

Original Research

Analyzing the Global Big Data Maturity Model Domains for Better Adoption of Big Data Projects

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Abstract

For many years now, big data has revolutionized the world. Today, companies know that creating the most value from their data is essential for their growth. However, not all big data projects are successful; in fact, it is fundamental for companies to make the correct assessment of their capabilities and identify the potential problems to address before the starting point, and this is through maturity models. In previous work, we proposed a new Maturity Model and its framework to track companies' progress toward successful big data implementation. We identified and categorized the factors influencing big data projects into six categories: strategy alignment, data, people, governance, technology, and methodology. The model provided a final score representing the readiness level for an organization to start its big data implementation. In this paper, we focus specifically on the Global Big Data Maturity assessment tool results. We analyze the importance of maturity domains and detail the final score calculation method using the AHP technique. For this research, we reached out to nineteen North African companies' big data experts to give us input about their ongoing projects, and the steps are: (1) Collect nineteen big data expert's ranks for each maturity domain using online forms; (2) Use these ranks alongside the Analytic Hierarchy Process method to have the domain's weights, which were [0.173, 0.278, 0.128; 0.190; 0.064; 0.166], respectively for the domains [strategy alignment, data, people, governance, technology, and methodology]; Then (3) use the domain's weights alongside assessment inputs, to calculate accurate weighted scores. As a result, AHP ranks show that the data dimension has the most impact on big data projects' success, followed by strategy, methodology, governance, people,

and, last but not least, technology. The framework dashboards show that most interviewed North African companies have great big data maturity levels.

Keywords: MCDM, AHP, Fuzzy AHP, Big Data Maturity Model, Big Data Projects.

Introduction

Today, we live in a world where data and artificial intelligence affect the future of every industry and human being. According to Goasduff (2020.) “By the end of 2024, 75% of enterprises will shift from piloting to operationalizing AI, driving a 5X increase in streaming data and analytics infrastructures”. This shows how important it is for companies to use emerging technologies to extract maximum value from their data. However, many articles (Weiner, 2020; Joshi, Su, Austin & Sundaram, 2021) illustrate why big data projects may fail; some even propose pitfalls to avoid. According to our previous research Mouhib, Anoun, Ridouani and Hassouni (2020), the first step toward the successful adoption of big data is to assess companies’ maturity in this area. Hence, we proposed a new Big Data Maturity Model (ibid) to help companies determine their ability to succeed in their big data journey. We deeply analyzed in the previous work the maturity models proposed in the literature, such as the Temporal BDMM (Olszak & Mach-Król, 2018), the Value-Based Maturity Model (Farah, 2017), the Maturity Model By Adrian, Abdullah, Atan and Juso (2016). Also, we went through editors offerings such as TDWI Big Data Maturity Model (Halper, 2020) , IDC MaturityScape (Turner, n.d.), Big Data Maturity Assessment Tool InfoTech (Big Data Maturity Assessment Tool | Info-Tech Research Group, n.d.) among others. Then, we proposed a model that we aimed to be exhaustive, including the methodology domain.

In this work, we have two main goals:

First, we focus on the assessment framework results: we offered our online assessment to nineteen North African companies. Thirteen of them provided their complete inputs regarding the actual status of their big data projects.

Second, we focus on how the score is calculated. None evaluate domain weights based on literature and editors’ assessment offerings such as TDWI (Halper & Stodder, 2014.). However, since the degree of contribution of each domain is not equal, it was crucial to use criteria weighting methods to define the domain’s weight, and consequently the final maturity weighted score. To achieve that, we studied multi-criteria decision-making (MCDM), which allows companies to evaluate and assign weights to conflict criteria in decision-making.

MCDM has been an active area of research since the 1970s. Standley Zionts (Zionts & Wallenius, 1976) proposed, in February 1976, a mathematical programming method for solving the multiple criteria problem involving a single decision maker. Over time, many MCDM methods were proposed: Analytic Hierarchy Process(AHP) (Brunelli, 2015), Fuzzy TOPSIS (Nădăban, Dzitac & Dzitac, 2016), Simple Additive Weighting (Kaliszewski & Podkopaev, 2016) and others. Recently, we have seen authors combine MCDM techniques, for instance, a novel hybrid MCDM model (Krstić, Tadić, Kovač, Roso & Zečević, 2021) or integrated MCDM-SWOT-TOWS model (Đalić, Stević, Ateljević, Turskis, Zavadskas, & Mardani, 2021).

To define the impact of each area on big data success, we surveyed to identify the maturity domain’s ranks. Then, we applied the AHP technique to have the final weighted score for

companies' ongoing big data projects.

Materials and Methods

Assessing maturity level is crucial for any company to evaluate their ability to start their big data journey. We proposed in previous work (Mouhib, Anoun, Ridouani & Hassouni, 2020), the Global Big Data Maturity Model, where we tried to be exhaustive in terms of maturity dimensions, and like any maturity model, GBMM consists of maturity domains and maturity levels. For the maturity domains, we grouped the maturity dimensions into six areas:

- Strategy Alignment: dealing with management sponsorship and the priority of big data projects for the company
- Data: covering data lifecycle, accessibility, and data quality
- People: evaluating team skills
- Governance: dealing with data protection and privacy
- Technology: evaluating the existing analytics platform
- Methodology: covering dealing with project processes, objectives, output, etc.

For the maturity levels, we provided five levels:

- Ad hoc level: the company is not using Analytics
- Explore level: the company is starting to learn about analytics and discovering some Tools.
- Transformation level: data management and traditional dashboards exist at this level.
- Adoption level: analytics is essential for running a company's business. The company is exploring big data use cases.
- Maturity level: agile self-service analytics and consistent data are available to everyone.

We created an assessment tool for the proposed model to collect companies' information about their current big data projects. This tool generates three outputs:

- Score
- Graphic to show the company's performance in each domain
- A list of areas of improvement.

Knowing that we have four questions per domain, for each question, the expert can give a score from 1 to 5, 1 being (Disagree) being (Fully agree). The final score was, initially, a linear sum of domains' scores. This paper aims to enhance these framework results through two research among the same population of big data experts. First, we surveyed to identify maturity domain ranks, and then we offered an online framework to companies to assess their maturity. We went through the steps shown in Figure 1 to have accurate results.

Step 1- We first sent a survey to experts to have a rank for each maturity domain. Of nineteen experts, sixteen of them provided usable ranks.

Step 2- we needed to convert ranks to weights, so we had to study multi-criteria weighting techniques.

Multi-criteria decision-making (MCDM) refers to prioritizing, ranking, or selecting criteria's alternatives based on human judgment. MCDM models are essential in defining criteria weights; many real-world decision-making problems in different industrial fields involve

MCDM. In 2022, we can still find reviews on Multi-Criteria decision-making and its applications, confirming that MCDM is highly relevant to applications in the high-tech market (Soniya, Ramachandran, Sathiyaraj & Mathivanan, 2021). Other reviews are more industry-specific, such as the study proposed by Jamwal, Agrawal, Sharma and Kumar (2021), which reviews multi-criteria decision-making (MCDM) applications in sustainable manufacturing. We can find analysis reviews in health care, such as the study by Alsalem et al. (2022) about multi-criteria decision-making for coronavirus disease applications. We can also find applications of MCDM in renewable energy (Shao, Han, Sun, Xiao, Zhang & Zhao, 2020), in information modeling (Tan, Mills, Papadonikolaki & Liu, 2021), in project risk management (Chen, Chuang, Sangaiah, Lin & Huang, 2019) or supply chain domain (Deepu & Ravi, 2021).

In the literature, we find three types of weighting techniques (Odu, 2019):

- Subjective methods based on decision makers' intuition or judgment, like the ranking ordering method (Roszkowska, 2013), the swing method improved by Mats in 2019 (Danielson & Ekenberg, 2019), the analytic hierarchy process (AHP) proposed by Saaty (1984) and others.
- Objective methods define weights through a mathematical calculation, for example, the entropy method (Zhu, Tian & Yan., 2020), Criteria Importance Through Inter-criteria Correlation (CRITIC) (Alinezhad & Khalili, 2019), and others.
- The integrated methods like the integrated approach by Wang & Parkan (2006) that mixes the decision maker's fuzzy preference relation to decision alternatives, also there is the Belton & Stewart (2002) technique which summarizes two types of weights: tradeoff-based weights and non-tradeoff-based weights, and others.

Step 3- We applied AHP to experts' rank to define the domain's weights

We chose the Analytic Hierarchy Process (AHP) because it is the most popular and well-known member of subjective methods. It is widely used in different fields: management (Al-Harbi, 2001; Liachovičius, Skrickij & Podvieszko, 2020), healthcare (Garrido, Ramírez López & Álvarez, 2021; Singh & Prasher, 2019), manufacturing (Astanti, Mbolla & Ai, 2020), E-Commerce (Bhattacharya & Raju, 2019), transport sector (Kumar, Singh & Vaidya, 2020).

Figure 2 represents thirty MCDM Methods. There is a dominant group of MCDM methods, which is composed of six methods: AHP at 19.25%, TOPSIS at 11.8%, Fuzzy AHP at 6.83%, PROMETHEE at 6.21%, DEMATEL at 5.59% and DEA with 3.73%. AHP represents an interesting and accurate approach to quantifying the weights of decision criteria, especially when the number of criteria is low, which applies to our case because we have only six criteria maturity domains. Finally, the authors claimed that rank-based weighting methods outweigh AHP and others like SWING, Point allocation, or Direct rating; because these methods practically require a decision maker (DM) to assign scores to reflect the degrees of importance of the criteria, results are subjective and hence might be inaccurate. In applying the AHP technique, we will base our pairwise matrix on decision makers' ranks, as we know that our experts are more confident in defining priorities than in providing scores. After collecting big data experts' ranks for each maturity domain, we will use these scores alongside the Analytic Hierarchy Process method for the final accurate weighted scores.

Step 4- We enhanced the framework by replacing linear and weighted scores.

Step 5- We proposed the enhanced assessment to nineteen big data experts in different companies running big data projects. We received thirteen complete feedbacks; the results are covered in the next section.

Results

Define Maturity Domain's weights

We conducted the first survey to identify the domain's rank as described previously. Then, the goal was to convert the results to weights, so we applied AHP to maturity model domains. When applying the AHP, the decision criteria' preferences are compared pairwise for each criterion using a scale table. That means when two criteria are equally important, we give that "1", while a value of "9" designates the absolute prominence of one criterion compared to the other. This is illustrated in the Table1 below:

Table1
Saaty's Scale of Relative Importance (Saaty, 1984)

Saaty's Rank	Compare ranks	Description
1	1 to 1	equally important
3	2 to 1	moderately important
5	3 to 1	strongly important
7	4 to 1	significantly important
9	5 to 1	extremely important

Based on this scale table, a pairwise matrix must be created (Roszkowska, 2013) . For n criteria C_i , we have:

$$A = [a_{ij}] \quad (1)$$

Where $a_{ij} = \frac{w_i}{w_j}$, w_i and w_j are the relative importance of criteria i and j , respectively.

Within our new maturity model, we have six domains, which mean $n=6$. As the length of the pairwise matrix is equivalent to the number of criteria, we will have a square matrix of order 6.

To create this matrix, we needed experts' feedback. Therefore, we surveyed big data experts to define domains' priorities. The experts were asked to give a rank from 1 to 5 to Maturity domains (strategy alignment "C1", data "C2", people "C3" governance "C4", technology "C5" and methodology "C6") and they also have the flexibility to give the same rank to more than one domain. Table 2 illustrates the results.

Table 2
Domain Ranks of Nineteen Big Data Experts

Experts/Domains	C1	C2	C3	C4	C5	C6
Exp 1	4	5	2	3	2	3
Exp 2	5	4	2	2	1	3
Exp 3	4	5	3	2	1	2
Exp 4	3	4	2	5	2	3
Exp 5	1	5	2	5	3	3
Exp 6	4	4	5	4	5	5
Exp 7	3	5	4	5	2	4
Exp 8	4	4	3	5	2	5
Exp 9	4	5	3	2	1	3
Exp 10	3	5	3	2	4	5
Exp 11	5	4	3	2	2	2
Exp 12	3	4	3	5	2	3
Exp 13	4	5	4	5	4	5
Exp 14	5	4	4	4	4	5
Exp 15	4	5	4	2	1	4
Exp 16	3	4	5	2	1	2
Exp 17	5	5	5	4	4	5
Exp 18	3	4	3	4	2	4
Exp 19	3	4	3	5	2	2

We translated each line of Table 2 in the Aij matrix. First, we will take Expert 5 as an example to illustrate AHP steps and then give the combined results of all the experts.

We converted expert five ranks [1, 5, 2, 5, 3, 3] to a pairwise matrix based on Saaty's scale of relative importance illustrated in Table 2. We have this mapping between domain ranks and Saaty scores in Table 3.

Table 3
Mapping Between Domain Ranks Comparison and Saaty Scores for Expert 5

Domains rank comparison	Scale according to Table 2	Saaty Pairwise Rank
w1 to w1	1 compared 1 is rank 1	1
w1 to w2	1 compared to 5 is rank 9	1/9
w1 to W3	1 compared to 2 is rank 3	1/3
w1 to w4	1 compared to 5 is rank 9	1/9
w1 to w5	1 compared to 3 is rank 5	1/5

A5 pair-wise matrix for expert5

$$A_5 = \begin{pmatrix} 1 & 0.11 & 0.33 & 0.11 & 0.2 & 0.2 \\ 9 & 1 & 7 & 1 & 5 & 5 \\ 3 & 0.14 & 1 & 0.14 & 0.33 & 0.33 \\ 9 & 1 & 7 & 1 & 5 & 5 \\ 5 & 0.2 & 3 & 0.2 & 1 & 1 \\ 5 & 0.2 & 3 & 0.2 & 1 & 1 \end{pmatrix} \quad (2)$$

The next step is to normalize each column of the matrix by dividing each element of the column by the sum of all its elements using this expression:

$$N_{ij} = A_{ij} * 1 / \sum_{k=1}^{n} A_{kj} \quad (3)$$

We obtain:

$$N_5 = \begin{pmatrix} 0.031 & 0.042 & 0.016 & 0.042 & 0.016 & 0.016 \\ 0.281 & 0.377 & 0.3287 & 0.377 & 0.399 & 0.399 \\ 0.094 & 0.054 & 0.047 & 0.054 & 0.027 & 0.027 \\ 0.281 & 0.377 & 0.3287 & 0.377 & 0.399 & 0.399 \\ 0.156 & 0.075 & 0.141 & 0.075 & 0.080 & 0.080 \\ 0.156 & 0.075 & 0.141 & 0.075 & 0.080 & 0.080 \end{pmatrix} \quad (4)$$

The next step is to calculate the criteria weights W_i using this expression (Table 4):

$$W_i = 1/6 * \sum_{j=1}^{n=6} N_{ij} \quad (5)$$

We obtain:

Table 4

Maturity Domain's AHP Weights According to Expert 5

Domain (C_i)	C1	C2	C3	C4	C5	C6
Weight (W_i)	0.027	0.360	0.050	0.360	0.101	0.101

$$\text{Of course } \sum_{i=1}^{n=6} W_i = 1 \quad (6)$$

The final step is to calculate the consistency to check whether the calculated values are correct or not.

To achieve that, we will calculate λ_{\max} , the highest Eigenvalue of the matrix A_{ij} .

$$\lambda_{\max} = 1/n * \sum_{i=1}^{n=6} \sum_{j=1}^{n=6} \left[\frac{A_{ij} * W_j}{W_i} \right] \quad (7)$$

Then, the Consistency Index (CI) will be:

$$C_i = (\lambda_{\max} - n) / (n - 1) \quad \text{where } n=6 \quad (8)$$

The Consistency Ratio (CR) will finally be:

$$CR = C_i / R_i \quad (9)$$

Where R_i is the Random Consistency Index, which is the average CI of randomly generated reciprocal matrices with dimension n .

For our case:

$$\max = 6.25 \text{ and } CI=0.05 \quad (10)$$

Since for $n=6$ $CI=1.24$, which finally gives us: $RC= 0.04$

Our matrix is sufficiently consistent because $CR \leq 0.1$ (Roszkowska, 2013)

Since we are confident with crisp AHP results, we did the same steps for the Nineteen Ranks Combination that we have (Table 5).

Table 5

Maturity Domain's Average Weight Of Nineteen Big Data Experts

Experts/Domains	C1	C2	C3	C4	C5	C6
Exp 1	0.237	0.454	0.045	0.109	0.045	0.109
Exp 2	0.462	0.251	0.062	0.062	0.030	0.133
Exp 3	0.247	0.473	0.130	0.061	0.030	0.058
Exp 4	0.109	0.237	0.045	0.454	0.045	0.109
Exp 5	0.027	0.360	0.050	0.360	0.101	0.101
Exp 6	0.083	0.083	0.250	0.083	0.250	0.250
Exp 7	0.063	0.318	0.135	0.318	0.033	0.135
Exp 8	0.135	0.135	0.063	0.318	0.033	0.318
Exp 9	0.238	0.452	0.113	0.054	0.029	0.113
Exp 10	0.071	0.333	0.071	0.034	0.157	0.333
Exp 11	0.464	0.251	0.128	0.052	0.052	0.052
Exp 12	0.100	0.193	0.100	0.465	0.042	0.100
Exp 13	0.083	0.250	0.083	0.250	0.083	0.250
Exp 14	0.300	0.100	0.100	0.100	0.100	0.300
Exp 15	0.098	0.423	0.200	0.051	0.028	0.200
Exp 16	0.133	0.251	0.462	0.062	0.030	0.062
Exp 17	0.228	0.228	0.198	0.076	0.043	0.228
Exp 18	0.095	0.255	0.095	0.255	0.043	0.255
Exp 19	0.109	0.237	0.109	0.454	0.045	0.045
Avg Weight	0.173	0.278	0.128	0.190	0.064	0.166

Our final domain weights [$w_1, w_2, w_3, w_4, w_5, w_6$] are [0.173, 0.278, 0.128; 0.190; 0.064; 0.166] for [strategy alignment, data, people, governance, technology, and methodology] respectively. Previously we introduced a design for our Global Big Data Maturity Model (Mouhib et al., 2020), now we will add AHP weight to complete the model with an average total score value $V_x = 72$ to decide if we start the project or no. See Figure 3.

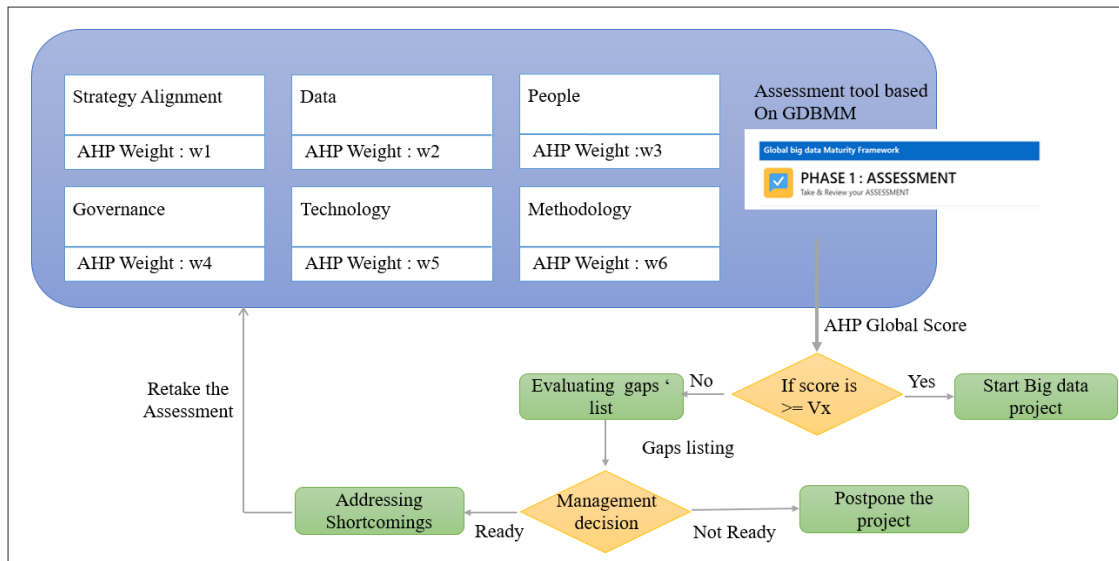


Figure 3: Global Big Data Maturity Model Design's with AHP weights

Global Big Data Maturity Assessment Insights

As mentioned, we created an assessment tool to assess companies' readiness to adopt big data projects and gave access to some companies. Big data experts gave feedback about their current big data project. Thirteen of them successfully submitted their grades and got results. The framework stored the results in a database, and on top of that, we created visualizations. See dashboard Figure 4.

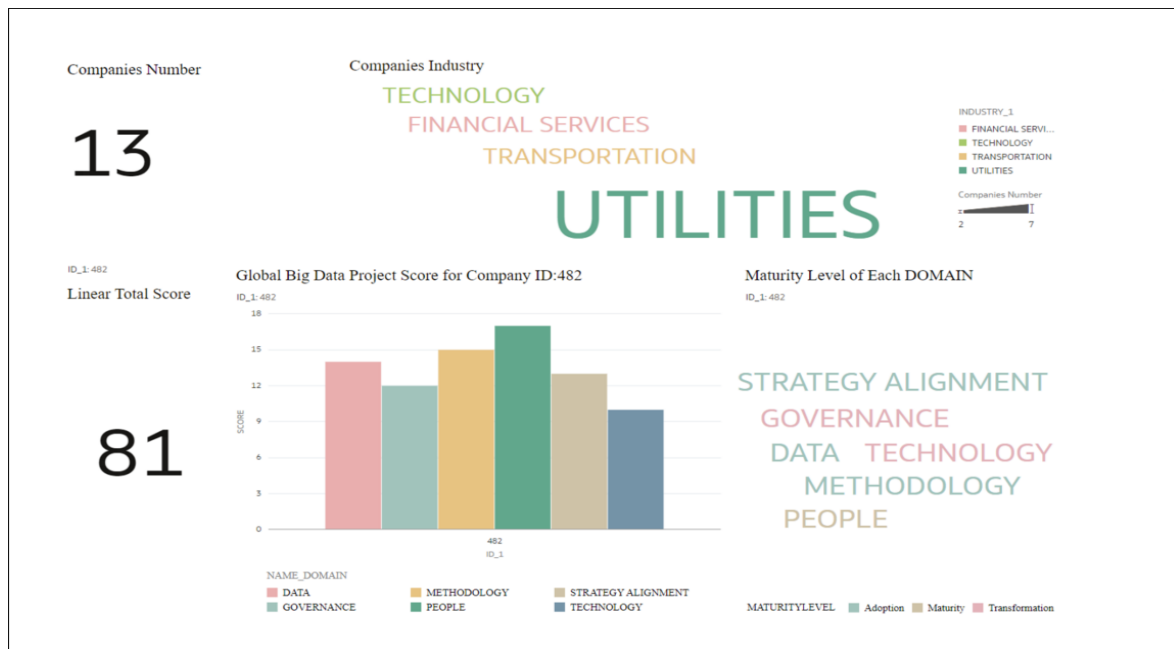


Figure 4: Big Data Maturity Dashboard with a Linear Total Score for Company 482

The dashboard shows that we evaluated thirteen companies' big data projects. These companies belong to four industries: utilities, transport, financial services, and technology. For company 482, we have additional charts:

- The bar chart represents the big data score of the six domains; when taken together, the

six domains' total score value is 81. People have the most important score (20.99% of the total score); methodology is the second biggest score (18.52%), and Data is third (17.28% of the total score); combined, the three other domains make up the rest, accounting for 43.21% of the total score.

The tag cloud chart shows the maturity level of each domain. For instance, technology and governance are on the transformation level; data, methodology, and strategy alignment are on the adoption level; and people domain is on the maturity level.

Initially, the score was the linear sum of domain's scores. Now, by using the domain's weights (Table 5), we have:

$$\text{New score} = \text{sum} (C1*0.173+ C2*0.278+ C3*0.128+ C4*0.19+ C5* 0.064+ C6*0.166) \quad (11)$$

To normalize the score, which means having identical 120 scores for complete maturity at all domains, we must multiply the score obtained by equation (8) by 120/20. Where 20 is the new complete maturity score using the domain's weights.

We added a calculation expression to reflect the new AHP score within the analytic tool. Figure 5 exposes the same dashboard in Figure 4, but this time with AHP scores.

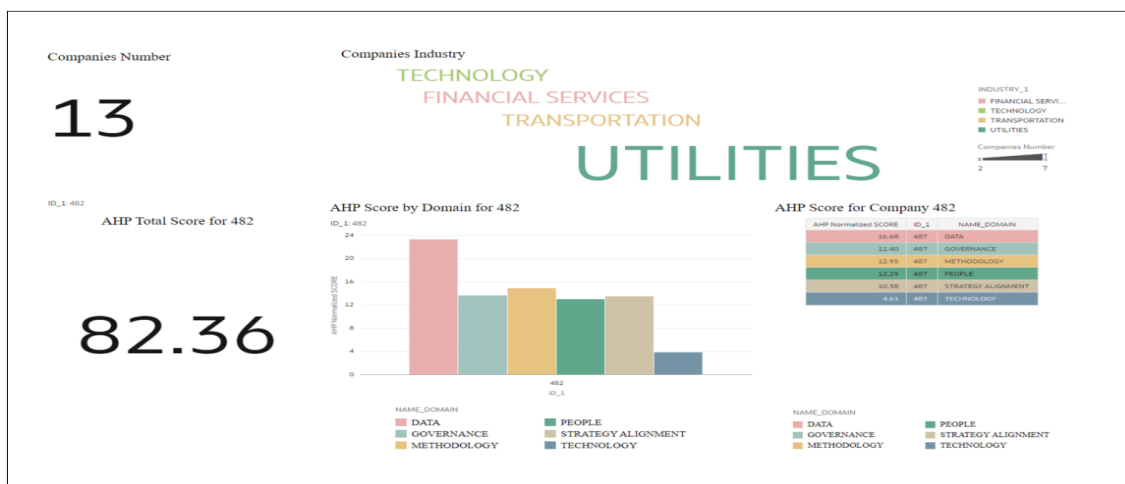


Figure 5: Big Data Maturity Assessment Dashboard with AHP Score for Company 482

For company 482, we have:

- Tile showing the AHP new total score,
- Table chart showing the recent AHP scores by domain.
- Bar chart representing big data score of six domains,

When taken together, the six domains' total score value is 82.36.

This time, data have the most critical score (28.35% of the total score); methodology is the second biggest score (18. 14%). Governance is the third (16. 62% of the total score); the three other domains comprise the rest, accounting for 36.89%.

We will have a second analysis for company 487 to compare the two companies. First, we have a dashboard with crisp scores. Figure 6 contains:

- Bar chart representing big data score of six domains; when taken together, the six domains' total score value is 71.

People domain has the most important score (22.53% of the total score); methodology is the

second biggest score (18.3%). Technology is the third (16.9% of the total score); combined, the three other domains comprise the rest, accounting for 42.27%.

- The tag cloud chart shows the maturity level of each domain. For instance, methodology and governance are on the maturity level; data and technology are on the transformation level; people and strategy alignment are on the adoption level.

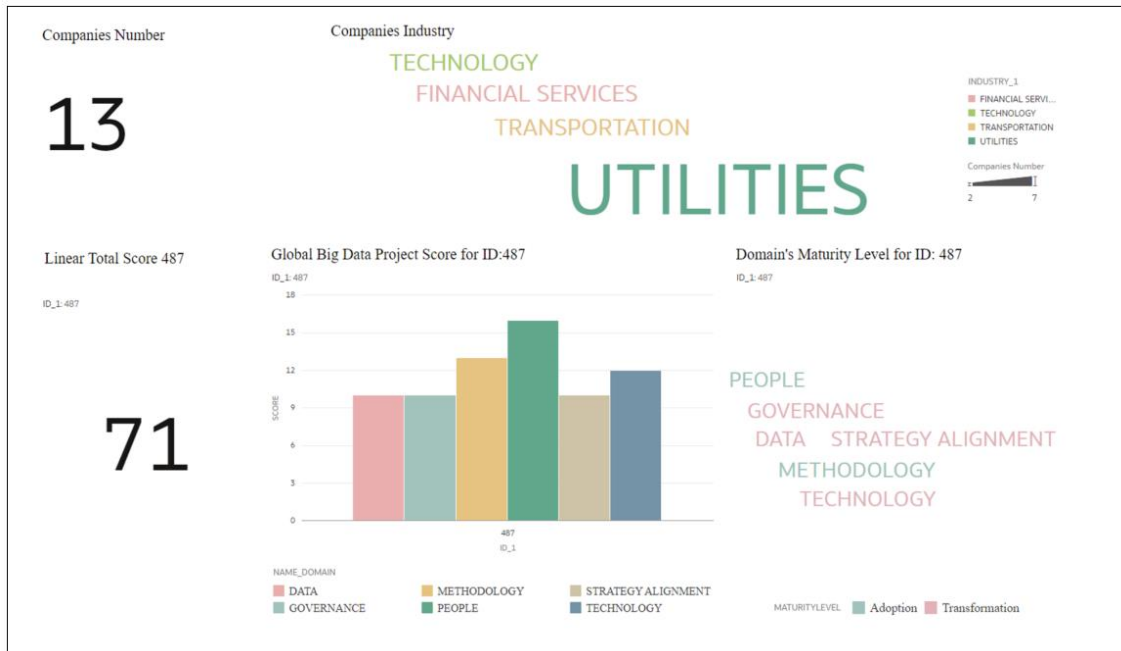


Figure 6: Big Data Maturity Assessment Dashboard a Linear Total Score for Company 487

We provide a second dashboard, Figure 7, for the same company, but this time with AHP scores.

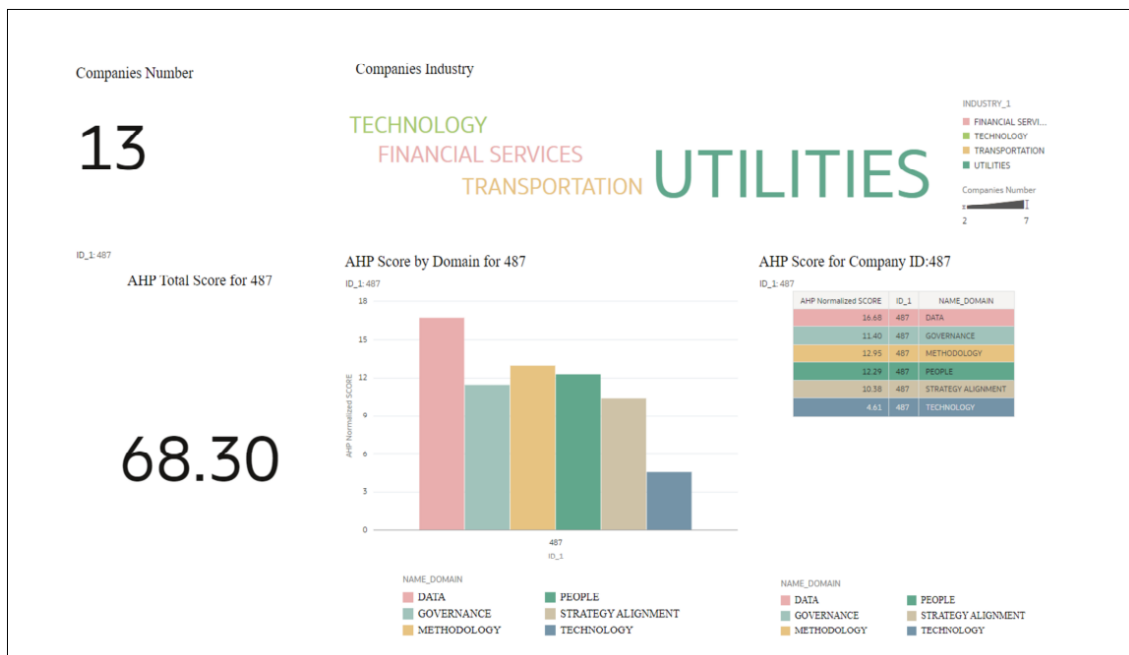


Figure 7: Big Data Maturity Assessment Dashboard with AHP Score for Company 487

It contains:

- Tile showing the AHP new total score,
- Table chart showing the new AHP scores by Domain.
- Bar chart representing big data score of six domains; when taken together, the six domains' total score value is 68.30

This last dashboard compares crisp and AHP scores for companies 482 and 487. See Figure 8.

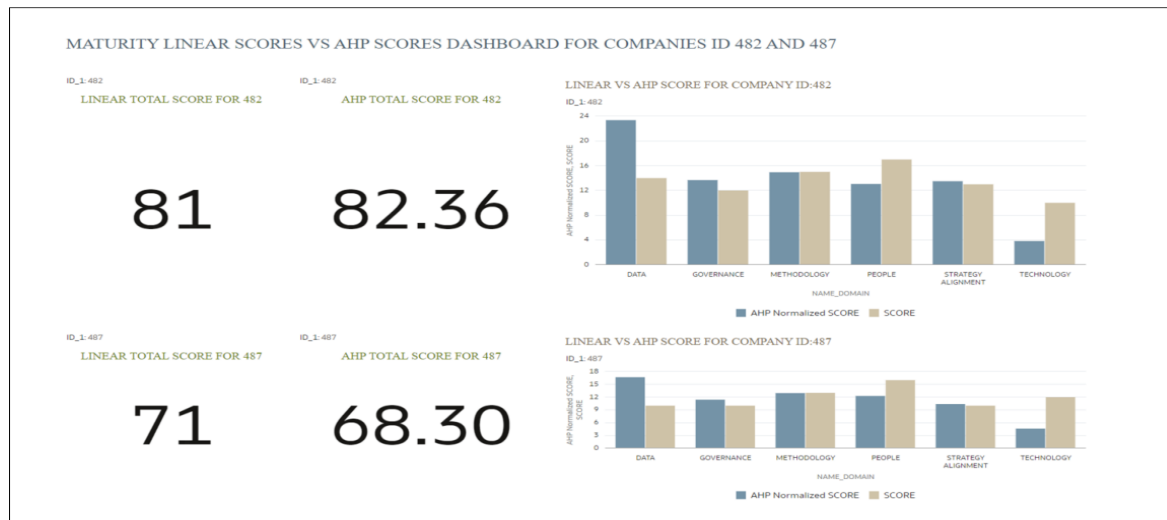


Figure 8: Maturity Dashboard with Linear vs. AHP Scores

In dashboard Figure 8, we have three charts for each company, 482 and 487:

- Two tiles showing the total linear score and the total AHP score,
- The third is bar charts comparing companies' linear scores with AHP normalized scores by maturity domains.

As we can see, because of the weights, sometimes the AHP final score can be higher than the crisp score (as noticed for company 482) and sometimes lower (as is the case for company 487). In addition, we noticed a dramatic change between crisp and AHP scores for domains such as data, people, and technology because of their respective weights. For instance, data's score for company 482 moved from 18 as the crisp score to 30 as the AHP score, and people's score moved from 19 as the crisp score to 14.59 as the AHP score.

However, the AHP and crisp scores are close for governance, methodology, and strategy domains. For instance, methodology moved from 19 as the crisp score to 18.92 as the AHP score.

Discussion

While studying big data maturity models in literature and among practitioners, we did not notice using weighted scores or methodology as a maturity domain. In previous work, we proposed a new Maturity Model incorporating methodology as a key domain. We also offered companies an assessment tool, but the final score was a linear sum of domains' scores.

The first purpose of this work was to identify the appropriate weight for each domain affecting the adoption of big data projects. The present study is diving into a new area in the domain of the big data maturity model:

First, there is no research conducted to identify big data maturity domains' weights.

Second, we are assigning weights to our proposed maturity domains.

To identify these weights, we surveyed nineteen big data experts to rank our identified domains, and then we applied AHP to these ranks to create weights.

The final domain weights were [0.173, 0.278, 0.128, 0.190, 0.064, 0.166] for [strategy alignment, data, people, governance, technology, and methodology] respectively.

If we compare the present findings with existing studies. Our findings establish that the three main factors affecting big data adoption are data, governance, and strategy alignment, followed by methodology, people, and technology. However, we have different results according to our previous work. Table 6 shows the proposed maturity domain occurrence within the studied maturity models.

Table 6

Proposed Maturity Domains Cited in Each Maturity Model

Maturity Models/ Maturity Domains	Strategy	Data	Technology	People	Governance
InfoTech (Big Data Maturity Assessment Tool Info-Tech Research Group, n.d.)	Yes	Yes	Yes	Yes	Yes
Darwiche (2014)	Yes	Yes	No	Yes	No
Radcliffe (Braun, 2015)	Yes	Yes	Yes	Yes	Yes
Nott and Betteridge (Journey to AI Blog - The IBM Data and AI Blog, n.d.)	Yes	Yes	Yes	Yes	Yes
Comuzzi Model (Comuzzi & Patel, 2016)	Yes	Yes	Yes	Yes	Yes
Temporal DBMM (Olszak and Mach-Król (2018)	No	Yes	Yes	Yes	No
TDWI (Halper & stodder, 2014)	No	Yes	Yes	Yes	Yes
IDC MaturityScape (Turner, n.d.)	Yes	Yes	Yes	Yes	No
Hortonwork (2016)	Yes	Yes	Yes	Yes	No
ADRIAN et al. (2016)	Yes	Yes	Yes	Yes	No
Number of time domain is cited	9	11	10	11	5

Besides the fact that the maturity models do not include methodology as a domain. We have the following convergence and divergence points:

- Models such as InfoTech (Big Data Maturity Assessment Tool | Info-Tech Research Group, n.d.), Radcliffe (Braun, 2015), Betteridge IBM (Journey to AI Blog - The IBM Data and AI Blog, n.d.), Comuzzi and Patel (2016) include data, strategy alignment, governance, people, and technology domains in their maturity model. They are consistent with the present study.

- Other maturity models conflict with our findings and miss one or more of our main domains. For instance, models like El-Darwiche, Koch, Meer, Shehadi and Tohme (2014), and Adrian et al. (2016) focus on data, strategy technology, and people and miss the governance domain. Whereas Temporal DBMM (Olszak & Mach-Król, 2018) focuses on data, technology,

and people and does not mention Strategy and governance domains.

From a macroscopic point of view, when we compare the importance of domains according to North African experts' ranks versus domains' citation frequency in studied maturity domains, we can say that:

- Studies and present findings both conducted that data is the most crucial maturity domain. Indeed, data accessibility, lifecycle management, availability, and quality are fundamental for starting any analytical project. Thus, the importance of the data domain for successful big data adoption.

- Studies and present findings both also concluded that strategy is an important domain. Big data initiatives are more likely to fail if there is no alignment between business people and IT.

- The principal divergences between studies and present findings are:

1. According to our research, experts rank governance as the second most important fact; however, it was cited only in five Maturity Models. It is well established that data protection, privacy, and security are big concerns among North African companies. That might be the reason why Experts flagged governance as a high priority.

2. Experts flagged technology and people domains as a little bit less critical. We can say that the reason behind this can be related to:

Technology evolution: For instance, Cloud Analytics solutions facilitate innovative technology accessibility. No need to be a coding expert to do machine learning; algorithms can be available and usable even for business users.

The Target community: For instance, big data experts are more likely to believe that the culture of being a data-driven company is already introduced among companies.

The second purpose of the present work was to explore the new assessment framework results. Thirteen companies provided their inputs that we translated into insights. In this work, we shared detailed results about two companies, 482 and 487. We discovered that the AHP score could be higher or lower than the crisp score Figure 8 which depends on the company's score for each domain and the domain's respective weights. If we compare the two companies' results, we can see that company 482 is more mature than company 487. Thus, it has more chances to succeed in its big data journey.

The last important finding is this positive trend within North African companies. According to Figure 9. Most companies are on high maturity levels and have admirable scores.

While calculating the AHP weights, we discovered that some experts could not differentiate between domains' importance. Experts 6, 13, 14, and 17 gave us close ranks for all domains. Even if we managed to have interesting domain weights thanks to the rankings of the other fifteen experts, it was preferable to require experts to give distinct ranks to each domain.

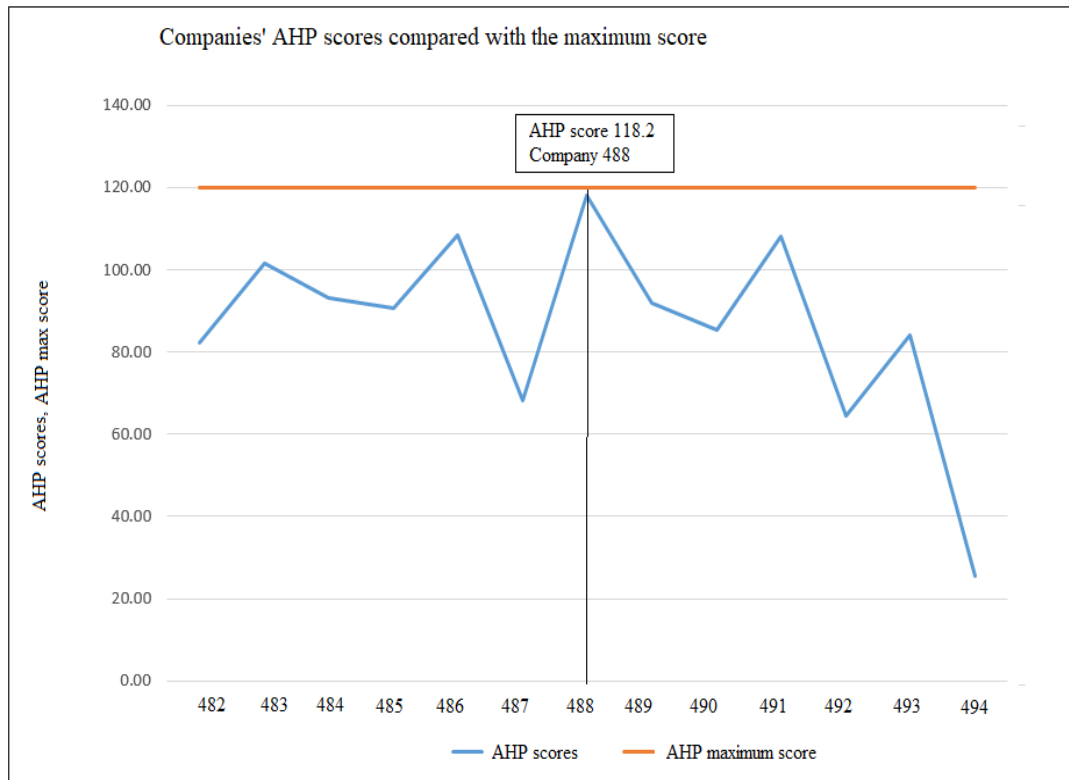


Figure 9: Companies' AHP Scores

Conclusion

In previous work, we proposed a global big data maturity model to assess companies' readiness to adopt big data. This paper aimed to identify the appropriate weight for each global domain within the proposed model. Literature study of multi-factor decision-making combined with domains' ranks survey among nineteen experts leads us to identify AHP weights [0.173, 0.278, 0.128; 0.190; 0.064; 0.166] respectively for Big data global domains [strategy alignment, data, people, governance, technology, and methodology]. AHP versus crisp scores can significantly differ, especially for domains like data and people. Thus, assigning weights to domains is essential for more accurate final scores. As domains' weights rely on big data experts' subjective ranks, the fuzzy model deals perfectly with the uncertainty of human judgment. It will be interesting to explore and compare fuzzy AHP scores with the actual results.

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References

- Adrian, C., Abdullah, R., Atan, R. & Jusoh, Y. Y. (2016). Towards developing strategic assessment model for big data implementation: a systematic literature review. *International Journal of Advances in Soft Computing and its Applications*, 8(3), 173-192. Retrieved from http://www.i-csrs.org/Volumes/ijasca/ID13_Pg173-192_SLR-Towards-Developing-Strategic-Assessment-Model.pdf

- Al-Harbi, K. M. A. S. (2001). Application of the AHP in project management. *International Journal of Project Management*, 19(1), 19-27. [https://doi.org/10.1016/S0263-7863\(99\)00038-1](https://doi.org/10.1016/S0263-7863(99)00038-1)
- Alinezhad, A. & Khalili, J. (2019). "CRITIC Method," International Series in Operations Research & Management Science, In *New Methods and Applications in Multiple Attribute Decision Making (MADM)* (Vol. 277, pp. 199-203). Cham: Springer. https://doi.org/10.1007/978-3-030-15009-9_26
- Alsalem, M. A., Alamoodi, A. H., Albahri, O. S., Dawood, K. A., Mohammed, R. T., Alnoor, A., Zaidan, A. A., Albahri, A. S., Zaidan, B. B., Jumaah, F. M. & Al-Obaidi, J. R. (2022). Multi-criteria decision-making for coronavirus disease 2019 applications: A theoretical analysis review. *Artificial Intelligence Review*, 55(6), 4979-5062. <https://doi.org/10.1007/s10462-021-10124-x>
- Asadabadi, M. R., Chang, E. & Saberi, M. (2019). Are MCDM methods useful? A critical review of analytic hierarchy process (AHP) and analytic network process (ANP). *Cogent Engineering*, 6(1), 1623153. <https://doi.org/10.1080/23311916.2019.1623153>
- Astanti, R., Mbolla, S. & Ai, T. (2020). Raw material supplier selection in a glove manufacturing: Application of AHP and fuzzy AHP. *Decision Science Letters*, 9(3), 291-312. <http://dx.doi.org/10.5267/j.dsl.2020.5.005>
- Belton, V. & Stewart, T. (2002). *Multiple Criteria Decision Analysis: An Integrated Approach*. Springer Science & Business Media.
- Bhattacharya, S. & Raju, V. (2019). Analysis of factors affecting customer satisfaction in e-commerce applications using Condorcet-AHP method. *International Journal of Internet Protocol Technology*, 12(1), 2-10. <https://doi.org/10.1504/IJIPT.2019.098486>
- Big Data Maturity Assessment Tool | Info-Tech Research Group. (n.d.). *Big Data Maturity Assessment Tool*. Retrieved, from <https://www.infotech.com/research/it-big-data-maturity-assessment-tool>
- Braun, H. T. (2015). *Evaluation of big data maturity models—a benchmarking study to support big data maturity assessment in organizations*. Master's thesis. Faculty of Business and Built Environment, Tampere University of Technology.
- Broniewicz, E. & Ogrodnik, K. (2021). A comparative evaluation of multi-criteria analysis methods for sustainable transport. *Energies*, 14(16), 5100. <https://doi.org/10.3390/en14165100>
- Brunelli, M. (2015). *Introduction to the Analytic Hierarchy Process*. Springer. <http://dx.doi.org/10.1007/978-3-319-12502-2>
- Chen, Y. S., Chuang, H. M., Sangaiah, A. K., Lin, C. K., & Huang, W. B. (2019). A study for project risk management using an advanced MCDM-based DEMATEL-ANP approach. *Journal of Ambient Intelligence and Humanized Computing*, 10, 2669-2681. <https://doi.org/10.1007/S12652-018-0973-2>
- Comuzzi, M. & Patel, A. (2016). How organisations leverage Big Data: A maturity model. *Industr Mngmnt & Data Systems*, 116(8), 1468-1492. <https://doi.org/10.1108/IMDS-12-2015-0495>
- Đalić, I., Stević, Ž., Ateljević, J., Turskis, Z., Zavadskas, E. K. & Mardani, A. (2021). A novel integrated MCDM-SWOT-TOWS model for the strategic decision analysis in transportation company. *Facta Universitatis, Series: Mechanical Engineering*, 19(3), 401-422. <https://doi.org/10.22190/FUME201125032D>

- Danielson, M. & Ekenberg, L. (2019). An improvement to swing techniques for elicitation in MCDM methods. *Knowledge-Based Systems*, 168, 70-79. <https://doi.org/10.1016/j.knosys.2019.01.001>
- Deepu, T. S. & Ravi, V. (2021). Supply chain digitalization: An integrated MCDM approach for inter-organizational information systems selection in an electronic supply chain. *International Journal of Information Management Data Insights*, 1(2), 100038. <https://doi.org/10.1016/j.ijime.2021.100038>
- El-Darwiche, B., Koch, V., Meer, D., Shehadi, R. T., & Tohme, W. (2014). Big data maturity: An action plan for policymakers and executives. *The Global Information Technology Report*, Chapter 1.3 43-51. Retrieved from https://www3.weforum.org/docs/GITR/2014/GITR_Chapter1.3_2014.pdf
- Farah, B. (2017). A value based big data maturity model. *Journal of Management Policy and Practice*, 18(1), 11-18. Retrieved from [file:///C:/Users/Reza/Downloads/ojsadmin,+FarahB_Web18\(1\)-3.pdf](file:///C:/Users/Reza/Downloads/ojsadmin,+FarahB_Web18(1)-3.pdf)
- Garrido, A., Ramírez López, L. J. & Álvarez, N. B. (2021). A simulation-based AHP approach to analyze the scalability of EHR systems using blockchain technology in healthcare institutions. *Informatics in Medicine Unlocked*, 24, 100576. <https://doi.org/10.1016/j.imu.2021.100576>
- Goasduff, L. (2020). *Gartner Top 10 Trends in Data and Analytics for 2020*. (n.d.). Retrieved from <https://www.gartner.com/smarterwithgartner/gartner-top-10-trends-in-data-and-analytics-for-2020>
- Halper, F. (2020). *TDWI analytics maturity model assessment guide*. TDWI Research. Retrieved from https://go.tdwi.org/rs/626-EMC-557/images/TDWI_Analytics-Maturity-Model-Assessment-Guide_2020.pdf
- Halper, F. & Stodder, D. (2014). TDWI analytics maturity model guide: Interpreting your assessment score. *TDWI Research*, 1-20. Retrieved from https://register.tableau.com/sites/default/files/2020-11/TDWI_Analytics_Maturity_Model_Assessment_Guide_Tableau.pdf
- Hortonworks, D. V. (2016). Big Data Maturity Model. Retrieved from <http://hortonworks.com/wp-content/uploads/2016/04/Hortonworks-Big-Data-Maturity-Assessment.pdf>
- Jamwal, A., Agrawal, R., Sharma, M. & Kumar, V. (2021). Review on multi-criteria decision analysis in sustainable manufacturing decision making. *International Journal of Sustainable Engineering*, 14(3), 202-225. <https://doi.org/10.1080/19397038.2020.1866708>
- Joshi, M. P., Su, N., Austin, R. D. & Sundaram, A. K. (2021). Why so many data science projects fail to deliver. *MIT Sloan Management Review: MIT's Journal of Management Research and Ideas*, 62(3), 85-89. Retrieved from <https://ir.lib.uwo.ca/etd/7629/>
- Kaliszewski, I. & Podkopaev, D. (2016). Simple additive weighting-A metamodel for multiple criteria decision analysis methods. *Expert Systems with Applications*, 54, 155-161. <https://doi.org/10.1016/j.eswa.2016.01.042>
- Krstić, M., Tadić, S., Kovač, M., Roso, V. & Zečević, S. (2021). A novel hybrid MCDM model for the evaluation of Sustainable last mile solutions. *Mathematical Problems in Engineering*, 2021, e5969788. <https://doi.org/10.1155/2021/5969788>

- Kumar, A., Singh, G. & Vaidya, O. S. (2020). A comparative evaluation of public road transportation systems in india using multicriteria decision-making techniques. *Journal of Advanced Transportation*, 2020, 1–16. <https://doi.org/10.1155/2020/8827186>
- Liachovičius, E., Skrickij, V. & Podvieszko, A. (2020). MCDM evaluation of asset-based road freight transport companies using key drivers that influence the enterprise value. *Sustainability*, 12(18), 7259. <https://doi.org/10.3390/su12187259>
- Mouhib, S., Anoun, H., Ridouani, M. & Hassouni, L. (2020, October). Towards a global big data maturity model. In *2020 Fourth International Conference on Intelligent Computing in Data Sciences (ICDS)* (pp. 1-5). IEEE. <https://doi.org/10.1109/ICDS50568.2020.9268720>
- Nădăban, S., Dzitac, S. & Dzitac, I. (2016). Fuzzy TOPSIS: A General View. *Procedia Computer Science*, 91, 823-831. <https://doi.org/10.1016/j.procs.2016.07.088>
- Odu, G. O. (2019). Weighting methods for multi-criteria decision making technique. *Journal of Applied Sciences and Environmental Management*, 23(8), 1449-1457. <https://doi.org/10.4314/jasem.v23i8.7>
- Olszak, C. M. & Mach-Król, M. (2018). A conceptual framework for assessing an organization's readiness to adopt big data. *Sustainability*, 10 (10), 3734. <https://doi.org/10.3390/su10103734>
- Roszkowska, E. (2013). Rank ordering criteria weighting methods-A comparative overview. *Optimum. Studia Ekonomiczne NR*, 5 (65), 14-33. <https://doi.org/10.15290/ose.2013.05.65.02>
- Saaty, T. L. (1984). The analytic hierarchy process: decision making in complex environments. In R. Avenhaus & R. K. Huber (Eds.), *Quantitative Assessment in Arms Control* (pp. 285–308). Boston: Springer US. https://doi.org/10.1007/978-1-4613-2805-6_12
- Shao, M., Han, Z., Sun, J., Xiao, C., Zhang, S. & Zhao, Y. (2020). A review of multi-criteria decision making applications for renewable energy site selection. *Renewable Energy*, 157, 377-403. <https://doi.org/10.1016/j.renene.2020.04.137>
- Singh, A. & Prasher, A. (2019). Measuring healthcare service quality from patients' perspective: Using Fuzzy AHP application. *Total Quality Management & Business Excellence*, 30(3-4), 284-300. <https://doi.org/10.1080/14783363.2017.1302794>
- Soniya, S., Ramachandran, M., Sathiyaraj, C. & Mathivanan, G. (2021). A review on multi-criteria decision-making and its application. *REST Journal on Emerging Trends in Modelling and Manufacturing*, 7(4), 101-107. <https://doi.org/10.46632/7/4/1>
- Tan, T., Mills, G., Papadonikolaki, E. & Liu, Z. (2021). Combining multi-criteria decision making (MCDM) methods with building information modelling (BIM): A review. *Automation in Construction*, 121, 103451. <https://doi.org/10.1016/j.autcon.2020.103451>
- Turner, M. J.(n.d.) IDC MaturityScape: Digital Infrastructure Operating Model 1.0.
- Wang, Y.-M. & Parkan, C. (2006). A general multiple attribute decision-making approach for integrating subjective preferences and objective information. *Fuzzy Sets and Systems*, 157(10), 13331345. <https://doi.org/10.1016/j.fss.2005.11.017>
- Weiner, J. (2020). Why AI/data science projects fail: How to avoid project pitfalls: Synthesis Lectures on Computation and Analytics. Springer. <https://doi.org/10.2200/S01070ED1V01Y202012CAN001>

- Zhu, Y., Tian, D. & Yan, F. (2020). Effectiveness of entropy weight method in decision-making. *Mathematical Problems in Engineering*, 2020, e3564835. <https://doi.org/10.1155/2020/3564835>
- Zionts, S. & Wallenius, J. (1976). An interactive programming method for solving the multiple criteria problem. *Management Science*, 22(6), 652-663. <https://doi.org/10.1287/mnsc.22.6.652>