Toward the implementation of a Consensual Maturity Model for Big Data in Consumer Goods companies

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Abstract

This paper presents the Consensual Big Data Maturity Assessment System (CBDAS) implementation in a multinational company leader in the Consumer Goods sector. The business case illustrates the objective and the approach which has been taken with the CBDAS initiative. The paper aims to justify the assessment system as a dynamic and flexible system for enterprises operating in the Consumer Good sector. It can be leveraged to understand the maturity stage in the big data domain and guide organizations about their status of advancement in proposing successful big data initiatives. Some results of the first cycle of evaluation by the Senior Managers and IT decision-makers of Procter & Gamble Company are pinpointed to illustrate the advantages and the exchange of good practices following the evaluation.

The paper introduces the CBDAS initiative, implemented on a web application, organized in eight business-relevant domains, comprehensively covering all aspects impacting big data initiatives' success. The assessment contains weights to evaluate the corresponding relevance of a certain domain within the organization's reality.

Company data activities generate value in synergy with other assets. Therefore, to estimate whether it is a priority to intervene, i.e., on the technologies, data strategies, or organizational culture, we isolate the processes and flows deriving from data initiatives in the company, mapping two exemplary processes to intercept priority actions of intervention. Therefore, by determining the type of interventions on processes and maturity levels in each data maturity domain, we derived concrete actions to bridge the existing maturity gap in higher priority areas.

Keywords – Big Data; Analytics; Maturity Model; Assessment system; Business Intelligence.

Paper type – Academic Research Paper

1 Introduction

In the "Big Data" era, the importance of data analytics to businesses has been acknowledged (Grover et al., 2018; Günther et al., 2017; Mikalef et al., 2019). Nowadays, data-driven decisions are required for defining a company's medium and long-term strategy and can turn into a huge competitive advantage (Kubina et al., 2015). Big data maturity models are proper frameworks to understand how to best integrate big data efforts into the company for long-term planning (Al-Sai et al., 2019).

By leveraging a maturity model, data maturity can be assessed at the sub-domain level when referring to micro-level elements like routines and organizational requirements. When referring to macro-level factors at the domain level, assess the required circumstances to reach maturity stages using a maturity model. Microlevels clarify the activities and processes to guide maturity within businesses, whereas macrolevels examine strategic determinants of big data initiatives' success. (Comuzzi & Patel, 2016; Halper & Krishnan, 2014; Nott, C. and Betteridge, 2014).

The maturity models can look into various topics, including IT management, the business intelligence ecosystem, and data warehouse adoption. Big data maturity models, in general, provide the most value to a company when they are used to examine how business and IT processes interact with big data projects, giving management the knowledge they need to make strategic and operational decisions. (Al-Sai et al., 2019). Data models help outline the optimal choices for a path of improvement of the business management system. Data model frameworks are often complemented by a practical assessment system, with a scorecard and recommendations on the immediate next steps to take for the organization. A prescriptive recommendation system assists in determining the best choices for a business management system improvement path (Wamba et al., 2017). Processes can be prioritized using maturity models depending on their progress and the company's maturity in its reference area. As a result, the organizations could build a progressive roadmap focused on relevant areas of intervention, actionable and easy to follow progressively.

In this study, we leverage the business case to understand the applicability of the CBDAS to a consumer goods multinational company. First, we analyzed the big data maturity of the company according to the consensual model proposed. Secondly, we examined two exemplary IT processes to understand their impact on big data initiatives. Third, we understood the criticality and the operating status that the company is called upon to face when acting on IT processes related to data analytics. The operating status and the criticality of the process indicate whether it is a priority to intervene in a certain process.

Lastly, we obtained a matrix to visually highlight the major critical issues and generate a roadmap of actions (Schumacher et al., 2016) to be taken with the related priorities. As a result, the paper derives insights on the priority processes that the managers give on data-driven choices and on the process improvements to apply to companies according to their maturity stage. An action plan priority-based specifies which maintenance tasks are related to high maturity/priority processes and which intervention actions are related to lower priority/maturity processes.

2 Literature Review

2.1 The Consensual Big Data Assessment System

The big data maturity models are frameworks that allow assessing the company's ability to exploit the information in its possession to create value from data. Those models address the choices of old and new big data initiatives that can generate new knowledge useful for business development (Grover et al., 2018). The CBDAS is a model for assessing big data maturity that assigns weight to critical success factors for initiatives related to the use of big data (De Mauro et al., 2021). It is organized in business-relevant domains and subdomains to provide a clear conceptual structure and recommendations for guiding organizations to the next maturity 'stage.' The assessment system – implemented on a web application - automatically evaluates the enterprises' ripeness levels on each subdomain, leveraging rule-based satisfaction criteria to recommend the immediate next steps for enterprises to achieve a higher maturity level. The CBDAS integrates the most critical success factors for firms' success, retrieved through a selection process and structured content analysis for critical success factors recognition and definition (Walls & Barnard, 2019). The CBDAS clarifies that specific stages of maturity expected for each key element should not be missing to drive successful big data initiatives. Those key elements of success are coherent with the essential components of big data and consensual with the most prominent existing models.

By investigating how business processes interact with big data initiatives, the CBDAS might be able to offer management the knowledge they need to make strategic and operational decisions.

2.2 Process mapping and reengineering

The process mapping can be represented through a graphical representation - the flow diagram - where it appears very clear every process legacy to the following ones. The mapping must concern the processes intended to be monitored, identifying the decision points of the process or the steps for which it is necessary to decide on a possible change. It is essential to know when the process is performed, the reasons, and other operations involved to determine which processes to reengineer. A process reengineering refers to a modification of the business processes or a total revision to develop significant improvements concerning the critical parameters, such as costs, quality, service efficiency, or any other aspect of business management that can be widely improved.

The reengineering of processes occurs after assessing the degree of criticality of the various processes and their state of operation. Based on this information, one can present four different situations, high criticality and low degree of operation, which will lead the company to opt for a radical improvement, high criticality and high degree of operation, will develop the decision of a continuous improvement, low criticality and low state of operation will determine an incremental improvement, low criticality and high operation will produce maintenance of the process in the state in which it is.

The process intervention can occur through incremental or continuous improvement or reengineering, which involves a radical change.

Introduced by Hammer (1993), the concept of Business Process Reengineering highlight that it is necessary to open up to a modernization of the most innovative technologies, redesigning the work and production processes of the company. Davenport (1993) supports the idea of adopting a remodeling of processes in which reengineering and continuous improvement find the right balance. The author recommends adopting the best and most innovative technological proposals and changing the organizational structure by involving customers in the process of reengineering, alternating with phases of control and continuous improvement. Harrington (1994) is directed towards redesigning the processes or to a more modest organizational change and consequently less risky. Daniel Morris and Joel Brandon (1994) support the idea that reengineering processes must be considered within a much broader organizational change that considers a reference scenario and long-term objectives and uses traditional management methodologies alternating with reengineering techniques.

The reengineering involves three phases: 1) definition of the scope of reengineering, 2) the diagnosis of critical issues and priorities, and 3) the redesign of processes. In particular, 2) aims to identify, starting from the analysis of the current situation and the modeling of processes to be reengineered, the main differences or gaps compared to the needs of users and priorities for action at the same time. Important aspects in the evaluation of criticality are the influence of the process to be reengineered on turnover, customer relations, and the possibility of obtaining a competitive advantage in the market that can be both cost and differentiation.
Concerning the criteria for identifying the operating states, the main aspects to be taken into consideration are the evaluation of the reliability processes that indicate the real possibilities of making the processes operational with the resources available the (Morris & Brandon, 1994), evaluation of the costs that will have to be faced with making changes to the process. In this case, a cost-benefit evaluation can provide decisive information for the final choice, the identification of any regulatory and bureaucratic restrictions that may prevent or limit the use of a particular process.

3 Methodology

3.1 Sample selection

We chose for the practical assessment a company operating in the Consumer Goods sector since big data analytics has a critical role in influencing company decisions and driving organizational change in this area (Mariani & Fosso Wamba, 2020; Zaki et al., 2017). The chosen firm has a consolidating experience in data analytics and data-driven projects. The managers who took part in the test have extensive experience launching successful big data initiatives and are mainly company directors, senior managers, and IT experts.
Inclusion criteria were related to the seniority of the respondents (Senior Managers and Directors) and their confirmed experiences in the area of data analytics or on data-driven projects. Table 1 present the overview of the subject's expertise areas, the experience, and the position covered in the organization, if directly or indirectly related to the data analytics field (Analytics area (direct link), Business area (indirect link)).

Position	Roles	Respondents	Expertise area
Analytics area	Analytics & Insights Senior Managers and Directors. Data Science Senior Manager	4	Corporate data strategy and design. Data integration into business processes long-term strategy. Corporate data architecture and data management to support strategic business-IT alignment. Implementation of data strategy to drive business value. Responsible for data analyst recruitment. Data architecture and pipeline design for the implementation of new capabilities. Responsible for data analyst recruitment and tech skills requirements.
Business area	Business Senior Manager and Directors	4	Business Sponsorship of Data Projects. Corporate strategy integration of data processes. Data projects prioritization and value tracking. Data-driven project leadership.

Table 1: Experts interviewed for CBDAS implementation

The sample covers the primary subjects who handle and analyze big data, establish big data business strategies, and monitor the impact of data analysis on creating business value for the company, as indicated in Table 1.

3.2 CBDAS assessment structure

The CBDAS assessment is based on a first part structured in 40 questions used to assess eight domains that allow the evaluation of data maturity on essential success factors for big data initiatives; the second part is made up of 15 questions that focus on a pairwise comparison of the company's data maturity characteristics, which reflect a multifactorial combination of the eight critical success factors. The Analytic Hierarchy Process (AHP) allows assigning different weights according to the manager's perspective on the key elements a business must have to become data-driven and make strategic decisions based on data. Therefore the weights allow for improving the final assessment of the maturity of a company concerning the domains that managers think are more important in a data-driven company according to the business reality. Table 2 synthesizes the domains and subdomains derived from the conceptual CBDAS (De Mauro et al., 2021), which are investigated in the assessment:

Domain	Subdomain
Data Strategy	Corporate data-driven strategy development and communication (Grossman, 2018; McAfee & Brynjolfsson, 2012); Top management sponsorship (Bahjat et al., 2014; Comuzzi & Patel, 2016); Data privacy (Davenport, 2018; Pham, 2018); Data procurement and utilization strategy (Grossman, 2018; Hornick, 2018)
Integrated architecture	Data architecture; data quality; DevOps; data integration and data management (Hostmann & Hagerty, 2010; Middelburg, 2019); data sources availability and relationships (Davenport, 2014; Fisher, D., DeLine, R., Czerwinski, M., & Drucker, 2012; Wu et al., 2013); data sources documentation, mapping, and communication across the organization (Marr, 2016; Olszak & Mach-Król, 2018)
IT Infrastructure	Data security and Risk Management (Pham, 2018); storage and computational resources (Davenport, 2018; Middelburg, 2019); cloud-based solutions and big data infrastructure (Menukhin et al., 2019)
Human Data Interface	Data accessibility and usability (Rimland et al., 2013); business intelligence systems, analytical toolkit, and data visualization platform (Bikakis et al., 2019; Farah, 2017); guidelines and documentation on data access and usage (Comuzzi & Patel, 2016)
Analytical human workforce	Analytics workforce competency and skills (Olszak & Mach-Król, 2018); job families definition; analytics workforce selection and training guidelines (Davenport, 2014; Davenport & Patil, 2012; De Mauro et al., 2018); corporate-wide development framework for analytical competencies (Popovič et al., 2018; Radcliffe, 2013)
Integrated organization	Collaboration on data analytics within the organization (Atzori et al., 2010; Hornick, 2018); power and knowledge flows (Comuzzi & Patel, 2016; Russom, 2011)
Data-friendly corporate culture	Data-driven decision-making; data exploitation and publicization (Brynjolfsson et al., 2011).
Data-reliant Business Process	Business-based analytics priorities definition (Farah, 2017); data analytics impact measurement and performance indicators (Farah, 2017; Hsieh et al., 2020); the centrality of data-based insights (McAfee & Brynjolfsson, 2012)

Table 2: Domains and subdomains of the CBDAS

3.3 Exemplary IT processes selected

We analyzed two exemplary IT processes, IT Risk Management and IT Talent Management. The exemplary data processes required the manager to evaluate their criticism and functional status.

- IT Risk Management provides information to IT Policies & Standards, Processes, and Tools to drive progression in behavior for how the organization acts towards risks while increasing the overall awareness to drive value as a function of risk and return. Risk Management is the process of identifying, evaluating, and prioritizing risks. The opportunity is in how an organization reacts. Given that every decision either increases, preserves, or erodes value, the intent of IT Risk Management is to reinforce the company's commitment to managing risks arising from Information Technology assets in accordance with the Business Impact Assessment so that the organization continues to work in the marketplace while maintaining an acceptable risk posture. The process also ensures management has visibility of IT policy gaps and takes appropriate decisions based on risk. From an IT Governance standpoint, this allows having central visibility to where there are compliance gaps so appropriate actions may be taken. As the second line of defense of IT for the Company, IT Governance teams are accountable for ensuring IT policy creation, deployment, and compliance. Legal review is required if the request is being made for an IT solution that processes or stores highly restricted or secret data; processes or stores PII data or is used for managing Company finances.
- IT Talent management process consists of identifying a vacant position, hiring a suitable candidate, developing the candidate's skills and expertise to match the position, and retaining him to meet long-term business goals. The steps in the process are 1) planning by identifying the need for human capital, creating a job description, and defining key roles; 2) proposing a workforce recruitment strategy; 3) attracting, choosing whether to recruit internally or externally, and looking for qualified candidates to fill open positions; 4) recruiting and hiring, it entails the procedures of making arrangements for written tests and interviews and examining the most suitable candidate for the position; 5) developing, preparing the employee according to and for the organization implementing a new employee onboarding or orientation program and enhancing personnel's skills, aptitude, and proficiency to match the profile. Employee counseling, guidance, coaching, education, mentoring, and job rotation. 6) Retention is critical for any company's long-term success. It is granted by promotions, pay raises and providing growth opportunities by entrusting special projects. Managers must lead in paving the way for personal growth and long-term affiliation with the company and ways to motivate and retain employees. A Talent Management process is created to effectively and efficiently facilitate assignment planning and staffing solutions across Organization Units for talent pools. The process enables longer-term career planning and guides assignment planning, staffing solutions, and Promotions. By having a properly designed Talent Management process, IT has transparent, simplified recognition and promotion procedures that recognize IT mastery and business results for individuals and teams through the Leading IT and IT Experts programs.

3.4 IT processes mapping to CBDAS domains

We can identify what are the CBDAS' domains that intercept the exemplary IT processes described since the assessment subdomains focus on maturity micro-levels (see Table 2) that clarify the processes and their interconnected activities carried out to convert a resource into a product or service that is designed to steer firm' data maturity (Comuzzi & Patel, 2016). Indeed, since the CBDAS defines domains to determine the maturity stages of the organization, one can map the areas, whereas the processes described are evaluated at the domain level. The "Infrastructure" domain of the CBDAS fully encompasses questions to evaluate the data maturity of a company on the Data Compliance and Risk procedures. In particular, some questions of the assessment falling in this domain ask the respondent to report the maturity stage related to Data Compliance procedures (i.e., *"Employees can access data as needed, including structured and unstructured data, through well-defined data governance and data compliance processes*") and Risk Management. We derive that the maturity of the IT Risk Management process is investigated within the IT infrastructure domain of the CBDAS framework.

At the same time, one can map the IT Talent Management process to the "Analytical Workforce" domain since many questions refer to how best to guide the process of talent acquisition and retention within the company, as reported in the CBDAS (i.e., "*There is a career model for Data Scientists and Business Analysts"; "The company has a clear recruitment strategy for data professionals"; "There is a broad and modular program for analytical skills development open to all employees and modulated according to career aspirations and personal interests*").

Each process analyzed fully collapsed in one domain of the CBDAS, whose maturity has been investigated through the submitted assessment.

3.5 IT processes reengineering evaluation

To explore how the assessment of data assets can support process prioritization and performance improvements, we carried out a reengineering assessment method to analyze the priority of reengineering the two exemplary business processes of IT Talent Management and IT Risk Management described. We set up an interview consisting of six questions related to aspects of criticality and operation of talent management and risk management processes.

The questions were submitted to eight managers with expertise in both processes, who used their experience within the business context to answer the questions, and whose scores were appropriately processed to determine the degree of priority in the reengineering processes. The possibilities to manifest the agreement or the disagreement with every question (affirmation) varies from 1 to 5 – according to a Likert scale measurement method - where "1" represents the maximum disagreement and the "5" the maximum agreement grade to the question.

Area	**Question**	Measurement Method
Criticality	It is a fundamental process for the turnover	Likert scale - from "1" to "5."
Criticality	It is a fundamental process for customer relations	
Criticality	It is a fundamental process for obtaining a competitive advantage	
Operating Status	It is a reliable process	
Operating Status	It is a process that causes extra costs	
Operating Status	It is a process that has legal constraints	

Table 3: Questions for process prioritization

The corresponding answers provided by the subject allow us to evaluate the criticality and Operating Status of each process analyzed to derive its prioritization according to its calculated relevance for business results and operations within the organization.

4 Results

4.1 Assessment Results

The CBDAS results are synthesized in Figure 1, which compares the sum of the Likert scores given by each people interviewed. As shown in the graph, thanks to the answers of the interviewees, we noted a high degree of maturity in the "Data Strategy," "Integrated organization," and "Tech infrastructure" domains. Overall, the maturity levels on the data domains appear high compared to the maximum achievable value (40). According to the manager's perspective, the lowest values are related to the "Data Interface" domain.
When one analyses not just how strongly each individual agreed on a particular subject but also how much weight each person would give it concerning the other domains, the situation changes radically. (i.e., by applying the AHP weights to the unweighted scores). This can be seen in Figure 2.

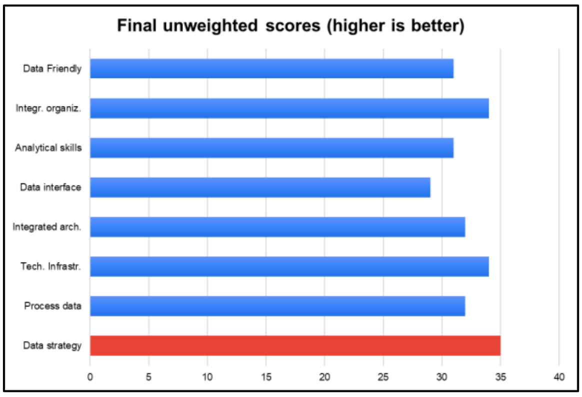

Figure 1. Unweighted scores - sum of the Likert scores given by each people interviewed.

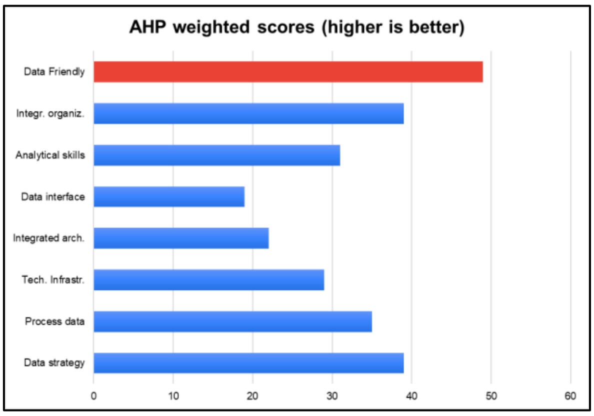

Figure 2. Final scores weighted using the AHP process.

When the weights from the AHP are taken into account, data friendliness in the organization emerges as the most desired attribute (see Figure 2). "Integrated Organization" and "Data Strategy" come next.

4.1.1 Domain Correlation

Due to their nature or the similarity of topics, there may be relationships among domains, as one might assume. We used the Spearman correlation (1904) to calculate the correlation coefficient between each domain in Table 1. The value of Spearman's R is always between -1 (showing a perfect negative correlation) and +1 (representing a perfect positive correlation). We constructed a correlation matrix using the software R 4.1.2 and the function rcorr. The results are depicted in Figure 3.

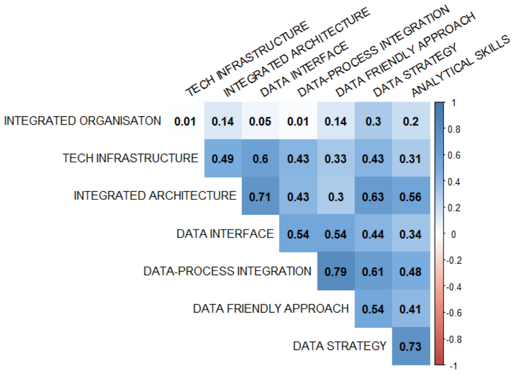

Figure 3. Spearman correlation matrix among domains scores.

Because all items on the Likert scale go in the same direction, it was assumed that only positive correlations would be detected. Data process integration and data-friendly approach have the strongest correlations, with an R=0.79 indicating a substantial association. With Spearman's R=0.73, there appears to be a high association between domain data strategy and analytical skills.

4.1.2 Degree of dependence

The fact that managers assign various ratings to different comments can be explained by the fact that the evaluations are subjective and not linked to objective characteristics of the criticality or function that was the subject of the interview. On the other hand, such discrepancies must be determined using appropriate statistical procedures.
The relationship between the business functions covered (Analytics or Business area) and the positive or negative score of the judgments attributed by managers appears to be particularly important, and it seems appropriate to analyze the degree of dependence between these statistical mutable statistically.
Cramer's index is the statistical index that lends itself best to determining the degree of changeable dependence:

$$C = \sqrt{\frac{\Phi^2}{min\{(r-1),(k-1)\}}}$$

To better understand the index's substance and meaning, we can look at the table below, which comprises the preliminary data used to calculate the Cramer index measure. Those numbers are referred to the sum of the Likert scores provided to the CBDAS by each person interviewed, broken down by business function, and categorized into positive and negative ratings.

Position	Positive Score	Negative Score	Total
Business-area	32	8	40
Analytics-area	26	6	32
Total	58	14	72

Table 4: Ratings to the CBDAS by business function

Table 4 reports the number of concordant or discordant scores attributed by managers belonging to the Business coded or Analytics coded function.
From the observed values in Table 4, we derive the corresponding theoretical values in Table 5.

Position	Positive Score	Negative Score	Total
Business-area	32,22	7,78	40
Analytics-area	25,78	6,22	32
Total	58	14	72

Table 5: Theoretical values for the ratings to the CBDAS by business function

Each value in Table 5 is obtained by multiplying the row total by the column total corresponding to a single value and dividing the result by the overall total.
For example, the predicted value of 32.22 is obtained by multiplying 40*58 and dividing the result by 72.
Now we can calculate all squares of the differences between the observed and theoretical values (contingencies) and divide the result by the theoretical values.

$\frac{(32-32,22)^2}{32,22}$ = 0,0015 $\frac{(26-25,78)^2}{25,78}$ = 0,0018 $\frac{(8-7,78)^2}{7,78}$ = 0,0062 $\frac{(6-6,22)^2}{6,22}$ = 0,0077

The values sum represents a measure of the dependence of the differences that exist between business functions and the agreement or disagreement of the scores attributed by managers and is named chi-square (χ^2).

χ^2= 0,0015+0,0018+0,0062+0,0077

χ^2= 0,0172

The chi-square index provides an absolute value of the dependence between the characters considered but does not identify in relative terms the strength or weakness of that dependence; in fact, that measure is provided by the mean square contingency index (ϕ^2) normalized, that is, related to its maximum value.

We start by calculating ϕ^2

$\phi^2 = \frac{\chi^2}{N}$

$\phi^2 = \frac{0{,}0172}{72}$

ϕ^2 =0,000238

The highlighted result shows a dependency value between the business functions and the concordance or discordance of the scores attributed by the managers because the index ϕ^2 varies from zero to one.

Now we can proceed to normalization by comparing this last value to the maximum value it would reach in a perfect dependency table.

In our case, the number of rows or columns is equal to 2, so the maximum value of the mean square contingency index is: $\phi^2 = \frac{\phi^2}{\sqrt{r-1}}$ with r being given by the number of rows or columns. In this specific case, the value of the contingency index remains unchanged.

When the dependency table is perfect, we can speak indifferently of the dependency of the character X on the character Y and vice versa, but when the table is not square, we must make explicit the direction of the dependency, X will depend on Y when it presents a number of modes (rows or columns) less than Y, Y will depend on X in the opposite case.

In such circumstances, the extent, strength, and direction of the dependency are determined by Cramer's index

$$C = \sqrt{\frac{\phi^2}{min\{(r-1),(k-1)\}}}$$

Obviously, in the case just considered, the number of rows is equal to the number of columns so that the Cramer index will assume the value:

$C = \sqrt{\frac{0.000238}{2-1}}$

C= 0,000238

The Cramer index varies between 0 and 1; therefore, the result just reached shows an absence of dependence between the characters taken into consideration, confirming the evidence reported in Table 4 that presents similar row values that indicate how the choice of the accordance or discordance of the scores does not depend on the business functions.

4.2 Processes results

Concerning the talent management and risk management processes, the matrix in Figure 4 reports the scores attributed by managers to the statements regarding criticality and functionality, marking the scores obtained for determining the level of intervention in those processes.

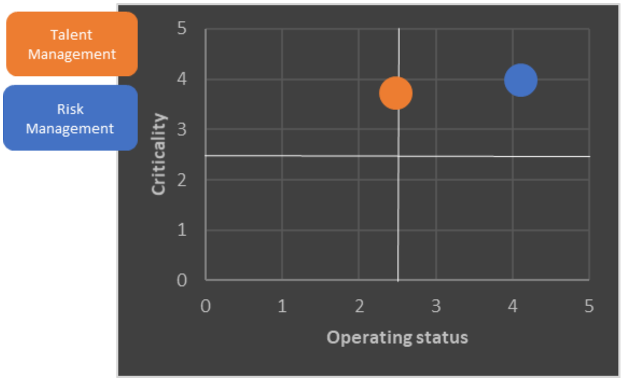

Figure 4 matrix on criticality and operating status for the processes analysed

The talent Management process has high criticality and low degree of operation, which will lead the company to opt for a radical improvement, while the Risk Management process shows high criticality and a high degree of operation. Therefore based on the results reported in the matrix, the company should choose continuous improvement in Risk Management. Since the processes are intimately linked to specific CBDAS domains, it would be necessary to integrate their reengineering with strengthening the aforementioned domains. The prioritization should be determined by the criticality of the process intervention, while the actions to bridge the maturity gaps are identified by the output of the CBDAS recommendation system.

5 Discussions and Conclusions

The CBDAS evaluation system assesses a company's data maturity and the importance managers place on data-driven decisions. According to our findings, the most important data-maturity estimation for the interviewed managers was "Data friendliness," followed by "Integrated Organization" and "Data Strategy."

Furthermore, we discovered evidence that the importance of the eight critical success factors contained in CBDAS is statistically independent of the business function, allowing for a broad assessment of general applicability to include business personnel working in data efforts.

We derive evidence on the criticality and degree of operation of the two exemplary Talent Management and Risk Management processes. By studying their link to specific CBDAS domains, we were able to justify the integration of reengineering and the potentiation of certain business areas identified as more critical for data maturity.

In this way, a roadmap of radical, discontinuous maintenance operations can be reconstructed, leveraging the matrix of processes criticality and operating status for their prioritization and the CBDAS recommendation system to identify improvement actions.

Therefore, starting from determining the type of interventions on processes and maturity levels in each data maturity domain, we could build a roadmap of concrete actions – based on a tested recommendations system - to bridge the existing maturity gap in higher priority areas.

According to our results, actions in the "Analytical Workforce" area could include a clear recruitment and training plan for big data experts based on role families and skillsets, capable of accelerating the transformation to a skills-based organization to increase business agility, productivity, and employee impact. The changeling would impact the design of the people strategy, improving the qualities of the employee skills analysis and the mapping of current roles with the related association of skills.

Furthermore, a relevant career path for data professionals should be offered and kept up to date with industry evolution. The company should regularly evaluate state-of-the-art algorithms, techniques, and tools to improve solution accuracy, insights, performance, and analytical workforce productivity.

Another action to consider consists of enforcing the modular development framework for analytical competencies and formalizing a business-rotation program further to increase the business-domain experience of the analytical workforce.

Indeed, the results suggest a proper level of integration between analysts, decision-making, and knowledge flows present in the organization. Continue to find, maintain, and nourish talented employees capable of implementing methods for big data, and working closely with managers to review company strategies will lead the organization to a long-term strategic integration of the analytical talents with the business-decision processes.

Those activities would increase the Talent Management process's reliability and, as a result, its overall operating condition. As a result of the improvement, the Analytical Workforce domain's overall maturity will improve, and the organization will be able to continue supervising the process with more sustainable actions focused on continuous development.

On the other hand, given the importance of the Risk Management process revested in the firm, it's critical to check in on it regularly to see if any corrective measures are available. The maturity of the corresponding CBDAS domain is relatively high, meaning the Information Systems are respecting the highest standards of security, reliability, and performance, and periodic security reports are already scheduled within the company.

A continuous improvement in this area should ensure the standards are maintained, encompassing the constant change in regulations/laws (GDPR, CCPA, et al.) and the evolution of security threats (e.g., formjacking, cryptojacking, IoT, et al.). Continuous improvement involves a regular reinforcement of the company's commitment to managing risks arising from Information Technology assets in accordance with a business impact assessment so that the organization can continue to operate in the marketplace while maintaining an acceptable risk posture. Some maintenance actions should consist in:

-assessing and updating business risk and compliance of information technology applications and platforms regardless of ownership and remediating these risks to protect the company by verifying compliance.

-Assessing and updating IT compliance exceptions with a list of controls linked to each compliance area.

-Ensuring that the maturity of IT Risk Management is continually assessed against industry standards.

-Building Risk controls by design to grant controls needed for each application are tested and working as expected.

Some acknowledged limitations affect the current work, although this provides opportunities for future research. For instance, the breadth of the interviewees was limited to a single company, making the conclusions susceptible to specific dynamics. A future objective for the research would be to develop a specific model for various firm contexts, capable of thoroughly examining how every component of data management changes as the organizational network becomes more complex. (Daryani & Amini, 2016; Gökalp et al., 2021).

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