Towards Managing Analytics for Incumbent Banks: A Maturity Model

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Abstract

Analytics improves organizational performance and becoming data-driven with analytics is therefore a vision for many incumbent banks. However, successful deployment and management of analytics in banks are often hindered by legacy systems, processes, and organizational challenges associated with lack of a data-driven mindset and resistance to change. Therefore, this research-in-progress paper presents a preliminary design of a conceptual maturity model for managing analytics in the context of incumbent banks. By using existing maturity model design and development guidelines, analytics-related literature from the banking sector and related fields, and empirical evidence from one incumbent bank, this research-in-progress paper presents a model with 4 dimensions, 13 sub-dimensions and 4 maturity levels. The research-in-progress paper also provides the basis for future development, and validation.

Keywords

Analytics, Maturity Models, Stages of Growth, Business Models, Value Creation

1. Introduction

Banking and financial services organizations are dependent on analytics to perform core business activities like calculating risk, control transactions and processing payment data as well as peripheral business activities like processing consumer habits to create of personalized products and services [6; 51]. It is understood that the utilization of data analytics improves organizational performance and competitive advantage [7; 11; 16; 17; 54; 58] and thus becoming data-driven with analytics is therefore a vision for many of these incumbent banks. These Incumbent banks often have large and aging systems consisting of various information technology (IT) and shadow analytics systems that have emerged in business units. These have been built on top of each other over the course of many years without going through the formal and controlled organizational IT structures [46]. Unlike digital companies (e.g., Amazon, Google) which are driven by data and analytics, these traditional banks are often challenged by legacy technology and embedded organizational factors unsupportive of analytics; with complex and large technological architectures, continuously growing pools of data and weak data governance [19; 44], the generation of value from analytics can be difficult [33]. In addition to the technological challenges, incumbent banks often face human (socio) challenges with lack of a data-driven mindset and resistance to change listed as the main inhibitor of retrieving business value from analytics [44; 50].

It is understood that the bringing about this change can be time-taking and complex because of the need of various stakeholders to establish a common language and interact with each other (e.g., IT, analytics and business functions or units like operations, sales, marketing, etc.). Information systems scholars [36; 56] argue that a maturity model is a useful organizational tool to guide such a change. However, despite the vast amount of maturity models within analytics [17; 54], maturity models for

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managing analytics[2] in the context of incumbent banks present a research gap, which is addressed in this research-in-progress paper. The rest of this research-in-progress paper is structured as follows. First, we briefly introduce the terminology associated with maturity models. Second, we present the methodological background and choices. Third, we review the extant literature and present the first iteration of the suggested maturity model. Lastly, we discuss the empirical evidence, present the second iteration of the conceptual maturity model, and discuss future work.

2. Maturity Models

Maturity models and stage of growth models are organizational tools that facilitate internal and/or external benchmarking while also showcasing future improvement and providing guidelines to help the audience towards some desired outcomes [40]. The term "maturity" is defined as "the state of being complete, perfect or ready" [40]. A maturity model usually consists of a sequence of maturity levels [48], mostly four or six [30] and are often represented as fixed level models, continuous level models or a matrix structure in form of focus area models [34; 45]. Each level expects a socio-technical entity (i.e. people, process, technology, organisation) under maturation to fulfil certain requirements that constitute that particular level [34]. Usually, this is determined by defining dimensions, benchmark variables, capabilities or critical success factors and boundary conditions or dominant problems [35]. The dimensions as prescribed by the maturity model also mean better outcomes and thus higher business benefits (value) as the organization progresses on the path to increased maturity. In general, maturity assessment is understood as a measure to evaluate the capabilities of an organization [34; 48], with an intention to provide a common vocabulary to facilitate discussion and thus a structure for prioritizing actions [36], which is also the purpose of this paper.

Following the prior meta studies on maturity models by Mettler, Rohner, and Winter [41], J Becker, Knackstedt, and Poeppelbuss [4] for this study we subscribe to the definitions and terminology proposed by L. Lasrado, et al. [34]: " (i) Maturity Level [Level1… Level n] are levels or stages the describe the archetypal states of maturity of the entity with each level having a set of distinct characteristics [34; 42; 47]; (ii) Dimensions (Xmn, m factors and n levels): "Elements", "Critical Success Factors", "Conditions", "Factors", and "Capabilities" are some of the other terms. Each dimension is divided into sub-dimensions with specific characteristics at each level [34; 47]; (iii) Boundary Conditions [B1… Bn]: Also termed "Triggers", "Dominant Problems" [56] and "Inhibitors", "existential crisis" [13] are specific conditions that the entity has to satisfy in order to progress from one level to another [35]".

3. Methodology

As discussed in section 2, information systems scholars [5; 18; 34; 41; 56] have prescribed approaches, guidelines, and definitions to design and develop maturity models in a systematic manner. For this study, we adopted the five step modelling process prescribed by Solli-Sæther and Gottschalk [56], while also using some of the guidelines and definitions prescribed by Mettler [40]. At the time of writing this research-in-progress paper, we are in the design phase i.e., developing a conceptual model as shown in Figure 1.

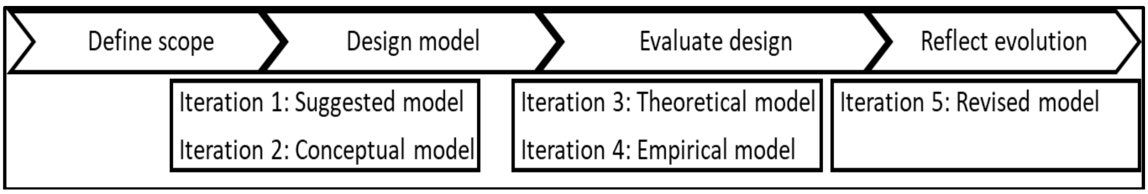

Figure 1. Maturity model development based on Mettler [40] & Solli-Sæther and Gottschalk [56].

[2] Within the scope of this current study, managing analytics is understood as "a set of activities and processes where data is analyzed, managed and used and where statistical and quantitative analysis, explanatory and predictive models are applied in order to drive more effective and fact-based decision-making that can enhance business value, performance, innovation, new product and services development, and transform business processes".

We have derived the suggested model through review of the literature and integrating ideas from practice (the process is discussed in section 4). According to Solli-Sæther and Gottschalk [56], the next step of deriving the conceptual model is a result of empirical testing wherein the descriptions of maturity levels are developed in an iterative cycle and the dominant problems or boundary conditions are also established [22; 34]. Solli-Sæther and Gottschalk [56] prescribe case studies for each of the maturity levels and in this research-in-progress paper, we present one such case which is at maturity level 2 of the suggested model. The selected case organization is an incumbent, leading Norwegian bank functioning as a full provider of banking and financial services. A total of nine semi-structured interviews were performed (see Table 1) at this case company, which were used to develop and enhance the maturity model. Interviews were transcribed and categorized continuously through the process. Transcription was conducted manually and simultaneously anonymized. In addition to these interviews, documents about data governance, the data product concept and ambitions for technical platforms were also examined[3]. Next, the data was categorized into main dimensions and sub-dimensions; while the components of the interview guide made the foundation for the categorization, the data analysis also resulted in the emergence of new sub-dimensions like data privacy and data & analytics presentation (section 5).

Table 1. Interviews for Case 1.

Informant and Role		Baking Entity	Department	Date	Duration (min)
1	Section Leader	Private	Data Driven Sales	18.01.22	60
2	Lead Information Architect	Private	Digital Architecture	24.01.22	90
3	Data & Analytics Consultant	Private	Data Driven Sales	25.01.22	60
4	Lead Advanced Analytics	Corporate	Advanced Analytics	19.02.22	60
5	Privacy Steward	Private	Quality And Risk	21.02.22	40
6	Section Leader	Wealth Mgmt.	Customer Insight	22.02.22	60
7	Data Scientist	Private	Data Driven Sales	23.02.22	60
8	Section Leader	Risk	Risk Data	23.02.22	50
9	Department Manager	Corporate	Data Governance	02.03.22	45

4. Suggested Analytics Maturity Model

Following the guidelines prescribed by Solli-Sæther and Gottschalk [56], the suggested maturity model was developed based on prior research (i.e., analytics maturity models, analytics in banking) and practice (i.e., digital consultancy maturity models). Peer reviewed journals articles on analytics in banking were fetched via Oria and Google Scholar using a combination of keywords in the titles: "analytics" OR "data analytics" OR "data-driven" OR "data-driven decision-making" OR “decision analytics” OR "decision support" OR "decision intelligence" OR "business analytics" OR "business intelligence" OR “data management” OR “data governance” OR “dashboarding” OR “data visualization” AND "bank" OR "banking" OR “financial services”. We were interested in articles that discussed applications, capabilities and challenges related to managing analytics in the banking sector, was relevant in today’s digital environment and hence set a timeframe of last 5 years.

The search process resulted in 341 articles, which after scanning titles and reading abstracts, resulted in 16 selected articles [1; 2; 3; 14; 19; 21; 25; 26; 28; 29; 31; 38; 43; 44; 50; 53] that were read in full and included in the review. Five more articles [10; 23; 27; 51; 52] were added because of backtracking and snowballing. In addition to the domain specific articles, we also reviewed articles within analytics (e.g., [24; 54; 55], [12; 20; 49],[8; 9; 15; 32; 39]). The process also resulted in us extracting 11 capabilities for analytics maturity into as shown in Table 2. These 11 capabilities (later referred as sub-

[3] These documents became available during the interview process as one of the informants suggested them.

dimensions) were broadly grouped under four dimensions i.e., Technology & Analytical techniques, Organization & Culture, People, and Data management respectively[4].

Table 2. Categorization of capabilities (sub-dimensions) for analytics maturity.

Authors	Systems & Tools	Analytical Techniques	Applications	Culture & Organization	Analysts	Leaders	Data Quality	Data Storage	Data Lineage	Data Sourcing	Data Governance
Ali et al. [2]		⌖		⌖	⌖	⌖					
Al-Nattar and Alazzavi [1]				⌖							
Clarke [10]		⌖					⌖	⌖	⌖		⌖
Cosic, Shanks and Maynard [12]	⌖	⌖	⌖	⌖	⌖	⌖					⌖
Dash and Das [14]		⌖	⌖								
Davenport and Harris [16]	⌖	⌖	⌖	⌖	⌖	⌖		⌖		⌖	⌖
Delgosha, Hajiheydari and Fahimi [19]	⌖	⌖	⌖	⌖			⌖				
Deloitte [20]	⌖	⌖	⌖	⌖							⌖
Dicuonzo et al. [21]		⌖	⌖					⌖			
Forrester [24]	⌖	⌖	⌖	⌖							⌖
Hajiheydari et al. [25]	⌖	⌖		⌖	⌖	⌖	⌖				⌖
Hung, He and Shen [28]			⌖								
Joshi, Pratik and Podila [29]							⌖	⌖	⌖		⌖
Karkošková [31]							⌖	⌖	⌖		⌖
Lacković, Kovšca and Vincek [23]	⌖	⌖	⌖					⌖		⌖	
Law and Chung [38]			⌖								
Owusu [43]			⌖								
Pillay and van der Merwe [44]	⌖	⌖		⌖	⌖	⌖					⌖
Rezaie, Mirabedini and Abtahi [50]	⌖	⌖			⌖	⌖	⌖		⌖	⌖	
Sadok, Sakka and El Maknouzi [51]	⌖	⌖	⌖							⌖	
Scherbaum, Novotny and Vayda [52]	⌖						⌖	⌖	⌖		
Schmidt, Drews and Schirmer [53]			⌖				⌖		⌖		
Count	11	14	13	9	6	6	8	7	6	4	9
	⌖	*Size indicates the level of Importance or mention in the article*									

Technology & analytical techniques characterizes the adoption and application of technology, infrastructure, tools, and techniques that support analytics in the organization. Lately, financial decision-making has become highly dependent upon sophisticated analytical tools; fraud and risk analysis is ranked as the most important applications of analytics in banking [19; 25]. Banks are also dependent on analytics to know their customers (KYC) for anti-money laundering (AML) regulations and risk management [21; 26] and utilizing analytics here is a matter of survival for banks because of laws and regulations. On the other hand customer analytics, which involves utilizing data for customer acquisition, satisfaction and retention, was ranked the second most important and was associated with a higher analytical maturity [19]. The third most important application was considered operational

[4] Sub-dimensions Systems & Tools, Analytical Techniques and Applications are grouped as Technology & Analytical techniques. Analysts and Leaders are grouped as People. Culture & Organization is left as is and rest of the 5 sub-dimensions are grouped under Data Management.

analytics, involving utilization of data to renew or innovate business models, products, and services, and streamline existing ways of working which strengthened employee learning, which enhanced innovation, NPD and internal processes [19; 43]. In addition to application of analytics, the literature lists security, flexibility, integration, accessibility, user friendliness and dependency on legacy systems as technological requirements needed to leverage value from analytics. Compatibility and integration problems concern insufficient data sharing across business units due to information silos [19; 25; 44; 50], with time and money invested in legacy systems that are incompatible with new analytics technologies is acting as a strong inhibitor or dominant problem towards higher analytical maturity.

Organization & culture includes organizational norms, values, and formalized departments or functional units to systematically work with analytics as the lack of a data-driven approach is a main inhibitor of realizing business value from analytics [19; 25; 44]. Top management support, empowerment of end users, analytics promotion towards the entire organization and all stakeholder groups [2; 19; 25; 44] and an agile culture [1] were all seen as enabler of data driven culture.

People includes professionals i.e., employees and consultants utilizing analytics in their job function and leadership support for analytical competence [15; 16]. Good recruitment processes and allocation of resources for analytics training is considered crucial to sustain skills and competence by several studies. The main organizational challenges are seen as lack of skilled professionals, especially on machine learning, and lack of TMS due to low managerial analytics competence, risk taking, and implementation costs [2; 25; 44; 50].

Data management includes data infrastructure, data sourcing, quality, warehousing, accessibility, and data governance [15; 57]. Data quality and quality of working flows (e.g., ETL) is critical during early stages of implementation [25]. Data sourcing involves both internal and external searches [19], with data lineage heighted as an important factor. To strengthen data lineage, master data should be managed in a way that ensures traceability and distributed discovery through the value chain [57] with a standard data catalogues including business glossary, information about data ownership, and technical descriptions being implemented across the enterprise. Data management dimension also includes data governance [31] which is as a framework of control mechanisms such as processes, policies, organizational structures and roles that ensures the allocation of decision rights and responsibilities for governing data and analytics in an organization [31; 57]. Higher levels of maturity prescribes a right balance between centralized and decentralized data governance [29] to ensure control, flexibility, productivity, data quality and transparency with strategic and operational data committees with well-defined data roles such as CDO, data stewards, and quality managers [31].

This process of content analysis of the sub-dimensions also resulted in us extracting four maturity levels and the characteristics of the four levels are as described in Table 2.

Table 2. Suggested Analytics Maturity Levels.

	Level Name	Characteristics of the Level
1	Analytical Beginner	Analytical processes are ad-hoc, unstable, inconsistent, and ungoverned. Analytics is only utilized for necessary banking operations. Analytical investments are incompatible with existing infrastructure. The organization is silo-organized, has poor data quality and technical debt which needs to be addressed before anything else. Lack of analytical talents and leadership visions, competence, support, and engagement in analytics.
2	Analytical Developer	Architecture and processes are developed and prepared to scale analytics. The organization is implementing some data management and governance and working on improving data quality. Analytics is promoted and beginning to attract interest enterprise-wide. Management is beginning to understand the importance of analytics, has some analytical competence and are willing to allocate some resources.
3	Analytically Established	Analytical architecture, processes, data management, governance and more advanced techniques are established. Data quality is improved, measured and transparent. Data-driven culture is extensively promoted.

		Organization and management are in support of analytics and has established enhanced analytical competence.
4	Analytical Differentiator	Analytical architecture and processes are optimized, governed, and continuously improved. Data quality is optimized and continuously monitored and analyzed. Analytics is considered the key source of competitive advantage as it has full enterprise-wide engagement and support. The organization possesses great analytical talents. Managerial competence is high and risk-taking is encouraged. Innovation is driven by analytics. The organization continuously adapts to market changes and delivers value back to the customer via real-time analytics. Analytical activities are unique and generate strong revenue growth.

5. Future Agenda - Towards a Conceptual Analytics Maturity Model

As discussed in section 3, the conceptual model should empirically test the characteristics of each level, significant differences between levels and the boundary conditions using case studies [56]. We applied the suggested model on an incumbent Norwegian bank (section 3) and assessed it to be at maturity level 2 (i.e., analytical developer) as shown in Table 3a, 3b, 3c and 3d[5]. During this assessment conducted via semi-structured interviews, we updated the characteristics of the maturity levels, tested the relevance of the dimensions, sub-dimensions, and boundary conditions. The data analysis resulted in addition of two sub-dimensions i.e., Data & Analytics Presentation and Data Privacy. Data & Analytics Presentation involves dashboarding, presentation, reporting and visualizing data towards decision-makers, management, and end-users. The bank has one primary tool for reporting data and was discussed by the interviewees as a significant factor towards maturity. However, low maturity in data quality and lineage affects the success of data presentation in terms of dashboard reusability.

Data privacy became a bigger talking point throughout the interview process and was continuously brought up as an obstacle for managing analytics. In 2018, the bank was forced to address data privacy to a greater extent due to the 'General Data Protection Regulation' (GDPR). The empirical findings show that data privacy is functioning as a very important aspect of data management in Norwegian banking, which in many cases functions as an obstacle of analytics applications. Moreover, the duty of confidentiality reduces the ability to share data between entities which doesn't advocate for producing less copies of the same data. This sub-dimension also produces a tradeoff between increased control over data lineage which strengthens data governance. Data privacy was therefore considered an additional sub-dimension of data management as shown in Table 3b.

Maturity in terms of Analytical Systems & Tools are assessed as between stage one and two. Multiple legacy systems with many integrations, usability and compatibility challenges are seen in stage one. Moreover, lack of operational central IT unit provokes shadow IT. We observed that analytical developers are attempting to address these challenges while new analytics infrastructure is established in the next stage. Results show that analytical differentiators possess an automated, cloud-based storage and distribution platform, with agile ETL and data management solutions realising business value. The assessment shows that the Analytical Tools & Techniques sub-dimension align with the DELTA model presented by [15]. Analytical differentiators are standardizing and monitoring the business value of their techniques and tools.

Maturity in terms of data quality was assessed as stage one. Analytical beginners are characterized by possessing adequate data quality on operational applications (e.g.., transactions, updating balance on accounts, credit risk) and low data quality resulting in gut feeling decisions on analytical applications (e.g., CRM, sales, pricing, management reporting, compliance, defining goals). The developing stage involves optimizing quality on critical operational data before moving ahead. To increase maturity in this sub-dimension, companies need to establish a common understanding of the importance of data quality improvement as it is commonly down prioritized because of short-term projects producing

[5] Maturity levels (of the case i.e., incumbent Norwegian bank) of each sub-dimension is shaded. At place, two levels are shaded, when the transition is taking place and some of the obstacles or boundary conditions are not fully overcome.

higher ROI. Findings also show low Data Lineage maturity where data management tools are employed but not utilized leading to numerous undocumented and uncontrolled data copies that decreases integrity and credibility. The journey towards stage four in this sub-dimension is difficult for incumbent banks. Realistically, analytical differentiators therefore manage to trace above 80 % of their data.

Our case was assessed as stage one with data storage as well. Several central data warehouses are seen to be the cause for low maturity in quality and lineage with batch processing, high operational costs, long lead-time by central IT units listed as major challenges. While data Lake and data mesh were discussed as possible solutions, the interviewees acknowledge that there is no right answer as to how data storage should be designed. Analytical differentiators are characterized by possessing a functioning, tailor-made storage solution that facilitates real-time analytics, increased user friendliness and accessibility regardless of what type of architecture or combination of architectures that they use.

The case is assessed as stage two regarding Data Governance because most units are not ready for implementation of established frameworks and roles. Moreover, a balance between centralization and decentralization is suggested for analytical differentiators as our findings indicate that a combination between a central data governance function and a federated model can ensure control, productivity, and transparency of data quality. Discovering new data sources was seen as an important dimension. However, informants did not bring much intel on data sourcing other than privacy and licensing being obstacles for continuous discovery, which is to be performed at the highest maturity level.

The organization is currently suffering because of historical technical and data competence outsourcing, with lack of skilled professionals being a major obstacle. Data engineers are observed to be lacking and analytical competence is missing in the business and product environments. The bank is assessed as between stage two and three as some routines for building competence and training via onboarding is well established. Leadership is assessed at stage two as several business units experience lack of TMS towards data management and governance.

As iteration 2 (conceptual model) is still work-in-progress, future work would involve to further refine this preliminary conceptual model (Table 3), verify the levels and dimensions further through more case studies by employing interviews and focus group discussions. To empirically test the maturity levels, we follow the steps prescribed in maturity model literature [22; 37; 56], wherein the preliminary conceptual model (Table 3) would be presented to the stakeholders in a bank and ask them to indicate which level they most closely see themselves. The preliminary version of the conceptual model would then be used to conduct self-assessment in these banks, which will also help in scoping the maturity model further, validating it and providing a foundation for the development of a maturity assessment tool, that can be used as a step towards managing analytics in banks. In the future, we envision this conceptual maturity model can also be modified to analyze a banks readiness and when used by multiple banks, benchmarking tool can also be created. Furthermore, in our future publications we plan to formalize the learnings from the different cases, share the assessments and prescribe strategies to successfully navigate the different levels.

Table 3a. Conceptual Analytics Maturity Levels - Technology & Analytical techniques.

	Analytical beginner	**Analytical developer**	**Analytically established**	**Analytical differentiator**
Analytical Systems & Tools	Analytical investments are incompatible with existing IT infrastructure. Central IT unit does not facilitate analytics and leads to shadow IT within business units.	There is an attempt to integrate existing systems/infrastructure and thus increased readiness for analytics projects.	Standardized IT infrastructure and SLAs are established for real time analytics. Information siloes and shadow IT is either nonexistent or their presence is well documented and monitored.	Technological architecture and system qualities optimized. Well established decentralized self-service data & analytics platform. Cloud-based scalable storage and distribution platform supports real time, heavy-duty analytics. IT investments generates business value. There is increased standardization of processes without hindering innovation.
Analytical Techniques	Ad-hoc descriptive techniques.	Some predictive statistical and forecasting techniques applied.	Use of predictive and prescriptive techniques in a systematic manner.	Standardized and optimized use of advanced analytics with monitoring of business value.
Data & Analytics Presentation	Reporting tools implemented, but poor data quality leads to inefficient reporting. No reporting on data quality. Dashboards developed in siloes are difficult to reuse.	Reporting tools are modified or switched out to enhance agility. Developing new reporting routines to improve quality, reusing of dashboards and improved end-user capabilities.	Reporting tools are well established. Most dashboards are considered data products and reused. End user capability is enhanced, and common vocabulary is developed.	Reporting tools & processes are optimized. Data is integrated and there is a sense of single source of truth. Reporting on data quality is discussed through monitoring of KPI's.
Applications	Analytics only applied to core operational activities and banking processes like risk/transaction data/AML to keep operations going.	In addition to operational activities, applications are using analytical data (e.g., CRM, price optimization). Privacy and confidentiality are considered as obstacles.	Exploring analytics for business model innovation, NPD, operational excellence, and compliance.	Operational and analytical data is optimized. Differentiating innovations and NPD is delivering value back to the customer through Fintech-like services. Innovation is driven by analytics across the enterprise.

Table 3b. Conceptual Analytics Maturity Levels - Data management.

	Analytical beginner	Analytical developer	Analytically established	Analytical differentiator
Data Quality	Most managerial decisions are on gut feeling. While quality is adequate on operational or transactional data, the data associated with KPI's or needed for analytics is not credible. Improving data quality and credibility is not a priority.	Optimizing quality of critical data is a priority and the organization starts exploring to define and improve quality on analytical data. The business value of working with data quality is communicated across business units.	Data quality is monitored and tracked. The business value realized from use analytics is measured. Data quality and credibility is more transparent. A clear understanding on data quality established across the enterprise.	Data quality is fully optimized. There are well established processes for monitoring, tracking, and assessing data quality. The metrics are discussed in well-established governance forums and is part of the higher management discussions.
Data Lineage	Data management tools are not employed across the enterprise. Undocumented, uncontrolled data workflows. Low data integrity and credibility i.e., multiple copies and versions of the same data. No single source of truth.	There is a drive to develop data management plans and processes. Business units begin to use data management tools and interact using common vocabulary. However, data and meta-data documentation is not standardized.	Standardized data and master data management processes established. Majority of the analysts employ data management tools and follows established protocols. There is a unified data catalogue and business glossary.	Data management and master data management processes are optimized and performed across the enterprise. Data and meta-data are well documented leading to minimal copies of the same version. Majority (>80%) of the data sources can be tracked.
Data Storing	Centralized Datawarehouse handling structured data and only understood by some specialists in the enterprise. Unmonitored, high costs and heavy batch processes. Centralized IT unable to deliver on time, thus leading to analysts establishing storage solutions in silos.	Developing centrally managed data storage to handle unstructured, semi-structured and structured data (e.g., Data Lake). Still batch processing, lack of control and user friendliness. Centralized IT unable to deliver on time, thus leading to analysts establishing storage solutions in silos.	New architecture is established (e.g., Data Lake) and modified to handle real-time processing. The centralized IT creates a more agile solution with increased accessibility for analysts. There are projects supported to decentralize ownership and move towards federated governance.	Scalable, distributed, and decentralized data architecture aligning with business needs (e.g., Data Mesh). Balance between centralized and decentralized architecture is optimized. Data architecture is tailor-made for analytics with data quality and data life cycle processes fully optimized.

Data Governance	Ad-hoc, inconsistent or non-existing data strategy, roles, responsibilities, and ownership. Lack of understanding why data governance is needed.	Central data governance structures are not operational. Some data governances (e.g., stewards) are being informally allocated within business units, but centralized data ownership or responsibility is not established. Existing data owners and stewards have too much to maintain and track. Some top management support and budget for data governance initiatives is allocated.	Data governance roles, responsibilities, ownership, data sharing routines, workflows, vocabulary, and frameworks are formally established both centrally and within business units (decentralized). Variation in maturity is seen across units, with initiatives to formalize across the enterprise.	Enterprise-wide data strategy aligned. Data governance is federated and the balance between centralized and decentralized decision-making policies optimized. Continuously improving data governance is prioritized and part of the KPIs across the enterprise.
Data Privacy	Privacy on operational data adequate. Lack of knowledge on GDPR and confidentiality for analytical purposes.	Development of privacy roles, routines for legal assessment, treatment protocols, deletion rules, access control for operational and analytical purposes is initiated. There is discussion on compliance, however. poor data lineage results in privacy concerns.	Privacy processes are established. Protocol list tracking is not standardized, and responsibility is not distributed towards business units. Trade-offs between compliance risk and data opportunities. NPDs not always considering privacy issues.	Privacy processes optimized, distributed, and anchored in business units and NPDs. Optimized processes to solve trade-offs between compliance risk and data opportunities.
Data Sourcing	Analysts are only utilizing necessary internal data and not working with data discovery.	Analysts are working with internal data discovery.	Internal sources optimized and some external data discovered. Licensing and privacy may be obstacles when sharing sources across entities.	Use of internal and external data is optimized. Processes and workflows for data sharing across business units and teams are well defined. Analysts and Stewards are continuously working with data discovery across the enterprise.

Table 3c. Conceptual Analytics Maturity Levels - Organization & Culture

	Analytical beginner	Analytical developer	Analytically established	Analytical differentiator
Organization and Culture	Weak understanding about the importance of analytics throughout the organization. No promotion of data-driven culture. People are sceptic in trusting analytics and often use gut feeling for decision making. Lack of data collaboration across business units.	Promotion of analytics has received some interest across the enterprise. People question analytics even if some errors occur and justify gut feeling over data driven decision making. Analytics is promoted by some but lack engagement among end users is seen. Data not considered in NPD processes.	Analytics is promoted heavily across the enterprise and business units have access to analytics support. End-users are empowered. An analytics understanding is established. Analytics initiatives are encouraged from analysts and engaged end users. Enhanced data collaboration is seen across units. Data concerns are part of NPD.	Data-driven culture (i.e., agile thinking, data-driven-innovation, trial-error culture) is promoted. Data and analytics are the top agenda across the enterprise. Collaboration across units optimized.

Table 3d. Conceptual Analytics Maturity Levels - People.

Analysts	Recruitment of analytical competence is insufficient. Not attracting the best talents. Weak analytical competence among employees.	Analytical competence is built up (e.g., external consultants). Data scientists must perform data pre-processing due to lack of data engineers. Need for more “light” analytics competence in business units.	Enhanced recruitment and training processes are established. Analytics training is established as part of onboarding processes. Attracting data engineers ensuring. Data professionals more like software developers.	Excellent recruitment process. The best analytical talents are attracted. Rich training of employees according to changing business needs. Analytics is standardized part of onboarding process across the enterprise.
Leadership	Low analytics competence among leaders. Leaders not supporting analytics and not allocating financial resources. Leaders not willing to take risks with analytics.	Leaders understand the importance of analytics, developing some competence and are allocating some resources. Analytics is becoming the main agenda, but strategic roles like CDO are appointed.	Analytics competence is established among leaders. Leaders allocate significant financial resources, and analytics is part of the vision.	Leaders prioritize analytics and are open to discover new analytics opportunities that could lead to change in business models.

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