LEADERSHIP DECISION-MAKING PROCESSES IN THE CONTEXT OF DATA DRIVEN TOOLS

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Abstract: *Digital economy vast streams of data have created a new paradigm for the business intelligence processes, increasing the potential of advanced analytics and cognitive data tools. Big data structures are used in business intelligence to work with massive amount of dataset to extract value for effective business decision. The current research seeks to address the following question: how can leaders integrate new technology in their decision process to achieve business goals? Emerging technologies directly created organizational power shift and internal bureaucracy adjustments as a result of data transparency trend and decision-making levels changes. A new type of organizational culture and the leadership role in the organizational development becomes necessary. The significant impact over the organizational systems and business goals requires a strategic approach in implementing data driven decision-making processes.*

Keywords: *Big Data, Advanced analytics, Machine learning, Artificial intelligence, Organization culture, Data management, Technology, Digital Economy, Business Intelligence, Agile, Continuous Development*

JEL Codes: *O33 Technological Change: Choices and Consequences • Diffusion Processes*

INTRODUCTION

In recent years, organizations have built extended sets of customers data, businesses, markets and environments, creating a disruptive data management context. Ongoing digitization has created vast streams of data, forcing businesses to become more data-driven than ever before. Digital economy transformed large data sets (Big Data) in a business asset that generates the need for a strategic approach. Big data can create strategic business value and potential to differentiate from competition. Organizations that understand their data assets, and how they can best be deployed to business advantage, can build a strong position in the marketplace [1].

The new technology has provided unprecedented opportunities for organizations to redesign decision process. Information technology revolution has changed radically the way we access and process information, knowledge becoming the most important resource for the development [2].

Accenture[1] and Gartner Research[2] had identified technology as a strategic priority, getting the right information to the right person, at the right time having a critical impact over the organizational results. A recent annual survey[3] on top 1000 Fortune companies on how executives in large organizations view data, shows that main risk is disruption from new entrants. Executives (84.1%) are actively investing in Big Data and AI initiatives to enable better decisions using advanced analytics, (73.2%) are reporting measurable results from their Big Data investments. In the same time an issue is the slow speed with which organizations make the shift to a data-driven culture, 99% consider their firms are targeting it, but only about one-third have succeeded at this objective. In the same time many startups have succeeded to create data-driven cultures from start, which is a key reason why large, established firms fear disruption from them.

LITERATURE REVIEW

Data-driven decisions tend to be better decisions, in every industry companies that figure out how to combine sector expertise with data science to create significant competitive advantage. There are five areas particularly important to manage change effectively a in data driven business environment: (1) leadership vision,

1 "High Performers in IT: Defined by Digital and Driving Growth," 2013, www.accenture.com
2 "Gartner Identifies the Top 10 Strategic Technology Trends for 2015," press release, October 8, 2014, www.gartner.com
3 "How Big Data and AI are Driving Business Innovation in 2018," 2018, NewVantage Partners, www.newvantage.com

(2) talent management hard to find, (3) technology correlated with big data strategy, (4) decision making processes maximizing cross-functional cooperation, and (5) a company culture that creates the environment to move away from acting on hunches and instinct [3].

Improving decision making performance is the main influence factor for organizations to significantly invest in technologies. Over the last decade, the costs and time of data analysis projects have dropped dramatically [1], while expanding power of prediction. In the same time in many companies' studies shown that they could not take full advantage of using these tools [4].

The traditional scientific research has limited business scholars from working on emerging problems with big data, mostly because the traditional method has mainly focused on modeling and analysis/explanation than on the real/practical problem and the data, and the complexity of the advanced analytics methods [5].

Advanced Analytics

The advanced analytics techniques for big data processing are used in business intelligence to work with massive number of datasets to extract value for effective business decision, where traditional tools are not able to address the issues of scalability, adaptability, and usability [6]. Based on large data sets, data analytics integrates processes and tools, including predictive analytics, statistics, data mining, artificial intelligence, and natural language processing, building invaluable insights to improve firm decision making [4].

Large data sets can create strategic business value and potential to differentiate from competition. Organizations that understands its data assets, and how they can best be deployed to business advantage, can build a strong position in the marketplace. Incorporating data driven decision-making processes into the strategic vision and building capabilities, are driving organizations to redesign existing business operations [7].

Gartner[4] annual report for advanced analytic solutions in the last 4 years had changed the name from "MQ for Advanced Analytics Platforms" 2014-2016, "MQ for Data Science Platforms" 2017, to "Magic Quadrant for Data Science and Machine-Learning Platforms" 2018. This report branding reflects the rapid changes in the industry (Table 1).

Machine Learning

Historically economists have used statistics to test hypotheses, now machine learning, as a subfield of artificial intelligence, has the power to find relationships that have not been identified by theory. Machine learning is based on algorithms that can learn from data without relying on rules-based programming. Machines can learn from the data through: (1) supervised learning machine which learns to use the input data to predict the desired output value, (2) unsupervised learning in which the input data are not labeled, the most common method of unsupervised learning being finding patterns in the data, to cluster data, (3) reinforcement learning in which the algorithm makes a decisions and is "rewarded" for taking good actions, for example playing games such as Go and Poker [8].

Current projects to apply machine learning are stopped by the lack of transparency, in interpreting machine learning models, but it seems also for humans is hard explaining their behavior and decisions compared with the most opaque machine. For example, a deep neural network probability to indicate that an individual will default on a loan is 95% — but at the cost of ability to explain [9]. Machine learning implementation success is related with building holistic systems to manage ethical aspects of the decision process and thinking critically about risks accepted.

Data science platforms[5] which allow data scientists to build and deploy algorithms are starting to grow and develop fast. We have considered five examples of Machine Learning platforms for building and deploying predictive analytics into live environments in table 2.

Artificial Intelligence

4 Gartner, Inc. https://www.gartner.com/doc/3860063/magic-quadrant-data-science-machinelearning

5 Gartner, definition for data science and machine-learning platform: "A cohesive software application that offers a mixture of basic building blocks essential both for creating many kinds of data science solution and incorporating such solutions into business processes, surrounding infrastructure and products."

Artificial Intelligence (AI) as a concept can be defined broadly as intelligent systems with the ability to think and learn [10]. Executives from America's largest corporations ranked AI and machine learning as the most disruptive forces in the business landscape of the near future[6]. We already have multiple solutions based on AI present, transforming the ways businesses operate, from systems, chatbots to self-driving cars. AI evolution is reflected in the recent years in the IBM's Watson's example defeating of Jeopardy's top human contenders and Google DeepMind's AlphaGo, which trounced one of the world's best at the board game Go. Exerting a greater computational information capacity, still humans have a more holistic, intuitive approach in dealing with uncertainty in organizational decision making, performing better at big-picture thinking. The rise of AI calls for a new human-machine symbiosis, which presents a shifting division of work between machines and humans. Humans will likely outperform AI in evaluating subjective, qualitative matters (e.g., norms, political interests, social factors, contextual factors) [11] .

Estimates are for AI to increase the effectiveness of the decisions' employees are making, lowering the control and centralize levels for decisions making and bringing about quicker and better distributed decisions, making companies more agile and responsive to market changes and opportunities [1]. Due to their intuitive capabilities, humans continue to perform better at big-picture thinking, having broader strategic questions require a holistic approach [11]

Artificial intelligence is prone to biases and must be understood and managed [12]. Limitations of artificial intelligence algorithms are related mainly to the need to have enough historical data for the analysis to identify reliably the prediction factors, data availability, and the lack of transparency [8]. In the same time research findings on the managers' decisions are still inconsistent, in terms of using a rational approach in decision-making process, and intuition, to cope with emotional influence at some stages in this process [13].

DATA DRIVEN DECISION-MAKING LEADERSHIP IMPACT

AI implementation raises questions on the relationships between technologies and the dimensions of organizational decision making. It is argued that the implementation of AI systems will lead to different complexity decision processes [14]. AI can be an opportunity for the leaders who are trying to become more agile and foster creative approaches to transformation [22]. In the same time the full potential of data and analytics generates the premises for leadership transformation.

Advanced prediction tools

In the decision they make, executives need forecast to handle the increasing complexity created by different influence factors (seasonality, sudden changes in demand levels, price-cutting maneuvers of the competition, strikes, and large swings of the economy). The selection of forecasting methods depends on the context of the forecast, the relevance and availability of historical data, the degree of accuracy desirable, the time available, the cost/ benefit relevance for the organization, and the time available [15]. Using Figure 1.a we are looking at the correlation of the decision accuracy with cost of decision (adapting the J. Chambers [15] model, figure 1.b). Lower decision accuracy is correlated with higher cost, determined by the cost of inaccurate decision. Rapid decreasing prices for advanced analytics and AI by recent evolution of data science platforms have the potential to shift fast the cost of accurate decisions curve. Organizations have the opportunity (or hard market pressure) to focus on optimizing decision-making as cost of prediction and decision accuracy will continue to decline.

Data driven decision-making adoption

The speed of data driven decision-making adoption is linked to the executive's behavior [16], potentially motivated by owners to accelerate profitable growth, and fast-growing startups competition. One of main steps for implementing advanced analytics is data driven culture, as a key factor for transforming data resource into a powerful competitive differentiator [17]. Using big data and analytics to make better decisions requires new skills and business understanding from a large area of employees. Some organizations are starting to use agile

6 New Vantage Partners. (2017). Big data executive survey 2017. Available at http://newvantage.com/wp-content/ uploads/2017/01/Big-Data-Executive-Survey-2017- Executive-Summary.pdf

strategies principles to run their data programs [18].

Limitations to machine learning must be constantly addressed to define control systems to monitor quality and ethics of decisions. Some industries have strong entry barriers due to the lack of transparency in AI models, so AI is a potentially large obstacle.

Looking ahead, occupations in manufacturing, professional and business services, food service, and retail trade will have the highest potential for advanced automation. Based on estimates on automation potential: 60% of occupations have at least 30% of tasks that can be automated, generating considerable risk of unemployment [19].

Data and analytics could generate productivity gains and an improved quality of life, but they carry the risk of mass unemployment, lack of transparency in models used for decisions, and ethics issues, that will need to be addressed by organizations leaders.

Organizational power shift

New technologies create access for managers and employees to accurate and extended data, predictions and expertise, changing the decision-making paradigms and traditional power distribution [1]. Access to information had become a source of power for decision making participants, increasing opportunity for strategic decisions to new segments [14]. Traditional decision processes in organizations are based on different levels of internal bureaucracy with time-consuming pre-authorization from senior managers before acting on the decision. To use the potential of data driven decision-making, current structures need to be redesigned, empowering employees [1]. The case of DBS Bank Singapore is a leadership strategy example on empowering employees, by breaking down traditional bank hierarchies and silos. The bank linked the customer and employee experiences, using data about customer interactions with the bank to redesign internal workflows, using hackathons, employee learning and workspace to adapt internal culture. DBS went to be considered the best digital bank of 2016, cutting more than 250 million customer waiting hours in the first year [20].

In this age of disruptive technologies and rapid change, we need to rethink the definition of effective leadership. Leadership may encounter radical changes in leaders hard skills replaced by smart machines, and in the same time leaders soft skills will become more important, capability to adapt to the rising challenges, building a strong vision, and constantly engaged with the changing world around them will be decisive [21]. Advanced analytics and AI will change the dynamics of political factors that are influencing decision processes.

Regulation framework

Every industry needs a new approach to regulate the risk level in adopting machine learning models, by setting policies for desired outcomes, monitoring results to track discrepancies, and updating models or data collection procedures to improve future results. Managing the integration of cognitive systems in organization decision-making process is critical for long term success.

Considering the limitation in explaining many machine learning models, the skill executive leaders need to develop is making judgment calls on how much risk and error a business accepts [9]. In this context of cognitive technologies, creating new roles that must relate to data strategy becomes a must (chief information officer, chief data officer, chief digital officer, chief analytics officer, etc.) [7].

Industries like financial system traditionally built on extended regulatory foundation are facing the competition from new business models. Entry barrier in the banking system are challenged by new entrants with higher operational efficiency business models, redefining client experience form face to face to on-line automated interactions, based on advanced analytics (Figures 4-5) [22]. Digital economy business model's efficiency and competition dynamics will create pressure for new regulation in many industries.

STRATEGIES TO ADOPT DATA-DRIVEN DECISION PROCESSES

Organizational data-driven culture

Organizational culture refers to a system of values, knowledge, attitudes, morals, customs, and norms which are common and resected by members of an organization, as a framework of organizational practices, behavior, and goals [18].

Correlated to organizational cultures, managers tend to have different perceptions over the benefits of analytics that generates the behavior in adopting data driven tools [19]. Studies reveal that managers in smaller organizations are more inclined to base their decisions on analytic results than managers in large organizations, motivated to remain competitive against their larger counterparts [17]. The leadership role is influenced by the decision-making processes, revenue responsibility culture and performance management.

Based upon the organization's maturity analytic-related processes, Grossman [23] defines five levels: 1) the organization can build reports; 2) the organization can build and deploy models; 3) the organization has repeatable processes for building and deploying analytics; 4) the organization has consistent enterprise wide processes for analytics; 5) the enterprise's analytics is strategy driven (figure 2).

The development of advanced data driven solutions requires tackling challenges such as eliciting analytical requirements, designing the machine learning solution, and ensuring the alignment of analytics initiatives with business strategies [24], and creating new skills and mindset for large areas of the work force. Strategic approach for implementing analytics is critical to achieve the desired results from data-driven insights [25].

Data driven decision-making adoption

Adoption of business process improvement strategies are now a concern of most business models [26], to create and adapt the processes. Research of business analytics projects implementation are characterized by uncertainty, and repeated changing requirements, that generate a high implementation risk ("it takes a special breed of project manager to execute and deliver them") [27]. Main risks in implementing this advanced analytics and AI are linked to low quality data, identifying appropriate data analytics tools [4], the available analytical skills, and also organizational culture and leaders' power approach [14].

Traditional power structures and levels of internal bureaucracy are on certain path of change. An inherent shift in power creates a new dimension for conflict in organization structures and will have the potential to create a new level of innovation opportunities. Decision making process based on data has the potential to lower the conflict level in organization, through increased transparency among people involved.

Strategies to Adopt Data-Driven Decision Processes

Considering limitations of traditional Business Process Management approaches in addressing changes in business requirements [18], in our research we have identified two methodologies that have the potential to accelerate new technologies adoption agile and continuous development.

Agile Strategy

Agile is a methodology originally used in IT organizations to build software or manage processes more effectively. Based on a collaborative cross-functional teams are design to build minimally viable products and features quickly, test them with customers, and refine and enhance them in rapid iterations. Agile is proven to accelerate the redesign of business models, creating the ability to quickly reconfigure strategy, structure, processes, people, and technology toward value-creating opportunities [18]. Agile data strategy relies on a similar approach to development and delivery: cross-functional teams (business and IT) can generate reliable insights to allow the organization to identify the highest business priorities and fast implementation [28].

Transforming companies to achieve organizational agility is in early stages, according to 2017 McKinsey Global Survey many respondents say their companies have not yet fully implemented agile structures, even if the advantages are clear. In the same time failure of agile implementation is linked with cultural issues like politics, internal conflicts, lack of coordination, working and protecting silos. Digital economy requests an innovative spirit in teams across the organization, to generate performance gains that keep businesses ahead of the competition. Senior executives have increased probability to succeed in creating agile organizations, empowering small teams with enough autonomy to act fast in the digital economy [29].

An HBR study shows that adopting agile strategy is best suited to innovative companies. Organizations like Spotify and Netflix were born agile and have developed more this strategy; and companies that, like Amazon and

USAA, are working on the transition from traditional hierarchies to more-agile enterprises [30]. Command-and-control leadership systems work best under stable and predictable operations, but today information overloads have a high probability to paralyze command centers, creating bottlenecks. Studies have shown the fact that agile turnaround leaders mitigate risks implementing the following steps: 1) continuously communicate the strategic ambition to a broader range of people, 2) serve as coaches, not commanders, 3) strengthen lines of communication among the teams, 4) shift measurement and reward systems to larger team [31].

Agile has evolved beyond software methodology development or operations management, becoming a capability strategic data management tool. Agile data concept is a business-driven approach, using cross-functional teams (business and IT), collaborating in "data labs" that have joint ownership on generating reliable insights highest business goals to realize targeted outcome fast [28].

Implementing right data management strategies organizations can better address client's needs, automate processes, competing more effectively, and create new growth sources. Joint ownership business-IT can accelerate innovation based on data-driven initiatives, and speed up the delivery of critical business information.

Continuous Development Strategy

Like Agile, Continuous Development also began as a software development methodology, and have been identified a powerful potential in business process development [32]. Continuous delivery with roots on agile methodology, different from agile in that it does not involve stopping and making a special effort to create a releasable build. Continuous development in software industry strategy is based on software updates made continuously, piece-by-piece, instead of improving software in one large batch, enabling software code to be available for delivery - accelerating the entire build-test-deploy cycle. There are leading companies adopting Continuous Development as a new business process methodology, with strategic implications towards faster time-to-market, run more experiments, fix errors faster, maximize engineering productivity [32].

Facebook, founded in 2004, adopted the agile software delivery methodology to create weekly release cycle, responding quickly to the market and the competition. But by 2016, the engineering team struggled to support the scale of the weekly releases taking 14 hours to deploy in production. In 2017, Facebook transitioned to a continuous development model, with a result in code deployment on average of 3.5 hours, by August 2017. The insight for business executives is that continuous delivery represents a strategic option towards competitive advantage. [32].

Leaders can decide over the strategic options correlated to different growth stages and organizations goals. Data continuous development strategy could permit fast deployment of data driven solutions on critical operational processes and new products development. In my opinion successful implementation is linked with defining key performance indicators and revenue responsibility for leaders and teams involved in data management projects.

ADVANCED ANALYTICS INTEGRATION FINDINGs

Business analytics projects implementation are characterized by a high implementation risk due to low quality data, identifying appropriate data analytics tools, the available analytical skills (Figure 3). Emerging technologies integration directly creates all the premises for organizational power shift and levels of internal bureaucracy as a consequence of data transparency and decision levels changes. This change requires a data driven type of organizational culture, structure and systems. In the same time regulatory initiative will have a significant role data driven tools integration in many industries and competitive dynamics will shape them.

Considering limitations in adopting data driven decision-making processes organizations must implement strategic methodologies that have the potential to accelerate new technologies adoption. The present article analysis agile and continuous development methodologies. Both strategies had been tested successfully as software development methodologies. Agile data concept could accelerate innovation, based on joint responsibility cross-functional teams, to better address client's needs, automate processes, competing more effectively, and create new growth sources. Data continuous development concept could permit fast deployment of data driven solutions, focusing on critical operational processes and new products development with high impact over the organization goals. Leaders can decide over the strategic options correlated to different growth stages and organizations goals.

From a risk point of view, AI is exposed to algorithms biases, ethics risks, and the lack of transparency in the models developed beyond current scientific research. The AI implementation raises questions on the relationships among technologies, ethical issues and the organizational decision-making processes, creating a new dimension for leadership development. Every industry needs a new approach to regulate the risk level in adopting machine learning models, and leaders in the organizations that can define adequate strategies, and ethics.

CONCLUSIONS

Digital economy vast streams of data have created a new paradigm for the business intelligence processes, increasing the potential of advanced analytics and cognitive data tools. Lowering cost of implementing advanced analytics, transformed large data structures in a business asset, that create strategic business value and potential to differentiate from competition. From a leadership point of view, the speed of adopting data driven decision-making tools and processes are motivated by multiple stakeholders' interest to accelerate sustainable profitable growth, build competitive advantage, and manage rising risk of fast-growing startups competition. Advanced analytics and cognitive data management tools have the potential to directly influence internal culture, future organization strategy and revenue streams. The new decision-making processes requires a data driven type of organizational culture, structure and systems, to manage organizational power shift because of data transparency and decision levels changes.

Future research should consider developing qualitative and quantitative approach, to develop more insight and knowledge on how data driven decision-making processes creates value in the organization. Study cases to trace transformational changes over a period of time would create a broader view over the long-term sustainability.

Table1: 2018 Gartner annual report "Magic Quadrant for Data Science and Machine-Learning Platforms"

Leaders	KNIME, Alteryx, SAS, RapidMiner, H2O.ai
Challengers	MathWorks, TIBCO Software (new)
Visionaries	IBM, Microsoft, Domino Data Lab, Dataiku, Databricks (new)
Niche Players	SAP, Angoss, Anaconda (new), Terad

Table 2: Machine-Learning Platforms

H2O.ai	Leader in Gartner's 2018 Magic Quadrant[7] for Data Science and Machine Learning Platforms after being chosen as a Visionary in the prior edition. Customers include eBay, Capital One, Comcast.
Microsoft Azure	The platform allows data scientists to deploy models into production quickly as a web service and then share them on the Azure marketplace to gain exposure. Customers include Carnival Cruises, JLL, Fujitsu.
IBM Watson	The platform comes with built in learning, collaboration features and notebook tools for working with Jupiter Notebooks for Python and RStudio for R. Customers include Chevrolet, Macy's, The North Face
Dataiku	Startup. The platform provides a host of guided data science and machine learning processes, integrating a level of abstraction so that anyone using it can either code in Python, Pig, R, Hive etc. Customers include L'Oreal, Trainline, AXA insurance
Databricks	Startup. New Entry Visionary. The platform provides a host for modeling machine learning processes, integrating a level of abstraction so that anyone using it can either code in Python, R, PySpark, etc. Customers include NBC, Viacom, HP

7 Magic Quadrant for Data Science and Machine-Learning Platforms Published: 22 February 2018, https://www.gartner.com/doc/3860063/magic-quadrant-data-science-machinelearning

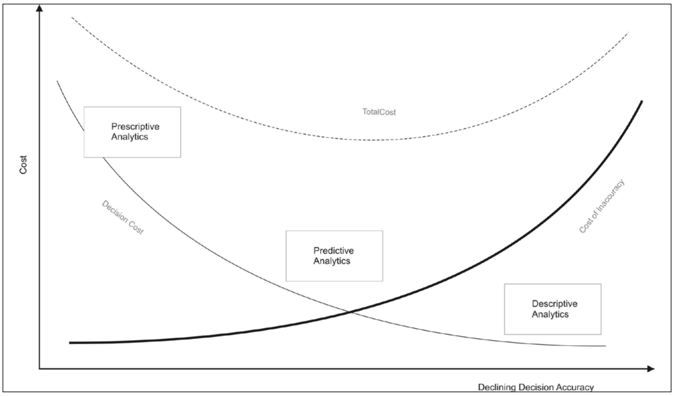

Figure 1.a.: Cost vs Decision Accuracy

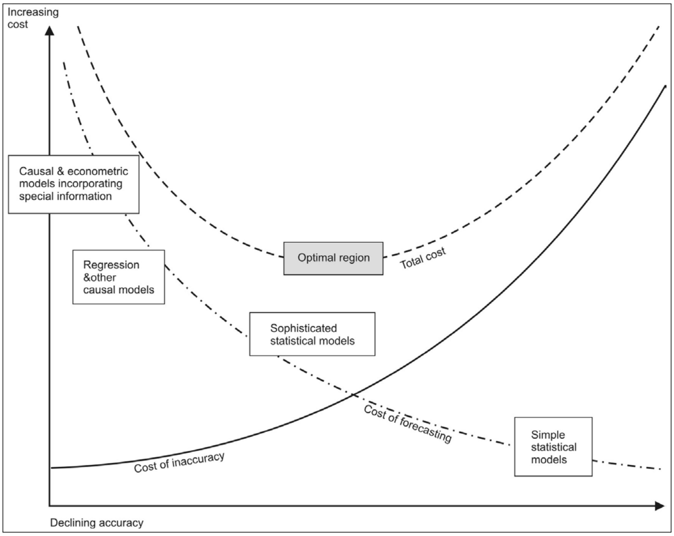

Figure 1.b.: Cost of forecasting vs Forecasting Accuracy [15]

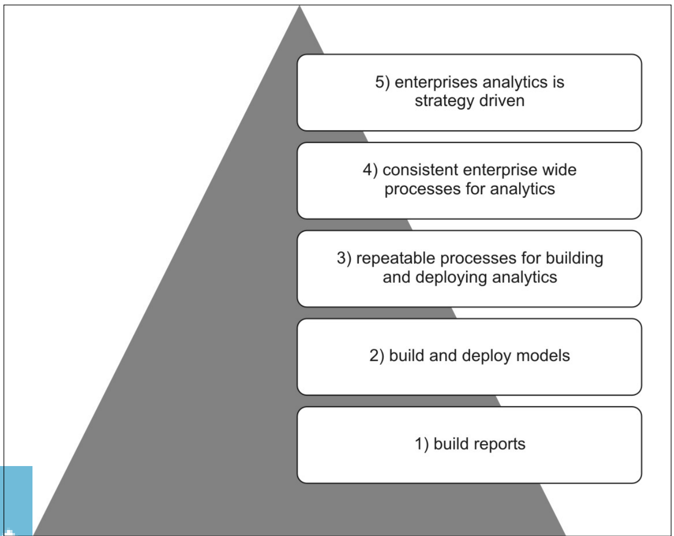

Figure 2: Organizations maturity on analytic-related processes

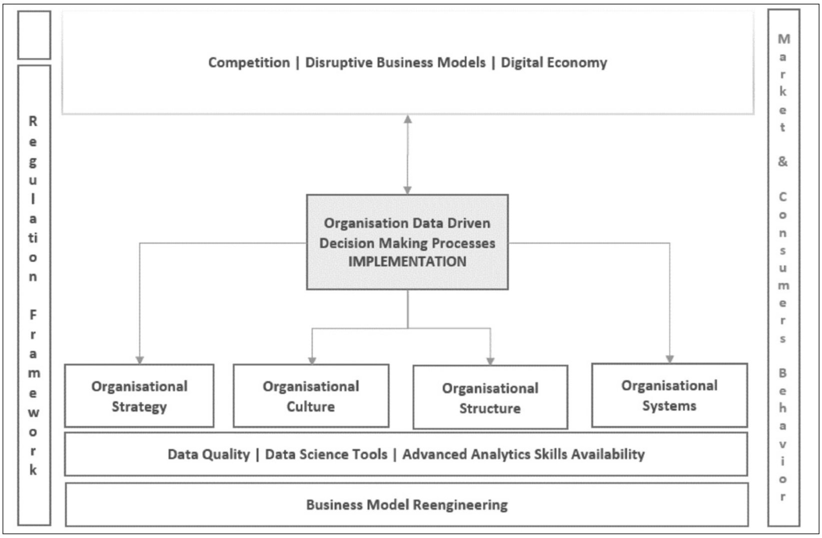

Figure 3: Data driven decision-making processes implementation

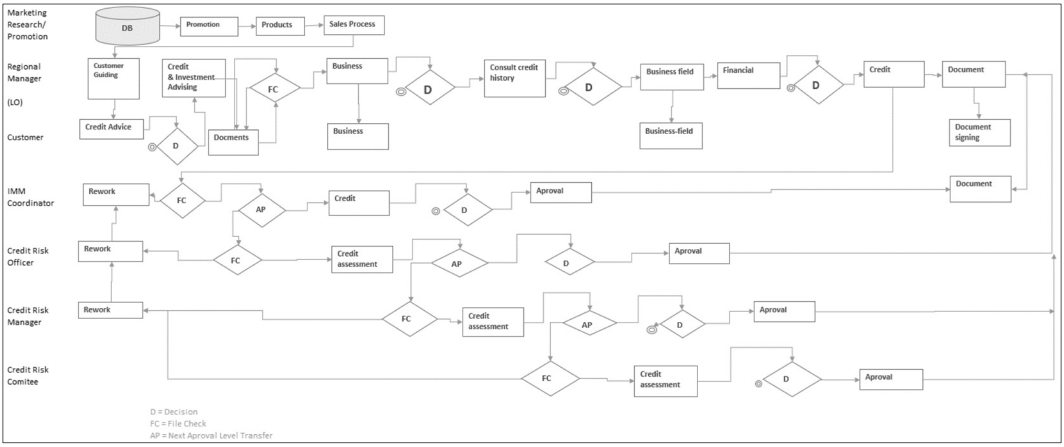

Figure 4: Traditional Loan Granting Process – Small Business Loans

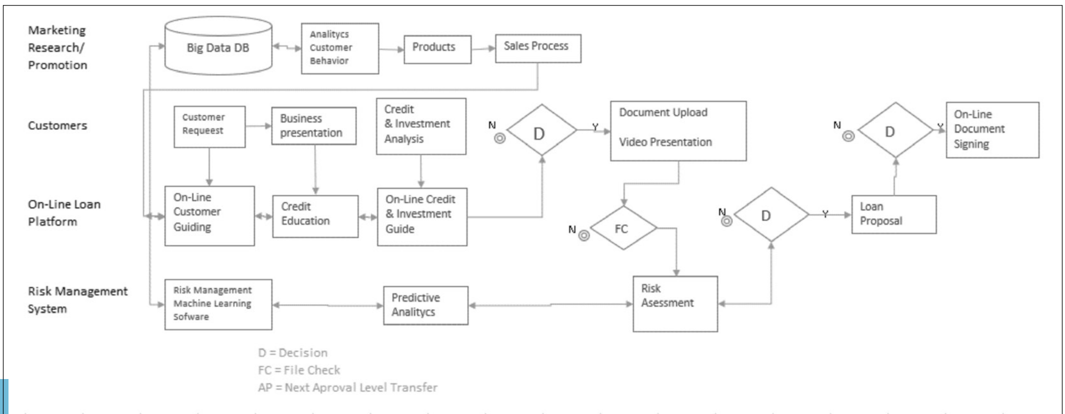

Figure 5: Digital Data driven decision process Loan Granting Process – Small Business Loans

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