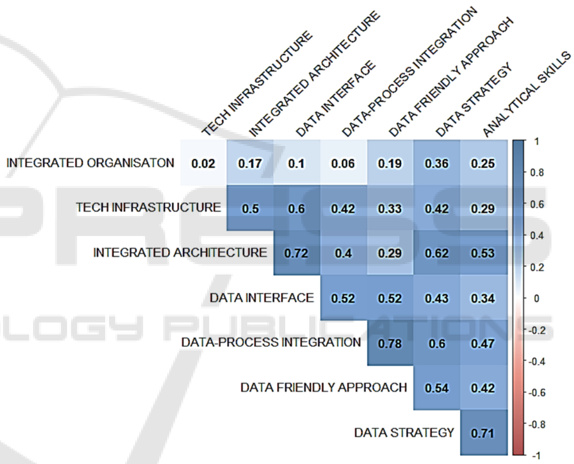

Figure 5: Spearman correlation matrix among domains scores.

4.2 Stratification By Company Sector and Size

A series of demographic questions were asked to the participants when the assessment was submitted to them. We collected information about the characteristics of the company to which they belonged. The questions were focused on the company size and the sector in which it operates. This allowed us to stratify for such parameters and search for statistically significant differences.

The results of this stratification are shown in Figure 6 and Figure 7.

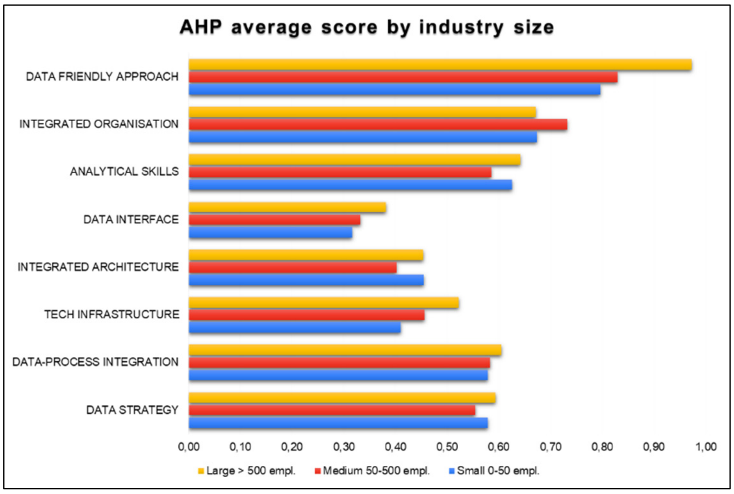

Figure 6: AHP-weighted average score by industry size. The results look very similar among different company sizes.

Table 3: ANOVA output. The p-value << 0.05 indicates that we can reject with a high degree of confidence the hypothesis that the average scores of companies by DOMAIN are the same.

ANOVA						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
DATA STRATEGY	3	1.726453388	0.575484463	0.000372		
DATA-PROCESS INTEGRATION	3	1.767461022	0.589153674	0.000201		
TECH INFRASTRUCTURE	3	1.389559865	0.463186622	0.003198		
INTEGRATED ARCHITECTURE	3	1.310043357	0.436681119	0.000883		
DATA INTERFACE	3	1.030418065	0.343472688	0.001125		
ANALYTICAL SKILLS	3	1.852298318	0.617432773	0.000828		
INTEGRATED ORGANISATION	3	2.077575264	0.692525088	0.001193		
DATA FRIENDLY APPROACH	3	2.597837495	0.865945832	0.008814		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	***P-value***	*F crit*
Between Groups	0.557008477	7	0.07957264	38.31854	**7.88E-09**	2.657197
Within Groups	0.033225746	16	0.002076609			
Total	0.590234223	23				

The stratification by company size shows that the only domain where there could verify differences among the different-sized company is the data-friendly approach. However, such differences have to be ascertained by means of appropriate statistical tools. We performed an ANOVA (ANalysis Of VAriance) test (Fisher, 1946) to search for statistical differences among groups. ANOVA tests the null hypothesis that the averages of the groups belong to the same distribution by testing the variance between and within groups. We first tested for significant differences among domains, the results of which are shown in Table 3.

Since the p-value is $p \ll 0.05$, we can reject the hypothesis that the different domains have equal means (i.e., there are significant differences).

Regarding the scores of companies of different sizes, the results were opposite and are summarized in table 4.

Since the p-value >> 0.05, we observe no statistically significant differences among different company sizes in this case. This can be interpreted as companies of varied sizes having the same data-maturity aspirations and ambitions. The stratification for the company sector also shows similar results. Figure 7 and Table 5 show no statistically significant differences in data needs and maturity scores among companies operating in different sectors.

Table 4: ANOVA output. The p-value >> 0.05 indicates that we **cannot** reject the null hypothesis that the average AHP-weighted scores of companies by SIZE are the same.

ANOVA (company size)						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Small 0-50 employees	8	4.433638116	0.554204765	0.023713		
Medium 50-500 employees	8	4.47730905	0.559663631	0.027267		
Large > 500 employees	8	4.840699608	0.605087451	0.031556		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	***P-value***	*F crit*
Between Groups	0.012485788	2	0.006242894	0.226917	**0.798916**	3.4668
Within Groups	0.577748435	21	0.02751183			
Total	0.590234223	23				

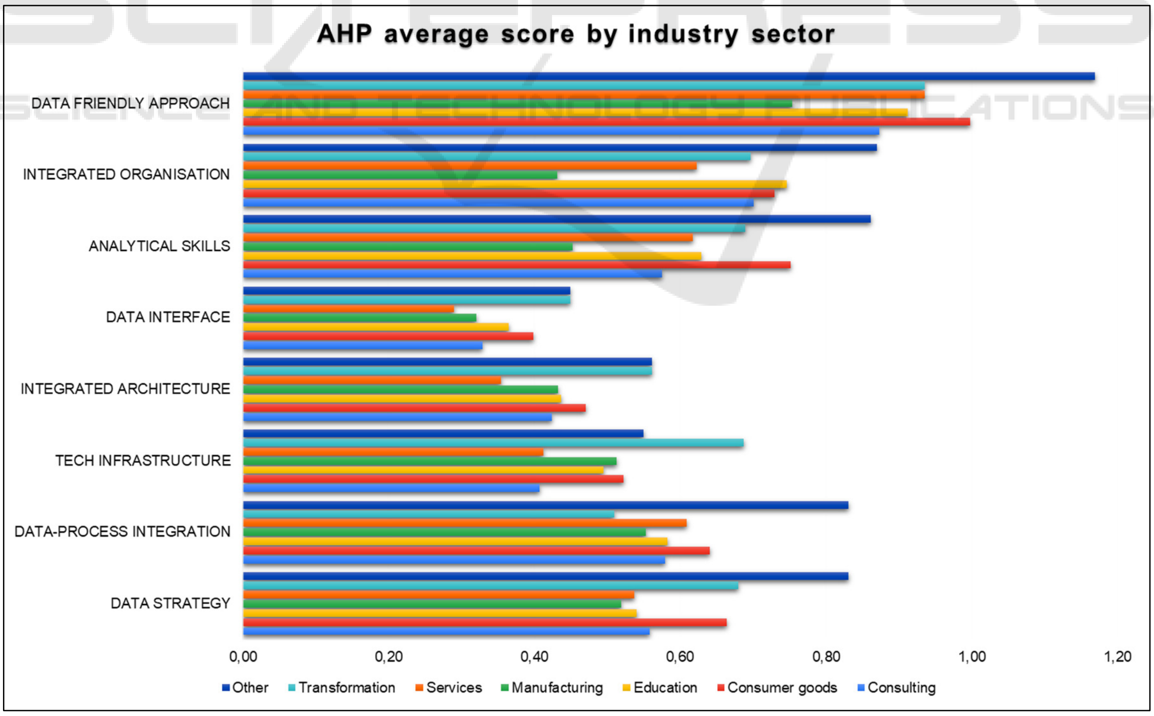

Figure 7: AHP-weighted average score by industry sector. The results look similar among different company sizes.

Table 5: ANOVA output. The p-value > 0.05 indicates that we cannot reject the null hypothesis that the average AHP-weighted scores of company sector are the same.

ANOVA (company sector)						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Consulting	8	4.445729	0.555716	0.030538		
Consumer goods	8	5.172092	0.646512	0.035667		
Education	8	4.705451	0.588181	0.030794		
Manufacturing	8	3.972509	0.496564	0.015973		
Services	8	4.37681	0.547101	0.040978		
Transformation	8	5.208651	0.651081	0.022189		
Other	8	6.123635	0.765454	0.054318		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.379039697	6	0.063173	1.918852	0.096414	2.290432
Within Groups	1.613199204	49	0.032922			
Total	1.992238901	55				

5 DISCUSSIONS AND CONCLUSIONS

We have created an AHP based evaluation system for estimating companies' data maturity and the importance that their managers assign to data-driven choices. Our results suggest that the data-maturity estimator that is considered as most important by the interviewed managers was "Data friendliness", followed by "Integrated Organization" and "Analytical Skills". Moreover, we have found evidence that the relevance of the 8 critical success factors included in CBDAS is statistically independent of the size of the company and the sector in which it is operating, making the assessment of general applicability for a broad range of business organizations. Our findings suggest that, when companies look for new opportunities to use analytics, the presence of data-driven culture is of primary importance for making data initiatives able to generate business value (McAfee & Brynjolfsson, 2012; Vidgen et al., 2017). We believe that managers' support rule should be promoting a broad sense of data ownership by all employees and a solid connection between data professionals and business functions (Bahjat et al., 2014; Comuzzi & Patel, 2016). This enables data experts to directly impact business decisions and influence business strategy. By having top managers seeking advice from data analysts, organizations recognize and accept the central role of data in decision-making, business transformation, and innovation. Our research also highlighted how the characteristics identified by managers as relevant (i.e., corporate culture) do not correspond linearly to those with a higher degree of maturity. This mismatch between managers' perceptions and the implementation of concrete actions suggests the usefulness of a system of recommendations for bridging the existing maturity gap in higher priority areas.

The current study is affected by some known limitations that provide opportunities for future research. Firstly, the limited sample size requires the assessment to be tested with a broader audience involving a larger number of enterprises respondents to confirm preliminary insights obtained from the current analysis. Secondly, the scope of the interviewed audience was limited to Italy, causing its findings to be prone to specific local dynamics. Thirdly, more robust qualitative research is needed to assess the sufficiency of the critical success factors included in the assessment model that was used in this study. A future direction of the study would be to create a specific model for different company contexts capable of thoroughly evaluating how every aspect of data management change according to the complexity of the organizational network (Daryani & Amini, 2016; Gökalp et al., 2021). This will allow increasing the practical applicability of the rule-based recommendations, obtaining specific indications to be implemented in the process of improving business choices.

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