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A Novel Method for Measuring Banking Data Analysis Maturity Level: A Case Study

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Abstract—**Assessing data analysis maturity is crucial for organizations, especially those heavily reliant on data-driven decision-making. This paper provides a comprehensive survey and deep comparison of several well-known data analysis maturity models. Based on this analysis, we select the BDO maturity model, an established model in the literature, and propose a tailored self-assessment method specifically adapted for banks and financial institutes. Our method includes a toolset designed to facilitate easy evaluation and interpretation of maturity levels. This approach has been successfully implemented in a private Iranian bank, where practical data analysis is pivotal for business operations, decision-making, risk management, and financial performance. The results demonstrate that our tailored method provides more precise insights into current data analysis practices and identifies areas for improvement, driving better financial outcomes. While the BDO model can be applied broadly, our self-assessment method enhances its utility specifically for banks. It offers valuable insights for data-driven enterprises aiming to boost their analytical competency and competitive edge.**

Keywords: Data Analysis Maturity, Maturity Models, Data-Driven Decision Making, BDO, Banking.

Article type: Research Article

I. INTRODUCTION

Data analytics is increasingly shaping profound transformations in our everyday lives, workplaces, and human interactions, propelling advancements across all digital economy sectors and unlocking novel, previously inaccessible opportunities [1]. A mature data analytics culture allows organizations to use data effectively in business decisions [2, 3]. Organizations tend to measure and evaluate their actions' effectiveness to optimize their business processes based on "collected data" and not based on guesses, gut feelings, or hunches. Few organizations have shown sufficient analytical capabilities that meet their current requirements, including infrastructure and human resources, as well as skills in their effective management [4]. In addition, few organizations can estimate their data analytics capabilities and answer the question of how to increase the effectiveness of business processes based on data analytics. Therefore, an increasing number of organizations are looking for ways to assess their data analytics maturity to recognize

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their need to boost their capabilities, which will consequently enhance the organization's competencies in the market.

Data-driven businesses have a higher output and productivity than similar organizations that do not utilize data-driven processes. In banking, data and data analytics are critical success factors. Unsurprisingly, 71 percent of banking firms have directly reported that they achieved a competitive advantage by using big data- each often finding a slightly different angle to the data application [5]. Data analysis dramatically impacts the performance of banks and financial institutions in several ways, including making better decisions on pricing, profitability, risk management, regulation compliance, and overall business strategy [6]. By analyzing data on asset and liability maturity, banks can make informed decisions about which products to offer, which to prioritize, and how to manage their balance sheet to optimize returns and manage risks.

Furthermore, Data analysis can help banks and financial institutions identify potential risks associated with maturity mismatches between assets and liabilities, allowing them to adjust their balance sheets accordingly. By monitoring the maturity profile of their assets and liabilities, institutions can better understand their cash flow and liquidity risks and make more informed decisions about managing them. A high level of data analysis maturity can help banks and financial institutions improve their operational efficiency.

Analytic maturity models have several strengths and weaknesses that affect their effectiveness and applicability in organizations. They provide a structured approach to assess an organization's current state of data management and analytics capabilities, allowing them to benchmark their progress against industry standards [7]. Furthermore, these models serve as a roadmap for organizations to follow as they progress through various stages of maturity, guiding their transformation process and helping them identify areas for improvement. Good maturity models include a wide range of indicators and dimensions, thoroughly assessing an organization's analytics capabilities. Because of that, maturity models can generate analytic insights, highlighting areas of disparity and imbalances, which are as crucial as overall maturity scores.

On the other hand, it should be mentioned that the transition between stages in maturity models is often gradual, and organizations may find it challenging to pinpoint their exact position within the model. Furthermore, maturity models may not account for individual organizations' unique characteristics and needs, potentially limiting their applicability in some cases. But some factors are contributing to the successful implementation of a maturity model:

1. Customization: Adapting the maturity model to the specific needs and context of the organization can enhance its effectiveness and applicability.
2. Involvement of stakeholders: Engaging key stakeholders, such as management and analytics teams, in the assessment process can help ensure buy-in and support for the model's implementation.
3. Continuous monitoring and evaluation: Regularly assessing the organization's progress and adjusting the model as needed can help maintain its relevance and effectiveness

By leveraging data analysis to understand the customers' needs and preferences better, the proposed maturity model assessment helps banks and financial institutions tailor their products and services to meet customers’ needs more effectively. The application of our proposed self-assessment method has provided deep insights into the data analysis maturity of the participating bank. By administering a comprehensive questionnaire, we systematically evaluated various dimensions of data analytics capabilities within the organization. This approach not only identified current strengths and weaknesses but also illuminated specific areas for enhancement. For instance, our analysis may reveal that while the bank excels in data collection and storage, there is a notable gap in leveraging advanced analytics techniques for predictive modeling. Such insights are invaluable for guiding strategic investments in analytics infrastructure, enhancing the bank's overall data-driven decision-making capabilities.

One of the pivotal outcomes of our study was employing the BDO-based self-assessment method; the bank could significantly refine its risk management strategies. Identifying maturity gaps in data analysis enabled the institution to prioritize enhancements in risk modeling. Consequently, the bank can now employ more robust predictive models to anticipate market trends and customer behavior, leading to more informed decisions on product offerings. Moreover, the enhanced risk management framework has bolstered the bank's resilience against market volatility and regulatory changes, which can occasionally hinder the stability of the bank's activities in Iran.

Implementing our tailored assessment method has also substantially improved operational efficiency and competitive positioning. The bank has streamlined internal processes and optimize resource allocation by benchmarking against industry standards and identifying inefficiencies in data analysis. For example, insights from the assessment prompted a restructuring of data governance frameworks and enhanced collaboration between the bank’s business units and analytics teams. This proactive approach not only reduced operational costs but also positioned the bank as a leader in data-driven innovation.

In the rest of this paper, we first overview the literature in Section II and then introduce famous models in Section III that measure the maturity of data analysis of organizations. Then, we introduce the main criteria to compare these models in Section IV. Based on these comparing criteria, we choose a model that best suits banks’ needs for data analytics, the BDO maturity model. Section V introduces an assessment method compiled according to the dimensions measured in the selected model using a questionnaire. This questionnaire aims to analyze the current state of data analysis maturity for the bank's self-evaluation. As a case study, the questionnaire was filled out from August 15, 2022, to September 15, 2022, by 89 assistant managers and expert employees of an Iranian bank. The results of this case are summarized and analyzed in Section VI. Finally, section VII concludes the paper.

II. Literature Review

The concept of maturity models originated with the introduction of the quality management process maturity grid by Philip B. Crosby in 1979. This grid categorized best practices along five maturity stages and six measurement categories [8]. The idea of maturity models further evolved with the Capability Maturity Model (CMM) developed by Carnegie Mellon Institute in the late 1980s and early 1990s, designed to measure software development capabilities. Since then, various maturity models have been developed to assess different aspects of organizational maturity across multiple industries.

Although the evolution of analytic maturity models over time has been a little vague in the literature, it can be inferred that the number of analytics maturity models has increased over time, with new models being developed and personalized for specific sectors or businesses [7].

Maturity models have been widely used in various fields, including healthcare, business process excellence, digital transformation, and enterprise management, to assess and improve organizational capabilities and performance. A study by Becker et al. (2009) highlights the importance of developing maturity models for IT management in healthcare organizations [9]. Several maturity models have been proposed for business process excellence, such as Bessant's continuous improvement capability model, CMM, and Capability Maturity Model Integration (CMMI) [10]. However, the use of these models in practice is limited due to challenges such as the scarcity of empirical works confirming their validity and usefulness, limited prescriptive properties and the lack of a clear distinction between the maturity model and the assessment model [11] Digital maturity models have also been the subject of papers with the aim of building models to assess the digital maturity of service provider companies in Colombia [9]. Berghaus et al. [12] presented a digital maturity and transformation report, which provides insights into organizations' digital maturity and readiness for digital transformation.

A systematic literature review have investigated enterprise maturity models, focusing on assessment models for classifying maturity levels and developing the research area [13]. A study by De Bruin et al. (2005) discusses the main phases of creating a maturity assessment model, providing a framework for organizations to evaluate their maturity levels and identify areas for improvement [9].

Data maturity is a critical factor in successful digital transformation. It is vital for financial institutions due to regulation and the need for well-controlled, well-managed, well-governed, and secure data. A survey of maturity models in data management investigates maturity models that are either for or related to data [14]. These studies show that a Data analytics maturity model is helpful for financial institutions to identify gaps in their analytics environment and improve their analytics effectiveness. Another study proposed a maturity model for assessing the maturity of Industry 4.0 in the banking sector [15]. The proposed model comprises five maturity levels: Initial, Managed, Defined, Established, and Digital Oriented. The maturity of the bank was assessed based on the proposed model [16].

The authors in [7] provide an overview of maturity assessment models, categorize them based on their properties and applications using a multivocal literature review as the research method, and highlight the need for further empirical research.

In [17], the authors propose a data analytics maturity model designed explicitly for Hospitals Information Systems (HIS) in the healthcare domain. The model includes six stages of HIS growth and maturity progression, which can help identify the strengths and weaknesses of data analytics and provide a way for improvement and evolution.

In the next section, we comprehensively compare analytical maturity models.

III. Maturity Models

This section overviews, analyzes, and compares the analytical maturity models. After reviewing the literature, 11 superior analysis maturity models are investigated in this section. Although good descriptions of an organization's data analytics maturity levels are available for all models, in most cases, there is no publicly available detailed description of the assessment process or the criteria for assessing an organization's maturity level of analysis. The selected analytical maturity models have been described in a way that makes their application possible in the independent assessment of the analytical maturity of organizations, including banks.

After reviewing these models, a comprehensive comparison was made regarding the coverage these models have on the dimensions or elements of maturity. The result of this comparison is choosing one of the methods and improving that model using other models. These 11 analytical maturity models are, in alphabetical order:

1. APMM: Analytical Processes Maturity Model,
2. AMQ: Analysis Maturity Quotient Framework
3. BDO Maturity Model,
4. Blast Analytical Maturity Assessment Framework,
5. DAMM: Data Analysis Maturity Model for Associations,
6. Delta Plus model,
7. Gartner maturity model for data,
8. Logi Analytics Maturity Model,
9. SAS Analytics Maturity Model,
10. TDWI (Transforming Data With Intelligence) Analytics Maturity Model, and
11. WAMM: Web Analytics Maturity Model.

Some methods mentioned above consider themselves frameworks, while others introduce themselves as models. In the following, the terms model and framework may sometimes be used interchangeably due to this difference in the subject literature.

A. APMM

The APMM model is a framework for evaluating the analytical maturity of an organization. This framework is based on several fundamental concepts: analytical models, infrastructure, and operations [18]. APMM is broadly based on the Capability Maturity Model [19], which is the basis for measuring the maturity of software development processes. The model identifies analytics-related processes in six key process areas: 1) building analytics models, 2) deploying analytics models, 3) managing and operating analytics infrastructure, 4) protecting analytics assets through proper policies and procedures, 5) implementing an analytical governance structure, and 6) identifying analytical opportunities, making decisions, and allocating resources. Based on the maturity of these processes, APMM divides organizations into five maturity levels:

1. organizations that can create reports,
2. organizations that can build models and put them to proper use,
3. organizations that have repeatable processes for building and deploying analytics,
4. organizations that have the same processes at the organizational level for analysis,
5. organizations whose analysis is based on strategy.

B. AMQ

The Analysis Maturity Quotient is based on the evaluation of the following parameters [7]:

- Data quality: Poor data quality can significantly impede an organization's capacity to gain insights into customer behavior through data. Therefore, the accuracy and reliability of data serve as the fundamental basis for any analytical analysis.
- Data-driven leadership: Effective leaders leverage data not only to support or challenge their assumptions about business opportunities but also to gain new insights and knowledge regardless of their preconceived beliefs.
- Skilled personnel: Individuals with the necessary analytical and technical expertise for data analysis, as well as strong interpersonal and business skills, are crucial for advancing an organization's data maturity.
- Data-driven decision-making: Data should be integrated into the decision-making process to drive informed and evidence-based decision-making.
- And infrastructure.

C. BDO

The BDO Analytics Maturity Model [20] is a maturity model developed by the services firm BDO to help organizations assess their analytical maturity and identify areas for improvement. According to the BDO framework, an organization is in one of the five data analysis maturity levels, where each level has its own requirements. The BDO framework introduces a method for evaluating the maturity of data analysis at each level in six dimensions:

1. Human resource
2. Skill
3. Architecture
4. Data analysis
5. Artificial intelligence
6. ROI (Return on Investment)

D. Blast

The Blast framework [21] tests the following six key process areas and success factor dimensions [21]: 1) strategy, 2) governance, 3) data management, 4) insight, 5) evolution, and 6) resources. Blast is based on the OAMM online analytics maturity model developed by Hamel [7].

In each assessment dimension of Blast, 1 to 6 points are awarded, which allows the organization to be placed in one of the five maturity stages of Laggard, Follower, Competitor, Leader, and Innovator. Analytical maturity assessment in this method includes a survey among employees that is conducted at three-month intervals. This provides an opportunity to assess real-world conditions and progress in implementing data analysis. The Blast framework offers a strategic roadmap for creating an analytical development strategy considering current conditions. This strategy provides the basis for an action plan that ensures the achievement of the organization's goals.

E. DAMM

Although data is a critical analysis component, it can be challenging to utilize it effectively, particularly in associations. To address this challenge, the DAMM model was developed by Association Analytics (A2) as a tool to support analytical maturity assessments for associations and nonprofit organizations. This model evaluates an organization's analytical maturity across four critical elements of data analysis: organization and culture, architecture/technology, data governance, and strategic alignment. By assessing an organization's performance in these dimensions, the DAMM model places it into one of the five analytical maturity stages: Learning, Planning, Building, Applying, and Leading.

The DAMM model identifies five areas where an organization can improve its analytical maturity:

1. Democratizing data by making it easily accessible and helpful to everyone in the organization.
2. Instilling a culture of analysis, especially by hiring business leaders who value data and can form a core analysis team to develop an electronic data strategy.
3. Developing well-defined key performance indicators (KPIs).
4. Creating a central repository that includes all key data sources.
5. Implementing a data governance program to ensure the active use of data in the decision-making process.

F. DeltaPlus

The DeltaPlus model is a framework developed by the International Institute for Analytics (IIA) that assesses an organization's capacity for organizational analytics [22]. It provides a structured approach for evaluating an organization's analytical maturity and identifying areas for improvement.

The DeltaPlus model measures an organization's analytical maturity across five components [2]: D for Data, E for Enterprise's focus on analytics management, L for analytics Leadership, T for strategic Targets, and A for Analysts. Each of these components has specific sub-components that are evaluated to determine an organization's level of analytical maturity. By assessing an organization's capabilities across these components, the DeltaPlus model provides a comprehensive view of an organization's analytical maturity and identifies specific areas for improvement.

The analysis maturity rating in the DeltaPlus model is a score awarded on a scale from 1.00 to 5.99 points. Each score represents a specific stage of analytics maturity.

G. Gartner

The Gartner maturity model is a framework developed by the technology research and advisory firm Gartner to assess and evaluate an organization's capabilities and level of maturity in a particular area, such as IT governance, data management, or project management. The model is intended to help organizations identify their strengths and weaknesses and provide a roadmap for improving their capabilities over time.

The Gartner maturity model typically consists of levels organizations can progress through as they improve their capabilities. The number of levels may vary depending on the specific model and the area being evaluated, but generally, they tend to follow a similar structure. The levels often include:

1. Basic (Level 1): Data is not being fully utilized, and analysis is conducted in silos. Data accuracy is often debated, and analysis is performed on an ad-hoc basis using spreadsheets.
2. Opportunistic (Level 2): IT teams try to communicate information availability requirements, but conflicting motivations among different parts of the organization create obstacles. Lack of leadership and a limited strategy hinder progress towards better data quality.
3. Systematic (Level 3): Different types of data are now treated uniformly, and the organization has a clear strategy and vision. Agile methods have been adopted, and external data sources are easily integrated. Business managers have become responsible for data analysis.
4. Differentiated (Level 4): The organization is driven by data-focused leadership and has a Chief Data Officer who drives innovation. The focus is on return on investment from data analysis.
5. Transformational (Level 5): Analytics is central to the business strategy and decisions. Data value is a key investment consideration, and strategy and execution are aligned and continuously improved. The SVP of data provides an external perspective.

Interestingly, Gartner's four-stage model of data analytics maturity can help both assess the current state of IT business analytics systems and indicate an optimal path forward. The four stages are:

1. Descriptive analytics: can tell you what's going on in your organization.
2. Diagnostic analysis: can tell you why this is happening.
3. Predictive analytics: can tell you what will happen or what will happen.
4. Prescriptive analytics: can tell you what to do about it.

H. Logi

The best way to make analytics a natural part of everyday work is to integrate it with business applications. The Logi Maturity Model developed by Logi Analytics provides a roadmap for organizations to assess their current analytics capabilities and identify areas for improvement, as well as a framework for setting goals and tracking progress over time considering the applications. In the Logi Maturity Model, it is assumed that the more complex opportunities for data analysis are created in the structure of the daily applications, the greater the use of analytics in everyday work. The Logi Maturity Model, referred to as LAMM in some sources, has five levels of analytics maturity and also provides a self-assessment tool [23]:

1. At Level 0, also known as a stand-alone analysis, primary applications exchange data with a separate analysis application. This means end-users must rely on independent solutions to analyze their data.
2. Security integration, also called Bolt-On, allows for analytics logging at Level 1. However, users still need to switch between applications.
3. At Level 2, or Inline, the user interface integration enables the co-presentation of analytics functions with core application content and functionality. This allows companies to embed business intelligence within their existing application, although they still face certain limitations.
4. At Level 3, or infused, the inclusion of workflows enables interaction between analytics and primary applications.
5. At Level 4, also known as Genius, self-service analysis is built into the application. This is particularly interesting because it supports unanticipated usage in an integrated environment. With built-in self-service capabilities, users can ask new questions about their data and explore their ideas. Companies have numerous opportunities for competitive differentiation, and their applications can deliver new business value.

I. SAS

The SAS analysis maturity score of an organization is prepared based on the analysis performed in four dimensions:

1. Culture: Decision makers' use of data and analysis
2. Internal process readiness
3. Analytical capabilities
4. Data environment: infrastructure and software.

According to the SAS Analytical Maturity Score, an organization can be placed in one of the five Analytical Maturity stages [24]:

- First Stage - Decision-makers in this organization lack analytical awareness and rely on their perceptions, previous decisions, and invalid beliefs to make business decisions. They do not have defined data management or analytical processes to support insight development, and historical reports are treated as analysis. The organization also suffers from inconsistency and duplication of software.
- Second Stage - Decision-makers in this organization are analytically aware and understand the benefits of analytics. However, analytics are not used consistently, and the full potential of analysis is not fully understood. Analytical decisions are made on a case-by-case basis, but reasonable results are still achieved.
- Third Stage - Decision-makers in this organization are analytically astute and have adopted analytics for all decisions. The organization has standard data management processes, and data sets and analysis are used for decision-making. Although analytics capabilities change slowly, departments have their experts and plans.
- Fourth stage - Decision-makers in this organization are empowered and use analytics across the organization to support business decisions. Data processes are widely deployed to support specific business insights, and management supports analytics to align business units.
- Fifth Stage- Decision-makers are exploring novel approaches to employ cutting-edge analytics in driving business decisions. Procedures for data augmentation and analytical methods are continually being improved to maximize resources. The organization is dedicated to leveraging inventive analytics for future expansion.

J. *TDWI*

The TDWI analytics maturity model offers a means to gauge and supervise the state of analytics implementation [25]. This model presents the necessary steps for cultivating an analytical culture within an organization. The TDWI model evaluates maturity based on 35 questions across five areas of analysis maturity: organizational, infrastructure, data management, analytics, and management. Regarding the organizational domain, questions concentrate on factors such as the level of support the analytics program receives from the organizational strategy, culture, leadership, skills, and funding. Infrastructure domain questions are centered on issues related to the availability and development of analytical application infrastructure. Data management domain questions pertain to the quality, accessibility, and management of company data. Analytics domain questions evaluate the analytics culture and the extent to which analytics tools are utilized (e.g., how does analytics assist decision-making within the company?).

The TDWI Analytics Maturity Model consists of five stages [25]: companies in the initial stages, such as Nascent, may not use analytics except for basic spreadsheet software. Although some employees may be interested in analytics, decision-makers may not invest in developing the necessary competencies. Instead, decisions are often based on intuition. As companies progress to the pre-adoption stage, they create an analytical culture through employee training, forming an analyst team, and purchasing appropriate technologies. Organizations have a high analytics culture in the corporate adoption stage, and data analysis shapes the entire operation. In the mature stage, organizations use analytics efficiently with a well-established data management strategy and infrastructure.

K. *WAMM*

The WAMM model consists of scoring an organization in six dimensions:

1. Management, governance, and acceptance
2. Definition of goals
3. Range
4. Analysis and expertise team
5. Continuous improvement process and analysis method
6. Tools, technology, and data integration

During the assessment, each of these areas is assigned a score from 0 to 5, with the lowest score indicating an organization that is analytically impaired in a particular analytical area and the highest score (analytically addicted) indicating that the analysis has been the primary source of competitive advantage.

According to the WAMM model, an organization that is not analytically mature (i.e., in stage 1 or data collection) has no clear goals or criteria to meet, even if it collects data. In such an organization, data analysis usually involves reviewing reports that are typically limited to basic metrics such as the number of customers or sales of a product. Everyone in the organization has access to the data. Meanwhile, no one has been identified as directly responsible for their analysis. Employees of an organization have only basic knowledge of analysis tools, which is often reflected in their incorrect configuration, leading to analysis results that are not always correct.

IV. Comparing Data Analysis Maturity Methodologies

In this section, we compare the data analysis maturity measurement methodologies. Therefore, we define criteria set to compare the methodologies. As mentioned in the previous sections, each methodology measures specific dimensions to evaluate the maturity level of an organization. After the comparison, we will introduce the model with which the Iranian Bank analysis maturity is measured.

Generally, the more comprehensive the dimensions, the more accurate the measured maturity level and the better the extraction of strategies for the future. However, the details of the dimensions are also important, which we will discuss further.

A. *Analysis Infrastructure*

The first criterion is the infrastructure. Most businesses rely on IT infrastructure to allow employees to use technology effectively to do their jobs. Infrastructure is critical when it comes to data analysis. Data analysis infrastructure includes hardware and software resources that help employees in different organization silos to test and present their analytical ideas. If the analytics infrastructure is poorly configured, employees cannot take advantage of these opportunities effectively, impacting productivity and costing the organization more on the analytics side in the long run. For this reason, analysis infrastructure is one of the dimensions considered in all the maturity measurement methodologies, according to Table I.

B. Process

Considering the process as a way to achieve the organization's goals from analytics helps achieve uniform standards, identify weaknesses in analytics workflows, and create standardized analytics processes that simplify enterprise application requirements. For this reason, some maturity measurement methods have considered process analysis a dimension of the analysis maturity measurement process. The APMM and BLAST methods have paid particular attention to the discussion of the process in measuring the maturity of the analysis in such a way that they have become the measurement of the maturity of the analysis process.

C. Analytical skill

While improving data analysis maturity, the number of analysts in an organization is expected to increase over time. This does not only mean hiring specialists in the field of analysis but also means developing the individual analytical skills of personnel with other specialties. A data analyst uses technical skills to analyze data and report insights. The exact definition shows that this person is not necessarily a member of the analysis team in the organization. AMQ, BDO, SAS, and TDWI have identified skill assessment as essential to the maturity assessment process.

D. Data governance

Paying attention to the definition of data governance shows that it can be considered as part of the data analytics maturity model: data governance means everything that needs to be done to ensure that data is secure, private, accurate, accessible, and usable. This includes the actions people must take, the processes they must follow, and the technologies that support data throughout its lifecycle. As a result, some methods such as BLAST, DAMM, and WAMM have looked at data governance as part of the analysis maturity measurement process.

E. leadership

Leadership means directing people in an organization to achieve goals. Leaders should approve the goals that an organization has achieved from analytics maturity. Leaders help to pave this path by influencing employees' behaviors in various ways. A leader also sets a clear vision for the organization, guides employees in learning skills, and creates a spirit of analysis. This has led to the fact that, as shown in Table I, except for 3 cases, all the studied methodologies consider the role of leadership in measuring maturity.

F. Return On Investment (ROI)

ROI measures the rate of return on investment in analytics and is used in the maturity analysis. ROI is a measure to shape analytics strategies for the future. BDO and Gartner consider having a method for measuring the return on investment from analytics as an essential dimension of analytics maturity to enable managers to determine which analytics use cases are significant and which areas can be improved using analytics.

G. Organization culture

As the last measure, an organization's culture defines the appropriate method of implementing analysis. This culture, which consists of shared beliefs and values about the use of data analysis in the organization, is created by leaders and then strengthened in various ways, and finally shapes the perceptions and behaviors of employees towards this phenomenon. For this reason, DAMM and DeltaPlus methodologies consider the measurement of organizational culture to be effective in measuring the maturity of the analysis.

H. Special focus on a type of maturity

Data analysis maturity models can be customized to cater to organizations' unique needs and priorities. For instance, some models may emphasize specific areas, such as processes or application maturity, limiting their general applicability.

I. Public access to the assessment

Some models are proprietary and may only be available to licensed users or clients, while others may be publicly accessible. Several publicly available data analyst maturity models can be used to assess an organization's data analytics capabilities.

J. Separate measurement and the layering of analysis maturity levels

One thing that is less discussed in methodologies is the existence of layering for measured dimensions. This means that the organization's maturity level in each dimension is defined. This helps the organization find out which dimensions it needs to grow and which dimension has progressed, and can use the costs and power of that part of the organization in the remaining parts. Of the methods measured according to the team's reviews, only BDO offers this capability.

Table I shows the application of the above criteria in the top 11 methods of measuring the maturity of data analysis. As we can see in Table I, BDO emerges as a robust framework for assessing data analytics maturity, especially for banking, supported by its comprehensive coverage of critical dimensions. Central to its effectiveness is the emphasis on analysis infrastructure, ensuring banks can deploy scalable and secure solutions to manage and analyze vast datasets. In today's rapidly evolving financial landscape, this capability is instrumental in driving operational efficiencies and enabling timely decision-making processes essential for maintaining competitive advantage.

Moreover, BDO's support for analytical skills and leadership fosters a culture of data-driven decision-making throughout banking organizations. This dual focus ensures that personnel possess the necessary competencies to extract actionable insights and that leadership prioritizes data initiatives aligned with strategic objectives. Such alignment not only enhances operational agility but also empowers banks to innovate and adapt proactively to market dynamics.

BDO's integration of ROI assessment is critical to its appeal, which allows banks to quantify the value derived from their data analytics investments. This parameter is pivotal in demonstrating tangible outcomes such as cost savings, revenue generation, and risk mitigation strategies. By aligning analytics projects with measurable business outcomes, banks can optimize resource allocation and justify further investments, thus solidifying their position as leaders in data-driven financial services.

BDO prioritizes leadership support as a cornerstone for effective data analytics implementation in banks. Strong leadership ensures data initiatives are aligned with strategic goals and operational priorities. Leaders play a crucial role in advocating for data-driven decision-making, allocating resources, and fostering a culture of continuous improvement. This leadership commitment enables banks to navigate digital transformations successfully and capitalize on emerging opportunities provided by data analytics.

Furthermore, BDO's capability to separately measure and layer analysis maturity levels further enhances its utility for banks. This structured approach enables comprehensive self-assessment, helping banks identify strengths, address weaknesses, and leverage opportunities across various maturity dimensions. Such flexibility is advantageous in navigating regulatory complexities and evolving customer expectations, ensuring continuous improvement and strategic alignment in a competitive marketplace.

TABLE I. COMPARISON OF DATA ANALYSIS MATURITY MEASUREMENT METHODOLOGIES

Maturity Model	# measured dimensions	analysis infrastructure	Process	Analytical skill	Data governance	Leadership	ROI	Organization culture	Special focus on a type of maturity	Public access to the assessment	Separate measurement of analysis maturity levels	The layering of analysis maturity levels
APMM	6	■	■						P*	■		
AMQ	5	■	■	■		■				■		
BDO	6	■		■		■	■				■	■
Blast	6	■			■	■			P*	■		
DAMM	4	■			■	■		■	EA*			
DeltaPlus	7	■		I*		■		■		■		
Gartner	5	■				■	■					
Logi	1	■							A*	■		
SAS	4	■	■	■		I*		■				
TDWI	5	■		■		■		■				
WAMM	6	■	■		■	■				■		

*P: Maturity of Processes; EA: Exclusively association; A: Maturity of applications; I: implicit

V. DEVELOPMENT OF A BDO-BASED ASSESSMENT FOR A BANK

The BDO methodology has devised an approach for assessing the level of advancement in data analysis. This methodology involves a three-pronged approach encompassing architecture, analytics, and AI, which must be integrated to establish the requisite technological framework for achieving a mature data analytics capability. Furthermore, an organization's capacity to effectively utilize its data relies heavily on human resources. Neglecting leadership development, fostering a conducive culture, and providing opportunities for employee upskilling would hinder a company's workforce from meeting the demands of the business's future state. Generally, the six dimensions include:

1. Human resource
2. Skills
3. Architecture
4. Data analysis
5. Artificial intelligence
6. Return on investment

BDO charted the most revealing signs that indicate a company's advancement in establishing a refined data analytics initiative [20] and introduces five levels shown in Figure 1.

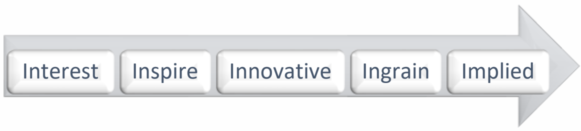

Figure 1. The Maturity Levels of BDO

Interestingly, BDO presents AI as a tool or a dimension in service of data analysis and introduces a clear distinction between dimensions and levels as follows:

1. *Human resource* dimension: At the first level, human resources stimulate enthusiasm and energy in cultural transformations, primarily emphasizing data. At the second level, human resources inspire data specialists to make well-informed business decisions. Moving to the third level, human resources exhibit innovation by forming collaborative teams with external entities to assess return on investment, concurrently encouraging employees to craft practical applications. Upon reaching the fourth level, data-driven decision-

making becomes deeply ingrained in the corporate culture, with employees routinely engaging in data analysis practices. Finally, at the fifth level, data utilization in various roles becomes implicit and intrinsic, manifesting as a paradigm wherein data underpin all decisions. Data analysis is vested with trust and credibility, even when challenging pre-existing convictions.

2. *Skills* dimension: An organization's level of interest is identified when it possesses business insight, creativity, basic data visualization, and foundational dashboard skills. Moving beyond interest, an organization can be said to inspire when it excels in data visualization and advanced dashboard skills (e.g., BI and Tableau mastery). Advancing further, innovation within an organization is recognized when it adopts cloud data architecture and designs scalable solutions, engaging in data engineering and immediate data skills application. Progressing to the level of ingrained skills, an organization is identified by its utilization of process automation and machine learning. Lastly, at the implied skills stage, an organization is recognized for employing cognitive AI, autonomous AI development, and intelligent automation.

3. *Architecture* dimension: Interest is marked by evaluating existing data resources, datasets, and long-term data modeling. Inspiration emerges through defined information governance and tailored data integration. Innovation involves data quality control and evolving data storage models. Ingrained architecture means adopting comprehensible reference architecture and automating data management. Lastly, implied architecture involves data integration and automated databases.

4. *Data analysis* dimension: An organization's interest is recognized when specialized and short-term project analyses are outsourced to third parties. An organization can be said to inspire when specific analysis approvals begin with a primary focus on program reporting and gaining meaningful insights from existing data. Furthermore, innovation within an organization is identified when internal insights lead to dashboard design under strict shared governance with critical stakeholders for decision-making. Progressing to the ingrained data analysis phase, an organization is recognized as operational analysis drives company-wide decision-making, employing advanced analytics, including forecasting and predictive models. Lastly, deep learning algorithms come into play at the implied data analysis stage.

5. *AI* dimension: In the AI dimension, an organization is considered ingrained when the return on investment analysis is considered at the outset of each operation, and an organization is classified as implied when AI is utilized in commercial products and essentially becomes invisible within the organizational framework.

6. *ROI* dimension: An organization's interest is identified when it leads to risk advancement and cost savings. An organization can be said to innovate when data analysis leads to more thoughtful decision-making and data-supported choices. An organization is recognized in the implied ROI level when data is fully acquired through collaborations, integrations, new revenue streams, and product recommendations.

Each six dimension is measured separately using a questionnaire (Appendix A) in the designed evaluation framework. Calculating maturity levels based on the answers to the questionnaire is described in Appendix B.

VI. Result and Discussion

The evaluation proposed in this research was used in one of the Iranian banks, and the maturity of the data analysis of this bank was evaluated in six dimensions. The bank's analysis encompasses critical insights and information that, if disclosed, could confer a significant competitive advantage to the rivals. Public dissemination of this data could undermine the bank’s competitive edge and market standing. Furthermore, the proprietary nature of the analytical methodologies and the sensitive financial data involved necessitate confidentiality to protect clients' interests and ensure regulatory compliance. Therefore, while we refrain from publishing the comprehensive results, we are pleased to publish key shareable findings from the analysis as follows. Among the various dimensions of BDO, we focus on Human Resources (HR) for public discussion. This is because HR insights primarily pertain to internal organizational practices and employee engagement strategies, which are less likely to compromise the competitive position or reveal sensitive financial information. By sharing our HR findings, we can contribute to industry best practices and thought leadership without jeopardizing the market position or breaching confidentiality protocols.

Among the announced online questionnaires in the bank, 89 were completed, including 23 managers and 66 expert employees. In some cases, there are interesting differences between the aggregated results of the managers and the aggregated results of the experts. Further details will be discussed in the following section.

The results of the self-assessment that all participants conducted show that in the bank, the employees of the operational departments can find and access small analyses of their department's data. Managers in different departments are interested in analytics but have little communication with each other. Many participants believe that colleagues do not trust software analyses of data. If the results contradict long-held beliefs, people use beliefs as a criterion for action. With a score of about 0.6 out of 1, the bank is at level 2 regarding the maturity of its human resources. Table II shows the evaluation of the human resources department's responses from all respondents' points of view. The results obtained from managers' responses also show the bank at the SP level, with the difference that the managers believe that the bank is a little far from reaching level 3, i.e., "innovator". Thus, the score of question 4 increases from 0.42 for experts to 0.46 for managers. This difference is most visible in measuring level 4. In question 5, the score of experts was 0.36, and this score was 0.44 for managers.

In the following sections, we endeavor to provide insights into other dimensions of our analysis to the permissible extent without compromising confidentiality or competitive advantage. This includes distinguishing perspectives between managers and employees and highlighting key distinctions in their roles, responsibilities, and perceptions within the organizational framework. While maintaining discretion on sensitive financial data and strategic insights, we aim to offer valuable perspectives that contribute to a deeper understanding of organizational dynamics and operational strategies across various dimensions.

In assessing the maturity of bank data analysis from the perspective of skills levels 4 and 5, the respondents are asked to evaluate the current conditions of the bank from the standpoint of using virtual or augmented reality, the Internet of Things, use of scaling methods, data engineering, cloud space, automatic system for detecting fraud and money laundering, chatbots, measuring the risk and personalization of offers. The response shows that the bank uses this category of analysis applications only to identify the risk when granting loans and other financial facilities. In this part, there is an exciting difference in the results of question 10 between the level of managers and expert employees, showing that managers see the bank at a lower level regarding analysis skills.

The results show that there is a slight difference between the opinions of expert employees and managers in the field of architecture, and especially regarding the amount of data exploitation (which supports level 4 or "ingrain"), the managers believe that the bank has a higher level of maturity.

Assessing the maturity of bank data analysis from the perspective of ROI shows that managers' opinions differ from employees' about question 25. The managers believe that the bank must be able to improve its marketing campaigns with its current data analysis.

TABLE II. MEANS AND STANDARD DEVIATIONS (SD) OF ANSWERS TO QUESTIONS RELATED TO HUMAN RESOURCE

Questions related to **Human Resource**						
Question	Q1	Q2	Q3	Q4	Q5	Q6
Mean (SD)	2.11 (0.90)	2.60 (1.13)	3.39 (0.89)	2.72 (0.95)	2.54 (0.88)	2.38 (0.80)

VII. CONCLUSION

In the era of drastically increasing data, including business data, the capability of data analysis is a competitive driver for most enterprises, especially those dealing with data, such as banks and financial service businesses. A data maturity model is necessary to know what an “As-is” situation is and understand the organization's strengths and weaknesses in data analytics. Based on the results of the maturity model and evaluated maturity level, the organization can plan to strengthen its capability in data analytics.

In this paper, we overviewed the data analytics maturity models and compared them according to our proposed comprehensive criteria. According to this comparison, we found the BDO data analytics maturity model a valuable base to be customized for the banking business. We have developed the questionnaire and how to assess maturity levels in various related dimensions. The proposed model has been applied to an Iranian bank as a case study and achieved valuable results that decision-makers could use to enhance the bank competition in the market. Any bank and financial business could use the customized model.

As this research's limitation, we presented just some parts of the results due to confidentiality issues, and more details remain confidential.

In future work, it would be helpful to validate the questionnaire with a larger sample size to ensure that it accurately measures the different dimensions of the data analytics maturity model. The questionnaire was developed for an Iranian bank, so it would be interesting to see how well it performs with different types of banks, such as banks in other countries or with various business models. Analyzing the data collected from the questionnaire could provide valuable insights into the strengths and weaknesses of the organization's data analytics capabilities, which could be used to inform future decision-making and guide the organization's data analytics strategy.

APPENDIX A: THE QUESTIONNAIRE

The questionnaire designed and used in this research is presented here. All the questions have a single-choice answer except those 11, 12, 22, and 23. The choices for the questions start with “Your opinion about:” are five-level Likert scale choices, including:

a) Strongly agree
b) Agree
c) Neither agree nor disagree
d) Disagree
e) Strongly disagree

A. *Questions related to human resources*

1. From the organizational analysis viewpoint, which of the following levels do you assign to the bank?
   a) Level 1: No organizational view of the data; system analysis is performed poorly.
   b) Level 2: Data is isolated in separate systems; technology and expertise are used to create local value on each island.
   c) Level 3: Different processes or units of the bank focus on infrastructure analysis
   d) Level 4: The bank's key analytical data is managed from an organizational perspective
   e) Level 5: Analytical resources are entirely focused on the organization’s priorities and differentiation

2. Which of the following levels best describes the bank's leadership approach to analysis?
   a) Level 1: There is little awareness and interest in analytics among bank managers
   b) Level 2: Managers in different departments are interested in analytics, but there are few communications among them.
   c) Level 3: Senior managers have realized the importance of analytical capabilities.

d) Level 4: Senior managers are developing analytics programs and building analytics capabilities.
e) Level 5: Managers are enthusiastically competing with other competitors using analytical capabilities.

3. Your opinion about: “Employees of operational departments can find and access even small analyses of their department's data.”
4. Your opinion about: “Employees at all levels can use the analytical knowledge generated by the applications.”
5. Your opinion about: “Employees perform data analysis regularly, and almost every employee has a good knowledge of how analytics is used in their department.”
6. Your opinion about: “All decisions are based on data analysis. Software analyses on data are trusted by our colleagues, even if the results contradict long-held beliefs.”

B. Questions related to skills

7. Your opinion about: “Data analytics skills are considered in the recruitment process.”
8. Your opinion about: “A good number of managers and employees have education related to technology.”
9. Your opinion: “Training classes related to data analysis and visualization are usually held.”
10. Which of the following best describes the organization’s analytics professionals (analysts, data scientists, etc.)?
    a) Level 1: They have few skills and serve particular functions.
    b) Level 2: They are separate categories that have a combination of unmanaged skills.
    c) Level 3: Analysts are recognized as key talent and focus on important business areas
    d) Level 4: Expert analysts are recruited and engaged in the organization
    e) Level 5: Professional analysts are in the organization, and there is a written plan for training amateur analysts across the *organization.*
11. Which of the following technologies does your organization currently use? Select all relevant options. (If none of them, go to the next question.)
    a) Collaboration with suppliers and different units through the cloud
    b) Data Engineering
    c) Using scalable methods (e.g., during the peak of transactions)
    d) Internet of Things
    e) Using virtual or augmented reality to communicate with customers
12. Which of the following customer experience capabilities do you currently have? Select all relevant options. (If none of them, go to the next question.)
    a) Personalization of the offers given to the customers based on their behavior and specific data
    b) Risk assessment at the time of granting facilities
    c) Chatbots to answer in the form of an automatic customer service center
    d) Automatic system to detect fraud and money laundering
    e) Other services based on machine learning that are not included in this list

C. Questions related to architecture

13. Your opinion about: “There is a common definition of data sources in the organization (e.g., customer forms, transaction forms, etc.) that enables data sharing in the organization.”
14. Which of the following levels best describes the characteristics of the bank data?
    a) Level 1: Our data are inconsistent, poor quality, and nonstandardized, making substantive analysis difficult.
    b) Level 2: Our data is standardized, structured, and primarily stored in a (functional or process) data warehouse.
    c) Level 3: Key data areas have been identified, central data warehouses have been established, and data quality is regularly reviewed.
    d) Level 4: Integrated, accurate, and common data exists in the central warehouses.
    e) Level 5: Besides Level 4, there is a continuous search for new data and metrics using structured and unstructured data.
15. Your opinion about: “Some data (transaction details, customer information, etc.) are managed uniformly across the bank to facilitate integration.”
16. Your opinion about: “An interaction exists between the IT department and operational departments, which enables the full exploitation of data.”
17. Which of the following levels best describes the bank analytics technologies?
    a) Level 1: Standard office suites, loosely integrated systems
    b) Level 2: Individual analytical initiatives, statistical packages, descriptive analysis, database query
    c) Level 3: Enterprise analytics platforms; Predictive analytics packages
    d) Level 4: Organizational analytical process, using data that is automatically generated
    e) Level 5: Complex significant data architecture and enterprise-level analytics, autonomous analytics

D. Questions related to data analysis

18. Which of the following levels best describes the bank's data characteristics?
    a) Level 1: Basic reporting tools and descriptive analysis
    b) Level 2: Data in relational tables and using BI and basic analytics tools
    c) Level 3: both relational data and unstructured NoSQL data

d) Level 4: both NoSQL data and relational data and using analytics on them.
e) Level 5: Besides the previous option, data are so important that they are handled by a large separate department (other than IT) and managed as a strategic asset.

19. Which of the following levels best describes the bank's data analysis capabilities?
   a) Level 1: We do not have analysis capabilities, and we outsource if necessary.
   b) Level 2: We use analytics on an ad hoc basis for specific needs, primarily for reporting
   c) Level 3: Insight into bank data in dashboards few people can access.
   d) Level 4: We use advanced analytics, including predictive models.
   e) Level 5: Our analysis using machine learning and deep learning algorithms provides a comprehensive understanding of the situation in the bank.

20. Which of the following levels best describes the bank's approach to aligning analytics with the bank's business goals?
   a) Level 1: Opportunities are not targeted
   b) Level 2: Several distinct targets that are usually not of strategic importance
   c) Level 3: Analytical efforts for a small set of important targets
   d) Level 4: Focused analysis on a few key business areas with precise results
   e) Level 5: Dynamic analysis for the bank's differentiated strategy is formulated and implemented.

21. Which of the following levels best describes the analytical techniques your bank can employ?
   a) Level 1: In the bank itself, it is mainly done temporarily using simple math and extrapolation, or the entire project is outsourced.
   b) Level 2: Basic statistics, segmentation, database querying, and tabulation of key metrics are used to gain insight into the bank.
   c) Level 3: Simple analysis is used for classification, clustering, and dynamic predictions.
   d) Level 4: Advanced predictive methods are used to optimize efficiency; for example, the bank uses text and image analysis tools.
   e) Level 5: Neural networks and deep learning are used in the bank, and algorithms such as genetics or advanced machine learning are used as analysis techniques.

E. Questions related to AI

22. Choose all the items you think are correct about applying AI in the bank. (If none of them, go to the next question.)
   a) Before any initiative, it is possible to calculate the return on investment.
   b) Some AI projects are defined in the bank as having a specific impact on the bank's vision.
   c) The data needed to support special AI techniques is well provided.
   d) There is a desired leadership pace for progress in AI.
   e) There is an AI roadmap aligned with digital transformation, innovation, research and development, human resources, and other strategies.

23. Choose all the items you think are correct about applying AI in the bank. (If none of them, go to the next question.)
   a) AI has taken root in bank business products, making improvements, saving money, and increasing profitability.
   b) AI is seamlessly integrated into the bank's overall organizational strategy.
   c) The bank's budget indicators for business and AI technology are integrated.
   d) New models based on AI in the bank are easily discovered and used.
   e) AI exists in the organization and has become one of the components of the bank's daily business.

F. Questions related to return on investment

24. Your opinion about: “The bank is investing in the areas necessary to extract value from data analytics.”
25. Your opinion about: “The bank has been able to improve its marketing campaigns with the current analytics for its data.”
26. Your opinion about: “The bank has been able to improve its brand with data analytics.”
27. Your opinion about: “The analysis has helped identify bank challenges before they occur.”
28. Your opinion about: “Using data analytics in the bank, human resources are used more efficiently due to less manual efforts.”

Appendix B: Calculating Maturity Levels

This appendix explains the method used to analyze the questionnaire answers to assign maturity levels to the six dimensions of BDO. The following abbreviations are assigned to the maturity levels:

- Int (for Interest),
- Ins (for Inspire),
- Inn (for Innovate),
- Ing (for Ingrain), and
- Imp (for Implied).

For questions stating “Your opinion about” these values are assigned to the options:

a) 0: Strongly agree
b) 0.25: Agree
c) 0.5: Neither agree nor disagree
d) 0.75:Disagree
e) 1: Strongly disagree

The average of the answers to each Likert opinion question (Qn) is calculated (Av(Qn)) and is interpreted as True (T) or False (F) according to the Boolean rule:

B(Qn) = T If Av(Qn)>0.5; and F, otherwise.

For the questions asking to select one of the five levels (questions 1, 2, 10, 14, 17-21), the overall answer is calculated as the mode of answers (M).

The average of the selected choices (L) for multiple-choice questions is calculated by considering items from 1 to 5.

The above abbreviations are used in the following rules; moreover, Qn implied the answers to question number n in the questionnaire.

For measuring the "Human resource" level, Q1-Q6 are used as follows:

If [(Min(M(Q1),M(Q2))=Ins) and (B(Q3)=F)] then level=Int
If [(Min(M(Q1),M(Q2))=Ins) and (B(Q3)=T)] then level=Ins
If [(Min(M(Q1),M(Q2))=Inn) and (B(Q4)=T)] then level=Inn
If [(Min(M(Q1),M(Q2))=Ing) and (B(Q5)=T)] then level=Ing
If [(Min(M(Q1),M(Q2))=Imp) and (B(Q6)=T)]then level=Imp

For measuring the "Skill" level, Q7-Q12 are used as follows:
Level of "Skill" = (Min(M(Q8), M(Q10)

Questions 7, 9, 11, and 12 are used in the questionnaire to improve the skill maturity level in the organization.

For measuring "Architecture" maturity level, Q13-Q17 are used as follows:

If [(Min(M(Q14),M(Q17))=Ins) and (B(Q15)=F)] then level=Int
If [(Min(M(Q14), M(Q17))=Ins) and (B(Q15)=T)] then level=Ins
If [(Min(M(Q14), M(Q17))=Inn) and (B(Q13)=T)] then level=Inn
If[(Min(M(Q14), M(Q17))=Ing) and (B(Q16)=T)] then level=Ing
If (Min(M(Q14), M(Q17)) = Imp) then level=Imp

For measuring "Data analysis" maturity level, Q18-Q21 are used as follows:

Level = M(Q18-21)

For measuring "AI" maturity level, Q22 and Q23 are used as follows:

If (Av(Q22)>2.5 AND Av (Q23)<2.5) then level =Ing
If (Av(Q22)>2.5 AND Av(Q23)>2.5) then level = Imp

For measuring the "Return on investment" maturity level, Q24-Q28 are used as follows:

If (B(Q24)=T) and (B(Q25) and B(Q26))=F and (B(Q27) and B(Q28))=F then level=Int
If (B(Q24)=T) and (B(Q25) and B(Q26))=T and (B(Q27) and B(Q28))=F then level=Inn
If (B(Q24)=T) and (B(Q25) and B(Q26))=T and (B(Q27) and B(Q28))=T then level=Imp

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