Multidimensional Data-Driven Artificial Intelligence Innovation

Sergey A. Yablonsky

"Information is the oil of the 21st century, and analytics is the combustion engine."

Peter Sondergaard
Gartner Research

This is a critical time for the development and adoption of Artificial Intelligence (AI). The field has existed since the 1950s and is only now emerging as viable for commercial markets. Many enterprises are placing bets on AI that will determine their future. Today AI innovation becomes useful when it enriches decision-making that is enhanced by applying Big Data (BD) and Advanced Analytics (AA), with some element of human interaction using digital platforms. This research investigates an opportunity for cross-fertilization between AI, BD, and AA with related disciplines. The paper aims to investigate the potential relationship of AI, BD, and AA with digital business platforms. In doing so, it develops a multidimensional BD-driven AI innovation taxonomy framework with an AA/BD/AA innovation value chain, related levels of BD, and analytics maturity improvement. This framework can be used with a focus on data-driven human-machine relationships, and applying AI at different levels of data driven automation maturity.

1. Introduction

Digital transformation of enterprises across industries enabled by new digital technologies is an emerging phenomenon. Firms are challenged to succeed in embracing transformation through digital technology to enable competitive advantages or they will face collapse at the hands of their competitors that do (Fitzgerald et al., 2014). For enterprises to digitalize their products, services, or business model, they need to find a role for digital innovation (Bughin & Zeebroeck, 2017; Manyika et al., 2016). The transition to digital business thus requires enterprises to make a leap toward a new view of data and analytics.

The future of digital business faces enterprises with abundant possibilities to create value for their company through data and analytics. Enterprises need to look at data as the raw material for decision-making, and consider that data comes from both within and outside the enterprise. The growing digitization of the economy is exposing the limitations of traditional assets, as the boundaries between the technologies and the business blur, and new data asset classes emerge.

Big Data (high-volume, -variety and -velocity information) continues to increase rapidly in all three dimensions, and is a major factor in many industries (Manyika, et. al., 2011). The volume of data is speedily growing. Manyika et al. (2011) define Big Data (BD) as datasets, the size of which is beyond the ability of typical database software tools to capture, store, manage, and analyze.BD is thereby interpreted as "information assets characterized by such a high volume, velocity and variety [as] to require specific technology and analytical methods for its transformation into value" (De Mauro et al., 2016: 103). BD now requires new forms of data processing to facilitate enhanced decision-making, insight discovery, and process optimization (Cavanillas et al., 2016). BD has become useful nowadays when it enriches decision-making that is enhanced by applying analytical techniques and some elements of AI. This research investigates an opportunity for cross-fertilization between BD and the field of AI with related business disciplines, based on the merging of data and information in contrast with knowledge and intelligence. It continues previous work done on big data and advanced analytics platforms (Yablonsky, 2018 a,b,c).

Along with the increasing importance of digitalization, digital innovation has become an important research agenda due to the rising need for new digital solutions. Digital innovation is defined by Nambisan et al. (2017), as the creation of market offerings, business processes, or models that result from the use of digital technology.

Their definition includes a range of innovation outcomes, such as new products, platforms, and services, as well as new customer experiences and other value pathways (Khin & Ho, 2018).

In our study, Artificial Intelligence (AI) is a digital innovation that offers solutions to transform enterprise products, service and business using AI, Big Data (BD), and related Advanced Analytics (AA). Indeed, AI is at the heart of digital disruption. AI disruption aims to drive better customer engagement and lead to accelerated rates of innovation, higher competitiveness, higher margins, and more productive employees (Jyoti et al., 2019). AI innovation is powered by BD and AA. BD involves collecting from of a wide variety of inputs, including publicly available data, information, or knowledge, human intelligence, and active gathering, then processing the resulting inputs to better understand and predict competitor strategies and actions (Erickson & Rothberg, 2015; Marr, 2015). In a number of ways, AA and AI actually anticipate interest in BD more than other BD disciplines do. Data and analytics need to be thought in terms of processing enterprise digital business platforms, thus taking on a more active and dynamic role in powering the activities of the entire organization (Yablonsky, 2018b).

Despite the growing research interest in AI innovation, most of the studies on AI innovation look at innovation from a technical, architectural, or information system perspective (Lyytinen et al., 2016), rather than from a managerial perspective. Hence, this study takes a different approach to AI innovation by choosing the BD and AA context. This is done to see how strategy, products, and solutions are transforming into innovative data-driven AI business strategy, products or solutions, that subsequently impact traditional business strategies, products, and services, and can even lead to the creation of new businesses.

This paper aims to investigate the potential relationship and value of BD, AA, and AI within a multidimensional framework that combines AI maturity and AI/BD/AA value chains. In doing so, it develops a data-driven AI innovation taxonomy framework with related levels of AI/BD/AA maturity improvement across innovation value chains.

The paper is structured as follows. Section 2 discusses the main definitions and conceptual backgrounds of AI, BD, and AA based on literature review. Section 3 describes the methodology. Section 4 discusses the place of AA in platforms. Section 5 illustrates the AI/BD/AA value chain. Section 6 presents a multidimensional data-driven AI innovation framework that combines AI/BD/AA value chains, and data-driven AI innovation. Section 7 explains the study's results, provides discussion and addresses implications.

2. Research Methodology

In our research we aimed for a multidimensional, multilayered framework development in order to facilitate understanding, analysis, and structure of AI, BD, and AA for enterprises. This approach proved particularly beneficial for the field due to the current lack of systematic empirical analysis in AI management research. Despite its increased importance, little research has been done to systematically examine why and how AI engages in BD and AA, or how BD and AA technologies impact AI. The current conceptual study seeks to develop an AI/BD/AA relation framework through the lenses of a growing AI research agenda in the age of BD and AA. It aims to categorize the main BD/AA dimensions of AI and create a strategic multidimensional data-driven AI framework that is adopted to identify the AI/BD/AA relationship and apply a strategic AI-driven enterprise transformation framework. The paper aims to address this critical gap by focusing on trying to answer why and how BD and AA engage AI.

The framework development was guided by the approach of Nickerson et al. (2012), which facilitates an iterative combination of conceptual-to-empirical and empirical-to-conceptual approaches. Leaning on Moyer (2016), an industry vision of digital transformation consists of four parts: concepts, capabilities, assets, and research. Using this framework, we collected qualitative data through literature review and semi-structured expert interviews. Subsequently, we collected qualitative data through the interviews for identifying sub-dimensions and instantiations of each framework. Our interview partners were members of technologies groups, founders, and CTOs of the Russian National Technology Initiative (NTI - http://www.nti2035.ru/; https://asi.ru/eng/nti/). We conducted one interview per NTI market, with an average duration of 50 minutes. All of the interviews were recorded, transcribed, and analyzed thematically.

The analysis showed that rather than searching for a single acceptable definition, a better approach would be to develop a classification system or taxonomy (Nickerson et al., 2012). This is because having a clear and precise description and structuring of information in the advanced analytics domain are prerequisites for conducting common research. Taxonomies and other types of controlled vocabularies are the preferred means of achieving a common understanding by specifying the terms of the domain, disambiguating them from each other, identifying synonyms, and structuring the domain via terminological relationships.

We use definitions from different information resources from 2010 to 2019 to conceptually ground the categories in advanced analytics taxonomy,. The pilot version of the advanced taxonomy is shown in the figures and tables below (mainly in the hierarchy of the 2 first layers of taxonomy concepts). Taxonomy includes a set of basic concepts, a set of relations holding between those concepts, and a set of instances, including both international and local AI and AA firms and service providers. The total number of all taxonomy features (>100) is too complex to be represented here in its entirety, but a sample part of the taxonomy is provided in order to demonstrate both the process of classification and the intermediate result. We suggest that although classification systems have traditionally been used in business and management disciplines, the more advanced quantitative methodologies now available have not yet been widely used.

3. Current Understanding

Digital business involves creating new business designs that blur the boundaries between the digital world and the physical one, due to the convergence of people, businesses, and smart things/machines/services. It promises an unprecedented convergence of a) people, b) businesses, and c) smart things/machines/services that change existing business models and create new revenue opportunities (Cavanillas et al., 2016; Yablonsky, 2018b). This is a critical time for digital business transformation in the history of AI development and adoption. The field is more than 70 years old, yet is only now emerging as viable for commercial markets. Artificial intelligence technologies nowadays impact most application categories and many business challenges. Vesset et al. (2018) state that many enterprises are placing bets on AI that will determine their future. Those sitting on the side-lines are risking being left behind.

Yet many organizations lack the AI literacy needed to make critical investment decisions. In recent years, one of the shortcomings in the AI commercial sphere has been the misrepresentation of the possible automation scope. Too often, we hear claims of AI systems automating end-to-end processes and predictions of what may result in massive labour losses. These proclamations and promises of AI's ability to solve all societal ills, from diseases to crime, and from hunger to war, do a disservice both to enterprises and individuals trying to plan for the appropriate level of investment in AI, as well as vendors developing marketing AI solutions (Gentsch, 2018). To help with planning and investment decisions related to AI-based enterprise automation, Vesset et al. (2018) developed a five-level framework that can be put to pragmatic use identifying industry and functional use cases, where current AI can automate specific tasks, activities, and processes.

Over the last decade, business has become more and more focused on data. This trend is a consequence of the success of many organizations that have used collected data to drive their business. Digital transformation is influencing big data creation (BDVA, 2017). The data landscape is rapidly changing and with it, organizations need to evolve the ways they manage and govern data. Most organizations today are faced with an increasing volume of data that is gathered through a wide scope of processes and range of formats. The increase in volume and variety adds complexity to data management. At the same time, data consumers now demand quick and easy access to data. They want to be able to understand data and use it to address critical business questions in a timely manner.

Today organizations must be flexible enough to work in a growing environment. To do so, organizations need to clarify basic questions about ownership, collaboration, accountability, and decision-making. Contemporary business decision-making that directs the share of different resources for exploration, discovery, building, or testing of ideas is based upon data, that when structured and processed creates information and knowledge. Nevertheless, the gathering of more and more data from multiple sources, coined as "big data" (BD) has led to challenges involving how best to integrate and meaningfully manage data to support improved decision-making for greater impact. The data lakes and databases that continuously store large amounts of data will eventually become larger and larger over time. Thus, applying BD analysis approaches will be inevitable (Cavanillas et al., 2016; Sivarajah et al., 2017; Günther et al., 2017). BD analysis is the collection of data and technology that accesses, integrates, and reports all available data by filtering, correlating, and reporting insights not attainable with past data technologies, while supporting more robust decision-making. Data-driven AI decision-making adds value to BD and is crucial for successful AI enterprise innovations.

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AI and advanced analytics

Artificial Intelligence (AI) started as a field at a conference at Dartmouth College in 1956 when John McCarthy coined the term "artificial intelligence." It was defined to be the field of computer science aimed at developing computer programs or applications that would have capabilities comparable in some way to human cognitive abilities (for example, speech recognition, visual pattern or image identification, language translation, natural language processing [NLP], or making inferences in decision-making) (Kumar, 2017). Today AI is an umbrella term for multiple technologies, including machine learning, deep learning, computer vision, machine reasoning, and natural language processing (NLP). There is still no single definition of AI that is universally accepted by researchers and practitioners (Kumar, 2017).

Gartner contends that AI applies advanced analytics (AA) and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions. However, research on AI focuses primarily on four key components of human intelligence: *learning, reasoning, problem solving*, and *perception*. The European Commission suggests AI refers to machines or agents that are capable of observing their environment, learning, and based on the knowledge and experience gained, taking intelligent action or proposing decisions (EU, 2018). AI systems are likely to play a key role in search processes on the Internet, shopping online, seeking a medical diagnosis, and many more. These AI systems seek the best plan of action to accomplish their assigned goals using assistive, augmented, and autonomous capabilities (see Figure 1).

What exactly is "analytics"? Davenport and Harris (2007) define analytics as "the ability to collect, analyze, and act on data". Gartner notes that analytics has emerged as a general term for a variety of different business intelligence (BI) and application-related initiatives. For some, it signifies the process of analyzing information from a particular domain, such as website analytics. For others, it means applying the breadth of BI capabilities to a specific content area, for example, sales, service, supply chain, and so on. Increasingly, the term "analytics" is used to describe statistical and mathematical data analysis that clusters, segments, scores, and predicts what scenarios are most likely to happen. Whatever the use cases, "analytics" has moved deeper into business dialect. Analytics has gained increasing interest from business and IT professionals looking to exploit huge mounds of internally generated and externally available data.

The field of analytics is broken down into five categories: *descriptive, diagnostic, predictive, prescriptive,* and *augmented analytics* (Hurwitz et al., 2015; Siegel, 2013; Quintero et al., 2015; Yablonsky, 2018b). Figure 2 illustrates how these five categories help to define advanced analytics.

4. Research Design

The complexity of the AI field often lends itself to classification schemas, or taxonomies, which provide ways to understand similarities and differences among objects of study. Developing a taxonomy, however, is a complex process that is often done in an ad hoc way. Nickerson et al. (2012) proposed a method that combines both empirical-to-deductive and deductive-

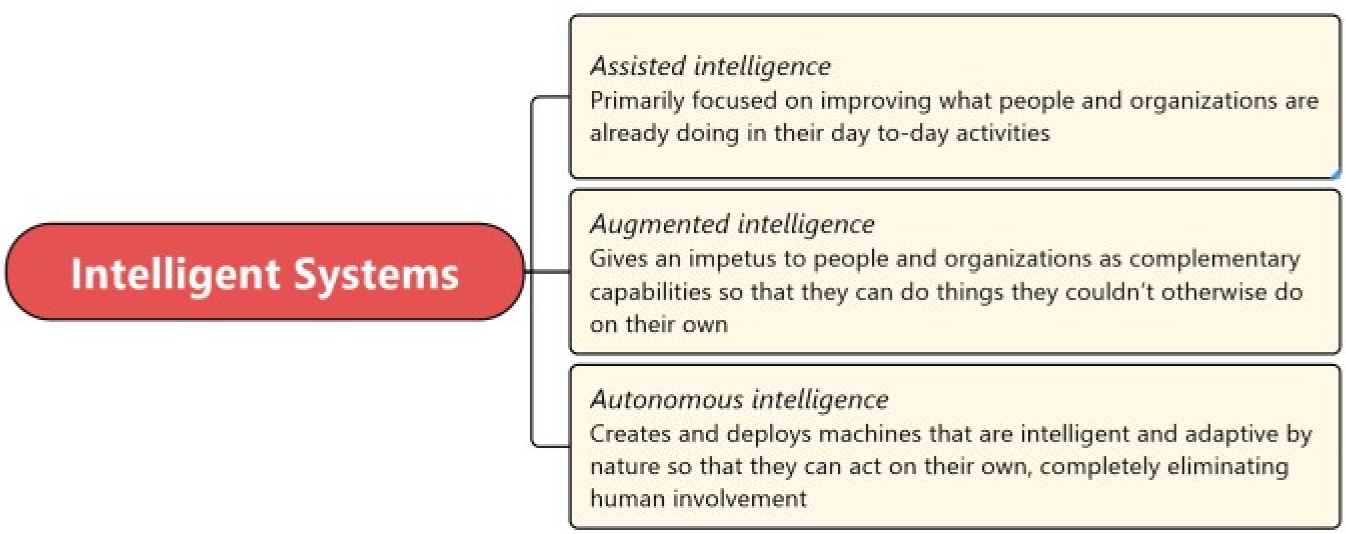

Figure 1. AI systems

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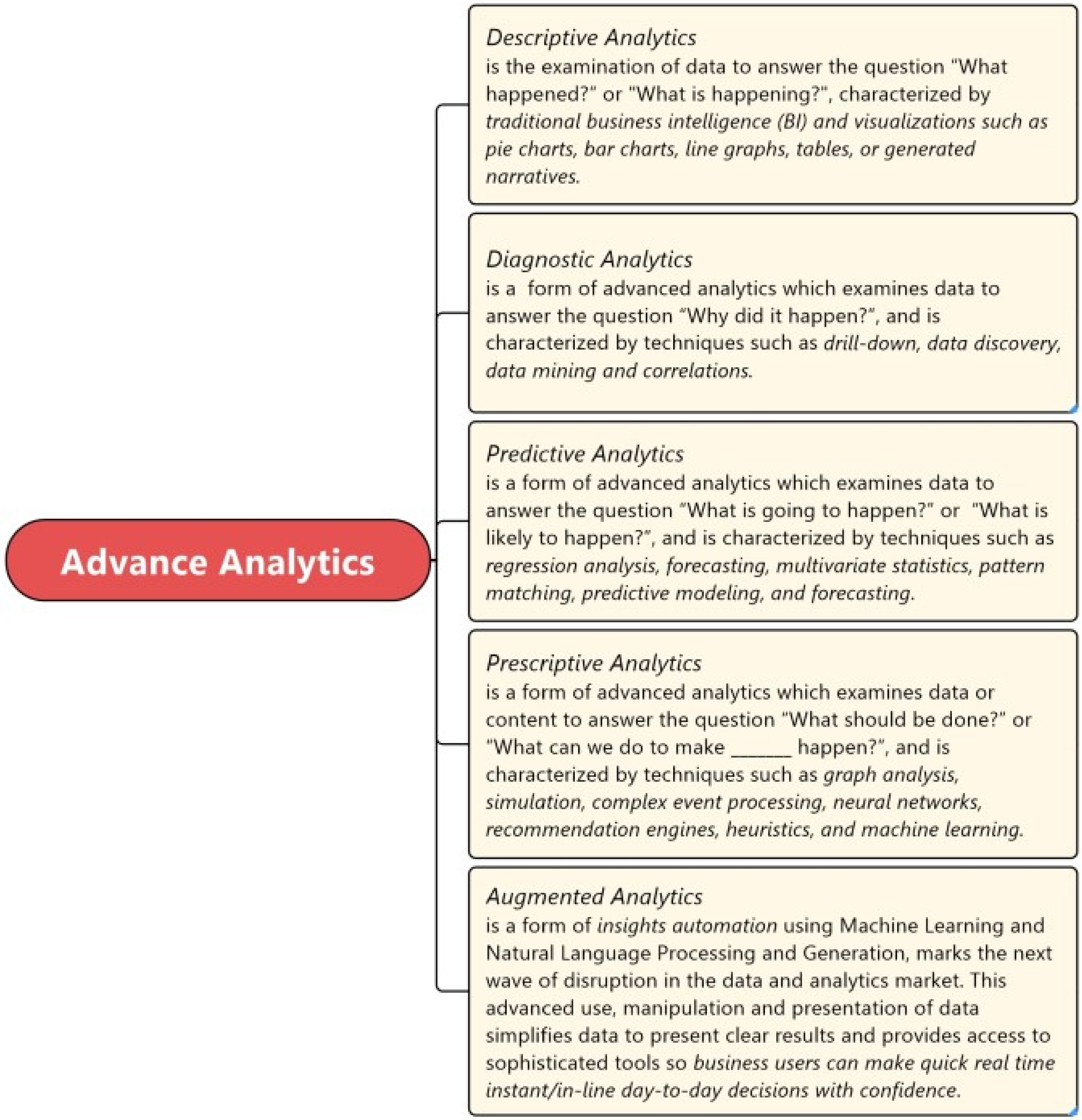

Figure 2. Advanced Analytics

to-empirical approaches. The method presented here facilitates the iterative combination of conceptual-to-empirical and empirical-to-conceptual approaches.

At this point, our research process consists of four distinct steps. We initiated our process through a conceptual-to-empirical approach by defining the primary 5 dimensions of an established data-driven AI/BD/AA operations conceptualization. We then evaluated this method by using it to develop a taxonomy of data-driven AI platform innovation. The resulting taxonomy contains seven dimensions with twenty characteristics.

AI platform strategy becomes extremely complex as firms consider the dynamic interactions in a multilayered business ecosystem (Teece, 2012). The concept of data-driven AI platform innovation can be widely defined as architecting new platform strategies and business models, making and promoting new platform products and services, developing new platform processes to facilitate platform activities, interacting with platform actors, and designing new platform structures for industry institutions (Yablonsky, 2018ab).

Drawing on existing knowledge in the field of platform research (Evans & Gawer, 2016) we argue that a meta-structuring perspective which aims to serve a data-driven AI landscape, represents an important missing contribution. The objective of this research was to create such a meta-structuring perspective. We applied a taxonomy-enabled methodology to create the consistent structure for an AI platform innovation framework.

In our research we sought a data-driven AI value chain and data-driven AI strategic innovation framework. Namely we were focused on a strategic conceptual multidimensional taxonomy-like maturity framework for AI decision making, with related levels of AI maturity improvement across AI/BD/AA innovation value chains. his approach proves particularly beneficial for the field due to the current lack of systematic empirical analyses coming from within management research.

The concept of “Industry AI platform innovation” entails changes to infrastructure, standards, and rules that enable transactions between multiple firms in industry (Leiblein, 2015). The vision of industry AI platform innovation shows what platform business could look like if enterprises used AI/BD/AA technology innovations to their full potential. Having an industry vision framework gives firms a structure to refine and fill out their thinking about digital business. When their ideas have matured, they can use the framework to explain the concept to the rest of their organization, as well as to their partners.

This paper addresses the following questions:

– What necessary data-driven AI innovation components/concepts are required to support the capabilities of information-based enterprises?
– What are possible data-driven AI value chains?
– Is there a necessary data-driven AI innovation framework?
– How can data be co-organized and managed in a strategic conceptual multidimensional framework for AI decision making, with related levels of AI maturity improvement across AI/BD/AA innovation value chains?

5. Platforms, AI and Analytics

A digital business requires much more than technology (for example, leadership, talent, skills, and new platform business models).

According to one definition (Burton & Basiliere, 2016), a digital platform is a business-driven framework that allows a community of partners, providers, and customers to share and enhance digital processes and capabilities, or to extend them for mutual benefit.

To design a digital business platform, organizations must lead their business to take a business driven, outside-in approach (Evans, Gawer, 2016; Yablonsky, 2018b). Digital business platforms empower flexible and dynamic digital business transactions. Digital platform disruption is a process of impacting multi-sided markets through digital capabilities, channels, and assets. Digital business innovation creates disruptive platform network effects or externalities. To manage digital platform business models and multi-layered platform business ecosystems, companies are building a digital business platform stack to share critical assets. The variance in a company’s digital business performance is a function of differences in their platform’s resources and capabilities in comparison with competing companies.

Contrast with clear inside and outside traditional business, a platform provides a digital business with a foundation where resources can come together in various combinations to create value. Some resources may be inside, permanently owned by the company, some may be shared, and others can come from an outside ecosystem. The combined value comes largely from the dynamic connection of resources and actors, and the potential network effects between them. Platform design facilitates matches among providers and consumers (“users”) or, in other words, the creation or exchange of goods, services, and social currency, so that all participants can capture value. Platforms offer unique opportunities to engage members of a business ecosystem in transactions to exchange value (Blosch & Burton, 2016).

Business platforms are supported by technology platforms in the following seven overlapping areas (Yablonsky, 2018ab):

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1. *Information Systems Platform* (ISP): Supports the front and back office and operations, such as ERP and other core systems.
2. *Customer Experience Platform* (CEP): Contains the main customer-facing components, such as customer and citizen portals, omni-channel commerce, and customer apps.
3. *Data and Analytics Platform* (DAP): Includes information management and analytical capabilities. Data management programs and analytical applications fuel data-driven decision making, while algorithms automate discovery and action.
4. *IoT Platform* (IOTP): Connects physical assets and things (devices) for monitoring, optimization, control, analytics, and monetization. Capabilities include connectivity, analytics, and integration to core and IOT systems. With the emergence of the IoT, these "things" develop through several stages, eventually gaining autonomous purchasing capabilities, and being recognized as "smart things" with their own rights and responsibilities.
5. *Ecosystems Platform* (EP): Supports the creation of, and connection to, external ecosystems, marketplaces, and communities. API management, control, and security are its main elements.
6. *Trust Platform* (TP): A blockchain technology used to foster trust.
7. *Integration Platform* (IP): Supports the integration of all the above platforms in a way that allows maximum flexibility to support business transformation demands.

Technological platform overlap is shown in Figure 3.

Each area of the platform can deliver insight that is descriptive, diagnostic, predictive, and/or prescriptive. Data, analytics, and algorithms are essential to the digital business platform, and should be integrated by integration platform services to permit other platforms to use external and internal data and analytics to execute its functions. To democratize data processing

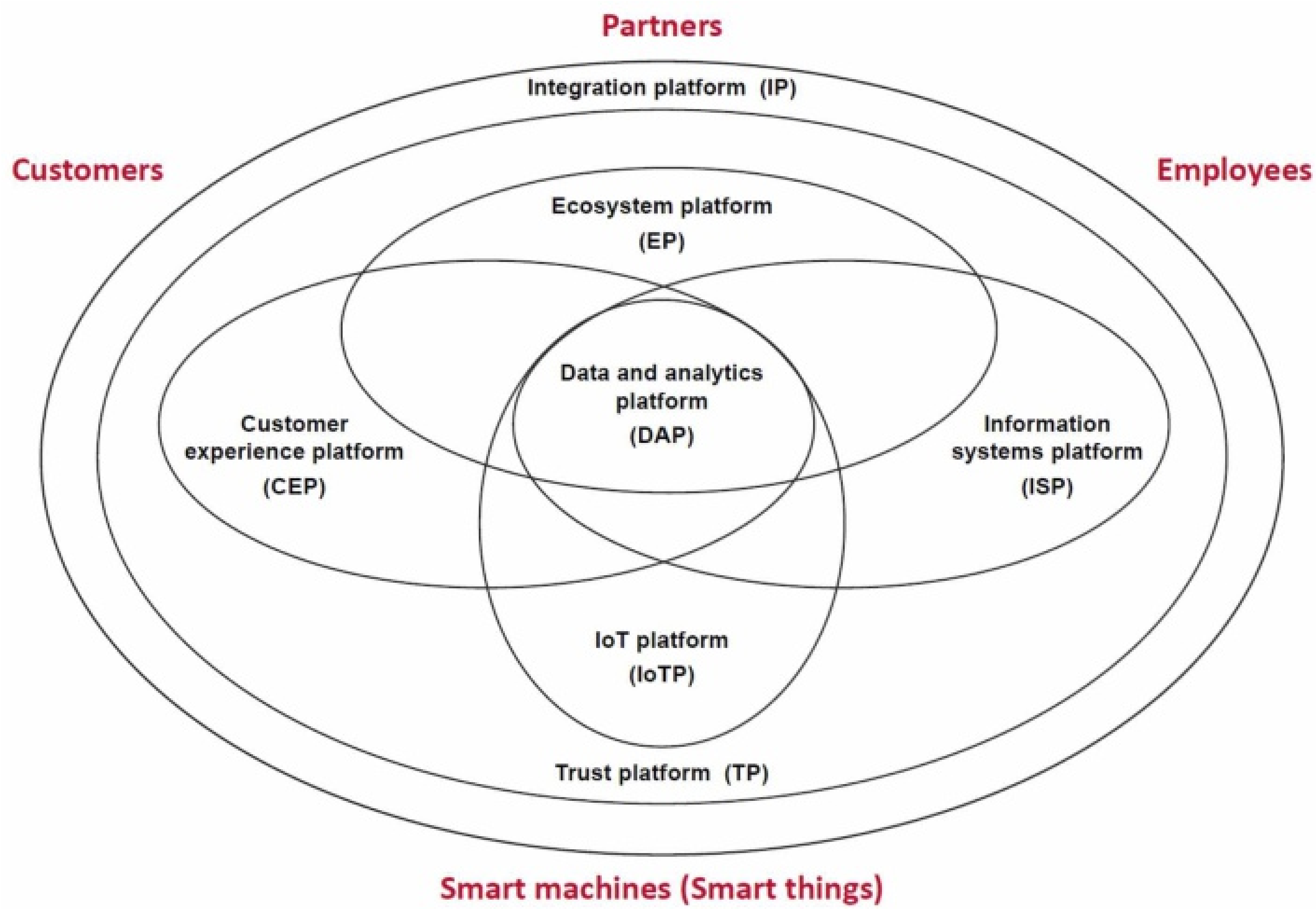

Figure 3. Technological platforms overlapping (Yablonsky, 2018a)

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Platform type	AA processing type	BD resources
D&A (Intelligence) Platform	Decision Models Algorithm and AI Engines	All
IoT Platform (Things)	IoT Analytics	Connected Things (Enterprise) Connected Things (Partner) Connected Things (Customer) Endpoint Computing
Customer Engagement Platform (Customers)	Customer Analytics	Multichannel Commerce Social Networks Customer Portal Customer Apps Customer Facing and Public APIs
Ecosystem Platform (Partners)	Partner and Supplier Analytics	Partner Facing Public APIs API Marketplaces Enterprise Run Ecosystems Industry & Partner-Run Ecosystems
Information Systems Platform (Employees & Suppliers)	Business and Operational Analytics	Core IT Systems Back-Office Systems Supplier Portal Supplier Apps

Table 1. AA/BD in enterprise platform

and visualization, this platform should include self-service features to enable onboarding of increasingly wider enterprise constituencies.

Data and analytics infuse business platforms in all of the above mentioned seven overlapping areas (Table 1).

6. AI/BD/AA Value Chain

New concepts for AI/BD collection, processing, storing, analyzing, handling, visualization, and, most importantly, usage, are emerging with data-driven AI-enabled strategies and business models currently being created around them. Identifying sustainable business models and ecosystems in and across sectors and platforms is an important pressing challenge. In particular, many SMEs that are now involved in highly specific or niche roles will need support to help them align and adapt to new value chain opportunities in the future.

The real value of AI/BD/AA could be determined through the life cycle of AI/BD/AA. We plotted the value of AI/BD/AA over its life cycle as a framework to consider how an organization might determine the value of enterprise data (Liebowitz, 2013). Curry (2016) defines “data value chain” as follows (p.31): “A value chain is made up of a series of subsystems each with inputs, transformation processes, and outputs … As an analytical tool, the value chain can be applied to information flows to understand the value creation of data technology. In a Data Value Chain, information flow is described as a series of steps needed to generate value and useful insights from data.” The European Commission sees the data value chain as the “centre of the future knowledge economy, bringing the opportunities of the digital developments to the more traditional sectors (e.g. transport, financial services, health, manufacturing, retail).” (DG Connect 2013)

The focus here is mostly on the BD micro-level value chain (Cavanillas et al., 2016) as defined by Curry

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(2016). BD micro level value chains are used to model the high-level activities that comprise an enterprise.

The proposed AI/BD/AA micro-level value chain identifies the following key high-level AI/BD/AA activities/dimensions:

– *AI Awareness/Big Data Acquisition* is the process of gathering, filtering, and cleaning data before it is put in a data warehouse, data lake, or any other storage solution on which data analysis can be carried out, meaning the availability of BD and access to BD sources. There are a variety of BD types and sources. Value is created by acquiring and combining data from

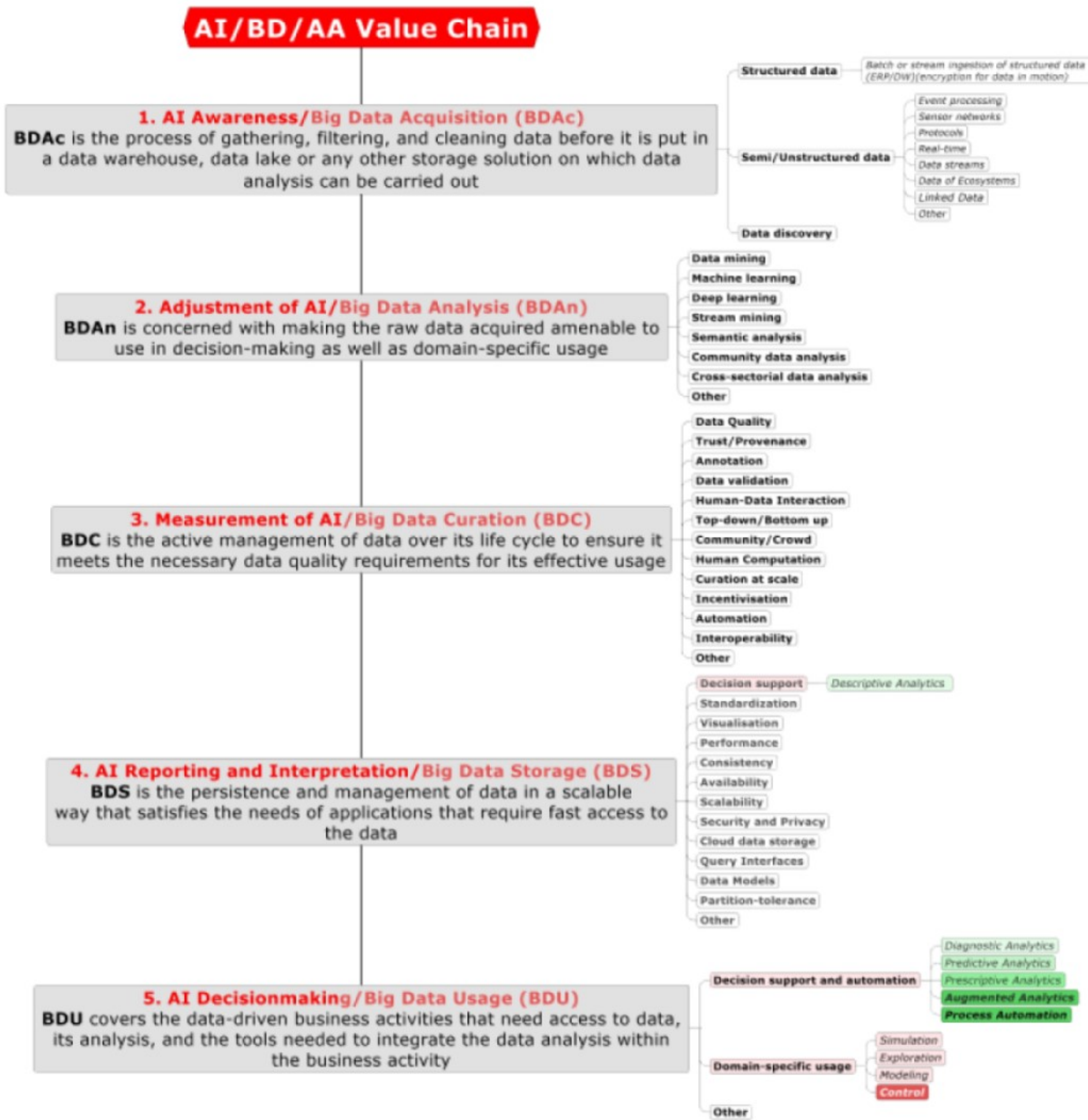

Figure 4. The AI/BD/AA micro-level value chain

different sources. BD pre-processing, validating, and augmenting, as well as ensuring data integrity and accuracy add enterprise value.

– *Measurement of AI/Big Data Curation* is the active management of data over its life cycle to ensure it meets the necessary data quality requirements for its effective usage. It is based on the active management and measurement of AI/BD assets over a life cycle to ensure it meets the necessary BD quality requirements for effective usage.

– *AI Reporting and Interpretation/Big Data Storage* is the persistence and management of data in a scalable way that satisfies the needs of applications that require fast access to data.

– *AI Decision making/Big Data Usage* covers data-driven business activities that need access to data, its analysis, and the tools needed to integrate data analysis within the targeted business activity. It covers the main AI/BD assets used in business decision-making that can improve competitiveness through reduction of costs, increased added value, or any other parameter that can be measured against existing performance criteria.

The AI/BD/AA micro-level value chain, as illustrated in Figure 4, is used to model high-level activities that comprise an enterprise.

Table 2. General multidimensional data-driven AI innovation framework (Adopted from Vesset et al., 2018 and Yablonsky, 2018b)

Stage of AI/BD/AA maturity	Who produces insights?	Who decides and how?	Who acts based on decision?	AA/BD level
1. Human Led	Human analyzers and produces insights using limited technology.	Human decides based on experience and rules.	Human acts or executives.	Partly* 1, 2
2. Human Led, Machine Supported	Human analyzers and produces insights using a portfolio of tools.	Human analyzers based on optimized machine prescriptions.	Human acts or executives.	Partly* 1,2,3,4
3. Machine Led, Human Supported	Machine analyzers and produces insights with human review.	Human decides based on optimized machine prescriptions.	Human acts or executives with machine oversight.	1,2,3**, partly* 4,5
4. Machine Led, Human Governed	Machine analyzers and produces insights without human review.	Machine decides within a framework of human governance.	Machine acts or executes with human oversight.	1,2,3,4**, partly* 5
5. Machine (Machine Led & Machine Governed)	Machine analyzers and produces insights.	Machine decides.	Machine acts or executes.	1,2,3,4,5**

Comments: * - levels of the AI/BD/AA value chain.
** - the specific completeness of the AI/AA/BD implementations are determined by the size of the organization, domain-specific usage and industry.

7. Data-driven AI Innovation Framework

Organizations now employ AI in data-rich aspects of their operations. To help paddle through the exaggerations associated with AI, BD, and AA innovations, we have developed a multidimensional framework. It allows the evaluation of AI innovation's dynamic nature by placing focus on data-driven human-machine relationships, and the application of AI at various levels of data driven automation maturity scope: from tasks and activities to AA processes and platforms, as shown in Table 2.

According to Vesset et al. (2018) we describe the general organizational characteristics at five levels of AI maturity, from a completely ad hoc approach with limited awareness to one in which an AI innovation strategy is integrated into the organization's culture at every level. The identifiable relation with BD/AA maturity is intended to help organizations evaluate current business transformation initiatives and thus identify the steps they need to take BD/AA to the next advanced stage of maturity.

To appreciate the likely growth of AI-based automation, it's important to evaluate the interaction of humans and machines across these five levels, and to understand who analyzes the data, who decides based on the results of the analysis, and who acts based on the decision.

Key stakeholders of AI-based transformation initiatives include executives, IT leadership, line-of-business managers, employees, partners, and suppliers.

8. Conclusion

Organizations worldwide must evaluate their vision and transform their people, processes, technology, and data readiness in order to unleash the power of AI and thrive in the digital era (Jyoti et al., 2019). To help with strategic innovation planning and investment decisions related to AI-based automation, we have developed a multidimensional data-driven AI innovation framework. This allows for evaluating the human-machine relationship supported by BD/AA platforms and their application at different levels of automation scope across any industry and functional use case.

The paper adds the following results to the current knowledge based about AI innovation.

1. An AI/BD/AA micro-level value chain was created (Figure 4).

2. A multidimensional BD-driven AI enterprise maturity framework was created through adoption from an earlier AI automation framework (Vesset et al., 2018) and AI/BD/AA (decision-making) value framework. It was shown that a multidimensional data-driven AI enterprise innovation framework has five levels of maturity:

– Human Led/Initial Analytics;
– Human Led, Machine Supported/Advanced Analytics I;
– Machine Led, Human Supported/Advanced Analytics II;
– Machine Led, Human Governed/Advanced Analytics III;
– Machine Controlled/Advanced Analytics IV.

3. Levels of AA maturity correspond to the following levels of the AI/BD/AA value chain:

– Initial Analytics: partly* 1, 2;
– Advanced Analytics I: partly* 1,2,3,4;
– Advanced Analytics II: 1,2,3**, partly* 4,5;
– Advanced Analytics III: 1,2,3,4**, partly* 5;
– Advanced Analytics IV: 1,2,3,4,5**.

4. For each maturity level, BD-driven AI innovation value chains as end-to-end processes related to BD-driven AI enterprises, ecosystems, and components were created and tested.

We believe our framework can be put to pragmatic use to identify industry and functional use cases where current AI can automate specific tasks, activities, or processes. It can also be used to better communicate to clients the value of AI capabilities through the lens of changing human-machine interactions and in the context of legal, ethical, and societal norms.

While business, IT, and analytics leaders need to recognize how AI is different from previous cycles of IT-based innovation, today's leaders need to embrace AI and become involved in contributing to the discussion of AI ethics. Not only because a few can co-opt AI for nefarious purposes, but also because in the absence of human-driven ethical norms, commercial self-interest and technological evolution that incorporates emotional AI will likely lead to negative unintended consequences for commercial organizations and society at large. With the broad participation of a diverse, global population in the conversation about the future of AI, we are more likely to advance through levels of AI-based automation while accumulating benefits for the largest possible population of humans.

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A clear and precise description and structuring of information in the BD-driven AI enterprise maturity framework are prerequisites for a common understanding of BD-driven AI innovation. We have provided for the first time a BD-driven AI innovation taxonomy framework with related BD-driven AI/AA innovation value chains. The new dimensions of BD-driven AI innovation maturity and value chain frameworks allow for repeating the analysis with different types of business components (technology, leadership, talent and skills, ecosystem, and new data-driven business models). The emergence of a new wave of data from sources, such as the Internet of Things (IoT), Sensor Networks, Open Data on the Web, data from mobile applications, and social network data, together with the natural growth of datasets inside organizations, creates new ways to reuse and extract value from BD assets through BD-driven AI innovation.

This paper looked at emerging issues that are becoming important and will require action in the nearest future. The evaluation logic presents a tool that managers, company owners, and investors can use for identifying and managing a multidimensional BD-driven AI enterprise innovation framework. This will allow them to interact with different groups of contributors in order to receive new ideas, feedback, and solutions, and later evaluate the effectiveness of AI innovation, and decision-making regarding the value offering design of BD-driven AI products and services. Since the BD-driven AI innovation taxonomy framework has been additionally designed for evaluating the innovation potential of BD-driven AI business platforms, it should prove to be particularly convenient for analyzing several types of data-driven AI business models. In our current digital age, when intangible assets are becoming more crucial for a firm's performance, new BD-driven AI value dimensions can support business leaders and their management teams to provide more effective measurement and management of their intellectual and informational capital assets.

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About the Author

Sergey Yablonsky, PhD in computer science, is an Associate Professor at Graduate School of Management, St. Petersburg State University in St. Petersburg, Russia. Author of more than 200+ publications. Co-creator of the Russian WordNet and the Russicon language processor and linguistic resources licensed by Adobe Systems Incorporated, Phoenix Int. (USA), Franklin Electronic Publishers (USA) etc. Engaged in 35 national and international research projects in Russia, and across Europe. Research interests include Digital Economy, Digital Business and Entrepreneurship; Multisided Platforms and Markets; Artificial Intelligence, Digital marketing; Big Data Governance; Computer linguistics and text mining; Semantic and Social Web. Courses taught: Data Governance (Bachelor Program); Digital marketing (Bachelor Program); Digital Commerce (Bachelor Program); Digital Business (Master Program); Smart Business Transformation in the Digital Age (CEMS Block Seminar); Multi-Sided Platforms and Innovation in a Global Era (CEMS Block Seminar); Digital Economy (EMBA). Visiting professor at WU (Vienna University of Economics and Business) in Austria, Stockholm Business School, Stockholm university in Sweden, Aalto University in Finland, Lappeenranta University of Technology in Finland, Hame University of Applied Sciences in Finland.

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