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Highlights

- A general definition of business analytics is upheld and completed by listing the building blocks and actors specific to the manufacturing industry.
- Five manufacturing domains are discusses and areas where business analytics can be a differentiating factor are highlighted.
- The challenges hindering wide adoption of business analytics in the manufacturing industry are identified.
- A pathway to market leadership is prescribed to guarantee business analytics returns

Business Analytics in Manufacturing: Current Trends, Challenges and Pathway to Market Leadership

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Abstract

The manufacturing sector is under constant pressure to increase profitability in a growingly competitive international market in which differentiation is not tied to manufactured products or utilized technologies but to business processes optimization. In this context, business analytics offer the opportunity to harness the knowledge and value hidden within enterprise information systems to revolutionize innovation, enhance supply chain management and production, accurately target marketing and sales efforts, as well as develop and manage profitable after-sales services. While the literature to date presents numerous specific applications in which business analytics techniques were successfully deployed to improve specific business units, it is evident that a comprehensive enterprise approach is missing. In the present work, a pathway to attain market leadership through the effective use of business analytics is defined suggesting focus must center on three increasingly challenging barriers. Firstly, "standardization" of collection, aggregation and storage of data must be accomplished. Then, an "organizational culture evolution" that outgrows intuition and embraces data-driven decision-making is needed to create the perfect ecosystem for business analytics to produce actionable results and recommendations. In turn, these must guide "business model innovation" efforts to tackle new value creation, and capture and secure market leadership.

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1. Introduction

Using past performance information in order to make informed business decisions has been an enduring trend. In fact, the term *business intelligence* (BI), often credited to Howard Dressner [1] but first coined by H. P. Luhn in 1958 [2], refers to the objective understanding of important business phenomena [3]. It concentrated on capturing and querying data with a strong focus on reporting of past events and gave managers fact-based comprehension of their organizations, allowing them to outgrow intuition when making decisions. However, with the pass of time, business intelligence started to show its shortcomings. It was designed to deal with small volumes of static data generally segregated on what are now known as legacy IT systems. In addition, it was a time-consuming process focused on describing past observations but offered no explanations with regards to their causes and it did not concern itself with the future of the business. Hence, BI evolved to include *business analytics* (BA), defined as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" [4]. In other words, critical business data is analyzed with the objective of aiding enterprises better understand their business and the market in which they operate. The focus expanded from answering "what happened", "how often" and "where" to include explanations as to "why", "what if this trend continues", "what will happen in the future" and "what is the ideal scenario". Using subject specific jargon, these questions correspond to analytical tasks widely known as statistical analysis, forecasting, predictive modeling and optimization. The insights obtained from the deployment of these tools are centered around business practices and methodologies and are used to make timely business decisions [5].

The manufacturing sector represents almost one tenth of all enterprises within the EU-28's non-financial business economy [6]. In 2013, it employed

29.7 million people and accounted for 26.1% of all the value added generated by the non-financial business economy. In contrast to this optimistic figures, the manufacturing sector was described as having the second lowest level of profitability with a gross operating rate of 7.9%, 1.6 percentual points below the non-financial business economy average. As such, the industry is under constant pressure to reduce costs and increase margins while competing with developing economies. As a result, manufacturing enterprises are transitioning what has come to be known as the fourth industrial revolution, popularized as "Industrie 4.0"[1] [21], in which automation is coupled with ubiquitous cyber-physical systems giving rise to the Internet of Things (IoT) and massive generation of data. This was expected to be the starting point of some remarkable solutions to well known manufacturing hurdles, especially after a 2011 McKinsey report [22] indicated that the manufacturing sector had a competitive advantage over others with regard to data availability and the talent to exploit it. However, the adoption of BA to derive insights and drive business decisions has been scant opening a chasm between industry leaders and laggards.

The present work reviews the accomplishments of the manufacturing industry in adopting BA to derive value from data. In Section 2, a general definition of business analytics is presented as a starting point for this study. In Section 3, specific examples of BA applications within different manufacturing domains are succinctly analyzed. The challenges associated with the application of BA in the manufacturing industry are discussed in Section 4. In Section 5, the definition of BA in manufacturing is completed by listing the building blocks and actors involved. Finally a pathway for successful application of BA that conducts to value creation and market leadership is prescribed in Section 6,

[1] "Industrie 4.0" (or "Industry 4.0") is a 2011 German initiative [7, 8, 9, 10, 11]. In Luxembourg, it is known as "The Third Industrial Revolution" after Jeremy Rifkin's homonymous book [12] and later policy and strategic advice to the Luxembourgish Ministry of Economy [13]. Close concepts in the Anglo-Saxon world are known as "Industrial Internet" [14, 15, 16, 17] and "Smart Manufacturing" [18, 19, 20].

before presenting some concluding remarks (Section 7). The objective of this work is two-fold. Firstly, to identify current trends as well as the reasons hindering the adoption of data-driven decision making. Secondly, to define a road map for practitioners to take their organizations from intuition decision-making to market leaders capable of creating and capturing value through data-driven business model innovation. While the concepts of "Industry 4.0" [8, 9, 10, 11], "smart manufacturing" [19, 20], "big data" [23] and the "industrial internet of things" [15, 16, 17] are related to the increased attention in business analytics in manufacturing, this work does not discuss them specifically. The reader is therefore encouraged to refer to the relevant literature.

2. What is Business Analytics?

While there are multiple definitions of BA (see [24] for a comprehensive list) and a widely accepted one was introduced in Section 1, this work upholds the more general definition proposed by Holsapple *et. al.* in which business analytics is "concerned with evidence-based problem recognition and solving that happen within the context of business situations" [24]. While the authors found that there is general consensus about the nature of business analytics regarding it being "fact-based" or "data-based" and involving "decision-making", they chose to expand upon these terms:

- "Fact" / "data" were replaced with "evidence" because the latter "includes hard facts, reliable measurements, justified estimates, well-reasoned approximations, unbiased observations, credible explanations, authoritative advice, and the like. It does not include arbitrary or unfounded beliefs, guesses, opinions, speculations, conjectures, suspicions, or hearsay. A body of evidence is not driven by desires, emotions, politics, or ideology; nor is it a captive of preconceptions."
- "Decision-making" was replaced with "problem recognition and solving", a richer and more flexible term that recognizes the use of BA in areas that are not decisional.

This choice of definition gives a first indication that, in the context of this work, business analytics is considered an ecosystem encompassing all business aspects of an organization. This ecosystem is composed of building blocks (Section 5.1) and actors (Section 5.2) that work in unison to boost organizational performance and deliver value to customers.

It must be noted that BA is different from knowledge management approaches such as knowledge discovery from databases (KDD). KDD is the "non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data" [25] and as such is fundamentally a statistical endeavor. Knowledge management approaches of this kind belong to what Chen *et. al.* [5] described as business intelligence and analytics (BI&A) 1.0, i.e. the use of data mining and statistical analysis developed in the 1970s and 1980s on mostly structured data collected by organizations through various legacy systems and stored in commercial relational databases. BA as understood by this work, is fed with data more in line with what Chen *et. al.* [5] described as BI&A 2.0 and 3.0 where web-based unstructured content and mobile- and sensor-based content are utilized in combination with structured data to extract value. Furthermore, BA techniques have evolved from traditional data mining and statistical analysis to include techniques that can adequately handle unstructured data (such as text, images, audio and video) as well as real-time data processing, cloud and distributed computing, among others.

In addition, given the context of Industry 4.0, the complementarity of human labor and cyber physical production systems (CPPS) cannot be ignored [26]. Human-machine interaction is an integral part of modern industries. Thus, a sustainable definition of business analytics must account for the transition from cooperation to active collaboration in human-centered CPPS in modern manufacturing plants. This active collaboration characterized by cyber-physical-socio interactions, knowledge exchange and reciprocal learning [26], has changed the roles of humans and machines from mere data workers and data producers to active collaborators capable of recognizing and solving problems towards a shared goal.

In this sense, we propose to extend the definition of BA proposed by Holsapple *et. al.* [24] as follows: *business analytics is concerned with evidence-based problem recognition and solving that happen within the context of business situations as the result of active collaboration between human labor and modern cyber physical production systems working towards a shared goal.*

3. Business Analytics in Manufacturing: domains to exploit

Insights derived from BA can enhance productivity [27] and competitiveness, boost innovation [28] and growth as well as generate new manners of competition [29] and value capture [30] across organizations. BA contributes to an organization's agility by providing timely and accurate information [31]. In addition, the prevalent use of data ensures transparency, aids the discovery of market needs [32], uncovers process or service variability, improves performance [27] and assists in the adoption of more sustainable practices [33]. In the specific case of the manufacturing sector, the previously mentioned McKinsey report [22] highlighted four main areas in which BA proves to be a differentiating factor for industry leaders at the expense of late adopters. These are summarized in Figure 1, and expanded upon in the following sections.

3.1. Research & Development and Product Design

The current paradigm of manufacturing involves global supply chains where an intricate chain of suppliers dispenses material resources to the original equipment manufacturer (OEM) to bring a product to the market. Communications among the numerous players involved are cumbersome for established value chains and even more so during the developmental stages of new products. Hence, the first domain in which BA could aid manufacturing is *research and development* (R&D) *and product design*. In this regard, technologies that facilitate interoperability along the value chain play a central role. For example,

Figure 1: The four manufacturing domains that can benefit from the adoption of business analytics according to [22]. A fifth domain, concerned with end-of-life and reverse logistics, is added as the result of product-oriented policies that increase industrial responsibility with respect to appropriate product disposal and/or recycling. While this figure lists several relevant disciplines within each domain, it is not a comprehensive list.

cross-enterprise Product Lifecycle Management (PLM)[2] systems provide a platform for co-creation of products using designs and inputs from numerous players along the supply chain. This collaboration and experimentation moves the

[2] Process of managing the entire lifecycle of a product from inception, through engineering design and manufacture, to service and disposal.

burden of innovation across the OEM organizational boundaries, and in this process aids decision making as well as the selection of appropriate suppliers while reducing costs and time to prototyping. Yet, consumer input is crucial for successful design-to-value [34]. Open innovation, where customers take a leading role in the design of new offerings, expands the information pool regarding needs, applications and solution technologies that would be most valued by a potential consumer [35] and, in turn, are most important to secure success in the market. Traditional point-of-sale data and customer feedback are complemented with customer-firm social media interaction changing the relationship between market actors and strengthening brand engagement.

3.1.1. Time-to-market

The time that it takes from the conception of a new product until it is available for sale is known as "time-to-market" (TTM). In general, it is used as a metric to determine competitiveness in terms of product development. In light of continuous product life-cycle shortening and increased international competition, the manufacturing industry strives to reduce the TTM of new product offerings for multiple reasons [36]. In first place, reduced TTM extends sales life and therefore improves profitability. In addition, getting to the market ahead of the competition results in the application of premium fees to products which increases revenues, a bigger market share, as well as giving the manufacturer the opportunity to establish industry standards and develop a technological edge [37]. Furthermore, a shorter TTM has been associated with increased flexibility to respond to changing customer trends leading to improved levels of customer satisfaction and customer loyalty which, in turn, may increase sales. Moreover, reduced TTM has been associated with lower product development costs, faster break-even and improved operational and business performance.

3.1.2. Shortening product development through open innovation

Since 80% to 90% of the TTM is absorbed during the design phase [37], involving suppliers and customers in the development of new product offerings have an enormous impact on TTM. To this end, a new paradigm for R&D was proposed by Chesbrough in 2003, known as open innovation [38]. It assumes that companies should make use of both internal and external ideas as well as, internal and externals paths to market to advance their technology [39]. Two possible sources of external ideas are customers and suppliers.

Customer involvement, also known as customer co-creation, gives manufacturers access to a pool of knowledge about needs and preferences that aid the decision making process. After all, managers agree that (big) data analytics should be applied to gain customer insights and adjust, customize and/or develop new service offerings [40]. Through customer co-creation, customers voluntarily and freely provide feedback and inform about products shortcomings [35]. This information can be used by manufacturers to make changes early on during the new product development process. The involvement of suppliers [41] reduces development costs, aids the standardization of components, ensures consistency between the design and the suppliers capabilities and limits the number of engineering changes. Involving suppliers gives the OEM access to knowledge and technical skills outside the firm [36] which improves quality and reduces the number of defects, helps identifying technical problems early on and increases the number of proposed solutions. However, it must be noted that companies embracing open innovation are expected to go through a learning phase, specially when it comes to structuring development agreements with external organizations, before truly benefiting from faster development cycles [39].

3.2. Supply Chain Management

Supply Chain Management (SCM) is another domain in which BA can derive insights to boost performance [42, 43, 40, 44, 45]. As with other manufacturing domains, promoting efficiency and minimizing operating costs are frequently cited as areas for the application of BA. In the words of an interviewed executive, BA helps “build a stronger relationship with our suppliers as a means of shortening lead times, and improving delivery reliability and certainty” [31]. In fact, one of the most critical issues in SCM relies on the volatility of demand coupled with insufficient flexibility and responsiveness from suppliers to continuously shifting consumer demands. A common consequence is known as the bullwhip effect[3] [47, 48], where orders to suppliers tend to have larger variance than sales, and this distortion amplifies as it propagates upstream. A related effect, called the ripple effect, occurs when a disruption cannot be localized and cascades downstream affecting SC performance and altering its structure [45]. Research [45, 49] has shown that business analytics has the potential to reduce these effects given the “volume”, “variety”, “velocity”, “value” and “veracity” levers of big data. Thus, the Holy Grail of BA for SCM is transparent information flow to aid accurate market trend predictions and guarantee data-driven decision-making [44]. In this regard, a competitive advantage is to be gained from aggregating high quality data from production, inventories and retailers [50]. This once far-fetched idea is now possible thanks to blockchain technology [45, 51] where distributed, immutable information contained in a ledger is visible to all stakeholders helping them overcome mistrust and boosting efficiency and visibility along the chain [52, 53, 54]. However, it must be noted that these technologies and applications require companies involved in the supply chain to collaborate and willingly share all relevant data [49].

3.2.1. Supply/demand match

Perfect matching of supply and demand requires accurate knowledge of customer preferences with regard to the products and features that are perceived as most valuable, as well as the quantities that consumers would be willing to purchase. In addition, products must be priced reconciling manufacturing costs and the rates that customers are willing to pay [55, 56]. This hints at a few different tasks: using customer input in order to produce successful products,

[3] Formally, the bullwhip effect is defined as the amplification of demand variability along a supply chain when a company purchases from suppliers more variably than it sells to customers leading to mismatches between demand and production, and hence, to lower supply chain efficiency [46].

forecast demand to manufacture the appropriate quantities, and suitable pricing. In the following paragraphs, a few examples regarding modern practices in these areas are presented.

From market research to customer co-creation using social media. Traditionally, customer input was obtained through market research where a representative sample of the target customer population would either respond to surveys, participate in focus groups or interact with prototypes and describe their experiences [57]. Products and innovations were developed within organizational boundaries and customers were external to this process. Nowadays, managers want to leverage BA to gain customer insights to adjust, customize and/or develop new products and service offerings [40]. Many industries are taking advantage of modern communication technologies to strengthen brand engagement through customer co-creation [58]. This term is used to describe the approach towards product development where customers take an active role on the design of a new offering, through collaboration with manufacturers on a voluntary, creative, social and sometimes competitive setting [35]. The main objective of such approach resides on increasing the pool of information held by the manufacturer with regards to needs, applications and technological solutions. The producer capitalizes on this information by increasing the "fit to market" of new offerings and their potential to capture monopolistic rents. One flourishing area of research in this regard evaluates the impact of social media in customer co-creation as part of the innovation process [35, 59, 58]. The challenge resides on extracting actionable insight from the myriad of social media posts comprised of mostly unstructured data in the form of text, audio, images and video. Actionable intelligence can be extracted from social media posts by means of social media analytics which refers to collecting, monitoring, analyzing, summarizing and making visualizations of social media data [60, 61], processed using innovative techniques such as natural language processing and text mining [62]. These insights are a key source of information for product design, innovation, marketing, and customer and stakeholder relations management and therefore, are an essential component of BA.

Demand forecasting. Demand forecasting refers to accurately estimating the number of units that will be sold and is of great importance to produce items in adequate quantities to maximize service levels while keeping capital investments on inventory low. In addition, demand forecasting is used to support strategic decisions such as capacity expansion and transformation, technology migration, tool procurement and outsourcing [63]. Deficient forecasting increases the likelihood of obsolescence, urgent orders, inefficient resource utilization and the spread of the bullwhip effect along the supply chain [64]. As with other aspects of the manufacturing industry, demand forecasting is highly variable across industry sectors and therefore cannot be easily standardized. For example, the fast fashion industry manufactures products with short life-cycles and brief selling seasons characterized by impulsive purchase patterns, great demand volatility and low predictability for a large variety of items [65, 66]. Research has found that short selling seasons along with high levels of uncertainty and lack of historical data (as a result of continuous innovative product releases) are hard barriers to overcome for accurate demand forecasting [67]. As a result, industry leaders found a trade-off with supply chain responsiveness that allows them to complement forecasting to operate under high levels of uncertainty [66]. One example is that of Spanish retailer Zara [68]. When trying to determine how to distribute items among stores, they use shipment requests from managers and past historical sales to build demand forecasts. Then, these forecasts are fed to an optimization model along with warehouse inventory levels and assortment decisions with the objective to determine shipment quantities while maximizing global sales. Thus, agile supply chains [43] that are closely connected to end-user trends, rely on shared information across all supply chain partners, and are highly flexible and interconnected have an upper hand. In this scenario, BA has the potential to harness currently unexploited predictive value out of product and customer information, retailer sales and manufacturing orders. This, in combination with vertical supply chain integration and fast responsiveness, guarantees that market leaders turn a profit while securing the shortest market lead-times.

Dynamic pricing. Pricing is a complex task in which variables such as a company's operating costs[4], the availability of supply, brand equity and future demand forecasts have to be considered to maximize sales and profitability [69]. A common practice, originally introduced in industries where the short-term capacity (supply) is difficult to change [70], such as airlines, hotels and sporting evens, is the use of dynamic pricing where the price of an item varies in real-time to account for fluctuations in market conditions such as demand, inventory levels, competitor offerings and customer history [4]. The adoption of dynamic pricing strategies has proliferated due to an increased availability of demand data, the emergence of new technologies that facilitate changing prices, and the availability of software for analyzing demand data and for dynamic pricing [69]. These new technologies allow retailers and manufacturers to combine information about sales with demographic data and customer preferences, and to use it to optimize pricing and markdowns as well as to evaluate the effect of promotions. Early adopters of dynamic pricing strategies have reported improved financial performance, fast return on investments, and no negative impact on price image. However, transparency of pricing practices is of outmost importance: while most customers accept dynamic pricing in response to shifting market conditions, backlash has resulted from pricing based on price elasticity of demand[5]for individual customers [71, 72].

[4] Costing is another area in which BA can increase profitability. As pointed out by [56], the use of prescriptive cost models can support decision making by providing ex-ante (rather than ex-post) analysis. Prescriptive cost models can assist in visualizing and planning what is needed to produce a specific product and ensure higher efficiency and cost effective strategies with regards to the use of resources.

[5]Price elasticity of demand is a measure used to show the responsiveness of the quantity demanded of an item to a change in its price, all other variables being equal. In this particular case, it refers to charging higher prices to loyal customers as opposed to one time or irregular customers.

3.3. Production

Production can also benefit from BA. The integration of ubiquitous sensors, the Internet of Things (IoT) [15, 16, 17], and the fusion of the physical and the virtual world by means of cyber-physical systems (CPS) give rise to real “smart factories” [8, 9, 10, 11, 19, 20, 21]. In these smart factories, real-time monitoring of operations generate the necessary data to maximize yield, reduce waste [73], cut operational and maintenance costs, optimize schedules [74] and support lean manufacturing projects [75]. Historical data can be used to create a “digital factory” [76, 77] to determine the most efficient production systems, a space-efficient layout for the construction of new plants, adequate step sequencing for a specific product, as well as enable cost reductions in terms of tool design, construction and assembly time, and improvements in delivery reliability. There are a number of successful applications of BA in the domain of production. Some examples include resources (such as energy and water) and processes [78, 79], tooling optimization [80], asset utilization [81, 82, 83, 84], quality [85, 86, 87], inventories [88, 89, 90], labor [91, 92, 93], among others.

3.3.1. Resources

The manufacturing industry transforms raw materials into finished goods while making use of other input resources such as energy and water. Hence, it is only natural for the manufacturing sector to be invested in the optimization of input resources to identify opportunities to reduce raw materials, water and energy consumption, eliminate waste, and therefore improve efficiency, yield and adherence to sustainable practices. In the remainder of this section, the use of BA to optimize energy consumption is explored as a motivating example. Parallels can be drawn between this application and the optimization of other resources.

How can BA optimize energy consumption?. In the past, energy consumption was estimated from calculations regarding the specific physical process energy requirements. However, recent studies [94, 95] have proved that the energy required for the specific task (cutting, machining, etc.) is only a fraction of the total energy consumed by the machine tool in charge of completing such task. With the adoption of CPS, the energy consumed by each machine tool can be easily tracked [78]. The knowledge extracted from this data is potentially useful not only to reduce energy consumption as a whole by means of identifying opportunities for optimization [96], but also can be fed into models dealing with other production aspects [78, 79]. For example, anomalous energy consumption patterns could be negatively correlated with the quality of the produced parts, aiding the discovery of products that do not comply with design tolerances at an early stage of the value chain. In turn, this would contribute to the reduction of waste, improving adherence to lean manufacturing practices. In addition, historical power usage profiles may be of importance to develop accurate models capable of predicting machine tool failure, since uptakes in energy consumption could be symptomatic of mechanical malfunctioning. Furthermore, accurate accounting of energy usage on a per-part basis could be used to derive the cost of energy embedded in consumer products. Lastly, as regulations promoting sustainable and environmentally friendly practices are drafted, careful attention to manufacturing carbon footprint is paid. Accurate energy consumption logs can potentially aid decision makers not only in terms of achieving operational excellence but also on bettering environmental performance of manufacturing equipment.

Unfortunately, challenges abound in this area. In first place, the traditional manufacturing industry must equip existing tools and machines with the necessary monitoring/sensoring devices to measure energy consumption. It must also outgrow legacy IT systems that lock data in silos and design an effective data architecture and technology infrastructure that allows to seamlessly aggregate data regarding energy consumption with that of quality, equipment performance and maintenance, manufacturing costs and others. To solve this specific challenge and appropriately deal with the analytical complexity of manufacturing processes and systems, proposed software solutions must fulfill certain requirements. The most pressing, as listed by [78], are simultaneous monitoring of energy use and process data, scalability for large data volumes and the ability to support analysis at various manufacturing scales.

3.3.2. Asset utilization

Many industries within the manufacturing sector hold high capital investments on machinery and equipment and, for this reason, are generally referred to as asset-heavy. For these industries, maximizing the Return on Assets (RoA), i.e. the profits made for each dollar held on assets, is of outmost importance to guarantee profitability [63, 86]. In order to succeed, careful job scheduling, timely maintenance and short changeover times must be meticulously planned, in addition to ensuring maximum machine life. Of the possibilities listed above, the exciting prospect of harnessing BA to deliver predictive maintenance is further discussed.

BA for predictive maintenance. Traditionally, maintenance has been regarded as a reactive measure and managed with the "run-to-failure" method: after failure has occurred, steps are taken in order to remedy it [97]. This is the most expensive method of maintenance management, translating into major expenses from spare parts inventory, overtime labor, long machine downtime and low production availability. Since asset-heavy industries rely on optimizing equipment utilization to reduce losses in terms of capital expenditures and revenue, many organizations adopt a "preventive" maintenance management style where repairs are scheduled periodically based on the equipment's Mean Time Between Failures (MTBF) [98]. However, this frequently leads to unnecessary repairs (and their associated unnecessary materials and labor costs) or catastrophic failures (and the already discussed run-to-failure maintenance drawbacks). Thus, in order to improve upon preventive maintenance, a more proactive approach known as "predictive" maintenance has gained traction. Predictive maintenance entails the "regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of machine-trains and process systems [to] provide the data required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages created by machine-train failures" [97].

Vast work has been done in terms of predictive maintenance, generally involving the use of sensors to record physical parameters such as temperature [99], vibration [100, 101], noise or acoustic emissions [102, 103], lubrication or oil physical properties [104] as well as corrosion and wear [80, 105]. In some cases [83], the input data is constituted of not only machine sensor data but also human (mood monitoring and sentiment analysis) and material data. The output produced is a longevity estimate, a probability of failure or a financial estimate on maintenance of a component [106]. In most modern implementations [83], the system provides a list of appropriate countermeasures based on historic data from former interventions or, when unseen situations are encountered, dynamically generated countermeasures.

There are several challenges associated with predictive maintenance. Firstly, the optimum type of sensors and their adequate localization must be chosen. In addition, collecting data that is directly related to machinery damage is far from trivial, and in some cases impossible [107]. Furthermore, there is a need for real time, i.e. low latency, algorithms with the potential to scale up alongside production while zealously protecting the privacy and security of manufacturing data. Finally, current predictive maintenance algorithms are developed for a specific machine or application and, unlike what [83] described as modern implementations, are not flexible enough to handle unprecedented events [84]. Thus, adaptive algorithms that harness data from an entire fleet of machines performing similar tasks or sharing service times can be used in order to widen the knowledge base concerning their health condition and the appropriate corrective actions.

3.3.3. Quality

Quality is by far the most exploited aspect of production that digitization has to offer to the manufacturing industry. Examples in literature include locating defect-producing steps within the production line [86], predicting whether a manufactured item will pass the quality check [87] and more. This is probably the result of a long standing tradition in detailed statistical analysis associated with quality initiatives such as Statistical Quality Control (SQC), Total Quality Management (TQM), *Kaizen*, ISO 9000 quality standards, 6σ, lean six sigma, among others [4]. Thus, improving quality requires focus on enhancing manufactured products and the processes they go through aiming at reducing wasteful use of materials, equipment and labor [55] as well as improving customer experience.

An exhaustive review of successful data mining applications to ensure quality within the manufacturing sector [85] identified four quality tasks associated with product design and manufacturing (see Figure 2). The authors found that 42% of BA associated with quality improvement is invested in prediction tasks in terms of quality of products, their physical properties and process parameters. Classification (25%) and optimization (23%) tasks followed with focus on modeling to understand cause-effect relationships, and traditional business intelligence associated with descriptive analysis (10%) remains a common practice. While all sectors within the manufacturing industry show an increasing trend in the use of BA to improve quality, industries concerned with metal, computer and electronic products were the front-runners, while plastic, paper, glass, food processing and chemical manufacturing laid behind.

Quality data entails several challenges in itself. In terms of volume, the manufacturing industry is known to have from very small datasets to very large in size. In addition, the data usually contains missing, outlying, inconsistent and incomplete records containing input and output variables of both discrete and continuous type. To add an extra layer of difficulty, quality data may be comprised of not only structured but also unstructured records. Furthermore, the data preparation step is key, given that highly correlated variables are frequently present making dimensionality reduction a prerequisite. Moreover, quality data are usually imbalanced, i.e. contain a much smaller proportion of instances of defective items than compliant ones [87].

In terms of deployment feasibility of quality improvement initiatives within

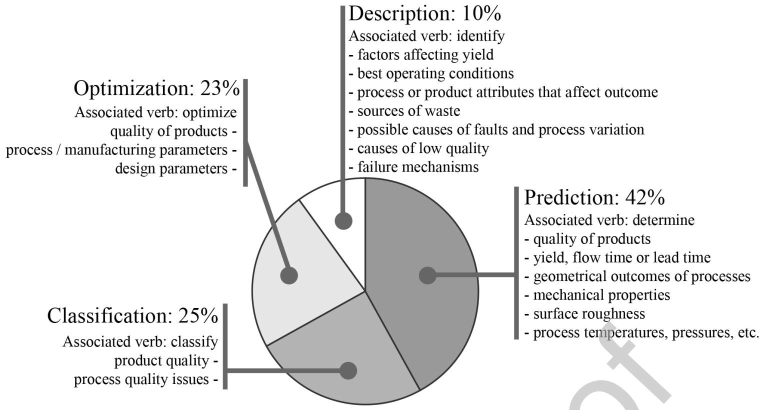

Figure 2: Quality assurance tasks associated with product design and manufacturing as described in [85]

the manufacturing industry, it is clear that organizations with integrated data collection systems have a competitive advantage given that quality data is usually aggregated with production data to obtain an appropriate dataset. In addition, the industry is faced with limited human capital with the right training in data mining and BA to handle quality improvement projects, to interpret results, and to use the knowledge derived from these. In that regard, robust algorithms and the development of affordable and user-friendly software could help in overcoming this challenge.

3.3.4. Inventories

Inventories represent a huge capital commitment and loss of liquidity for the manufacturing industry. In addition, keeping safety stocks requires physical space and thus its cost is increased as the result of storage, additional personnel requirements and administration [108]. Inventoried items also suffer the risk of obsolescence, and essentially conceal production problems and prevent their elimination. To counteract these costly disadvantages, the industry constantly searches for an equilibrium that allows it to minimize safety stocks [109] but, at the same time, ensure delivery reliability and customer satisfaction [110].

To this aim, inventory tracking has been widely automated using barcodes or more sophisticated Radio-Frequency Identification (RFID) technology [111] in the form of tags attached to individual products. The data produced can be used for inventory analytics to identify potential stock shortages and to avoid incidents in customer delivery. In addition, it can be useful to diagnose supply shortfalls, backlog accumulation and inadequate inventory levels at strategic stocking points [110, 112]. Inventory analytics can also be used for ABC inventory classification[6] as well as review and update the classification in real time for optimal item distribution. Furthermore, the use of BA on inventory data aids the identification of obsolete goods as well as those at risk of obsolescence, and helps avoiding excess stock while securing sufficient inventory to handle demand fluctuations [88].

Example: Safety stock optimization in Procter & Gamble. This real application of BA concerns Procter & Gamble [89], where optimization was conducted locally using spreadsheet-based models at each stage of the supply chain followed by a multi-echelon optimization[7]. The model used for the latter was trained using multiple variables. For example, not only actual past demand was utilized but also the forecasted shipments for the previous thirteen weeks as well as those for the coming thirteen weeks. Other variables included materials lead times, production times, review periods, time for transportation and movement, quality assurance duration and cost variability at each location. The objective of such model was to minimize safety stocks and hence, reduce capital investment while satisfying existing service policies regarding a case fill-rate[8] of 99.5%. The

[6] ABC inventory classification is a technique used to divide inventoried items depending on the accuracy and control of their records. In general, A items account for the largest proportion of the value and the lowest number of items while the opposite is true for C items.

[7] Multi-echelon optimization looks at the problem of inventory holistically across the supply chain while taking into account the impact of inventories at any given level (or echelon) of the supply chain on other echelons.

[8] Case fill rate is a measure of the depth of demand that was satisfied by the inventory on hand. For example, a customer orders 20 units of an item, but the seller ships only the 15

full two-step optimization process accomplished a reduction in total investment in safety stock of 17% that was improved by an additional "what-if" analysis of operating policies, while ensuring the target service levels.

There are several challenges associated with the use of BA to optimize inventories. It is not possible to use a one-size-fits-all inventory optimization strategy, and therefore the analytics used to reduce safety stocks must be customized to satisfy the specific organization in order to determine the most appropriate inventory levels. In addition, the models must avoid bias towards excessive levels of safety stock, as well as dangerously low levels that may result in customer service incidents [89]. Furthermore, model robustness is required to accurately extrapolate to different business units and geographical regions. Finally, the model must appropriately handle unexpected events in line with the risk management policy of the company.

3.3.5. Labor

The use of BA to handle all the aspects of the workforce life cycle, from hiring to training and development, including retention, assignment, compensation and benefits is known as "workforce analytics" [91, 113, 114]. As Huselid put it [113], "workforce analytics refers to the processes involved with understanding, quantifying, managing, and improving the role of talent in the execution of strategy and the creation of value. It includes not only a focus on metrics (e.g., what do we need to measure about our workforce?), but also analytics (e.g., how do we manage and improve the metrics we deem to be critical for business success?)". An optimized workforce management does not only lead to labor cost reductions and thus, to increased organizational profitability, but also results in improved overall operational performance [92]. It allows for reallocation of labor resources when and where necessary in a flexible fashion to meet deadlines and to ensure customer satisfaction [115]. Problem areas can be readily identified, resulting in appropriate action being swiftly taken without

units it possesses. The fill rate equals $15/20 = 0.75$ or 75%.

compromising neither the quality of the service provided nor its profitability. In addition, workforce analytics provides real-time labor data that can be potentially aggregated with payroll data for accurate job costing analysis that result in more precise pricing. Finally, labor scheduling is optimized by minimizing non-productive time, over-scheduling and preventable overtime. The problem can be described as one of matching available jobs profiles, uniquely defined by variables such as job role, tasks involved, project, requirements and others, with human resources profiles represented by candidate ID, skills, experience and so on. The main challenge identified by [91] is assigning a single candidate to each available job and trading off individual (pairwise) matches for an overall assignment that fills all jobs.

A recent interview of a Shell HR Manager published by Predictive Analytics World [93] looked into the challenges that workforce analytics needs to overcome in order to be widely adopted by the industry. In first place, as with any other value driver, the need for clean and accurate data as well as personnel accustomed to using data analytics and producing trustworthy outcomes are required. Fairness of workforce analytics results may be an obstacle to wide adoption, since even analytically sound models may have undesired consequences. An interesting example put forward by the consulted executive was hiring predictive models whose recommendations uphold hiring people of a specific gender or age group. Human intervention was suggested as a countermeasure and is supported by other authors [109], who predicate that personnel decisions should be grounded on a combination of analytics, instincts and personal experience. These authors claim that assessments regarding personality and character can be swiftly and accurately made by human beings based on simple observations. Hence, workforce analytics should only be used as a complementary tool for optimizing all activities related to the workforce.

Beyond the technical difficulties, organizational barriers may hinder BA wide adoption for labor optimization. Resistance from labor unions based on privacy laws, and a lack of senior stakeholders' buy-in may be the biggest limitations [93, 115]. Crafting a compelling story around the outcomes of data analytics projects [116], using visualization tools (charts, graphs, etc.) to aid complexity and tying those outcomes back to the business bottom line should help in getting the message through. However, if the results contradict management thinking, executives may mistrust them [115] and the deployment of recommended actions may be hindered by personnel defensiveness. In turn, if managers do not make different and better decisions as a result of workforce analytics insights, returns on investment will fail to materialize [117].

3.4. Marketing, sales and after-sales support

The fourth domain in which BA can have a transformative impact within the manufacturing industry are the areas of *marketing, sales and after-sales support*. Analytics conducted on data about interaction with customers are not limited to co-creation and open innovation initiatives, but also exploited to improve marketing and sales [40, 118]. For example, social network chatter analytics can help identify pools of new potential clients [86], as well as enhance product development. Statistical analysis, forecasting, predictive modeling and optimization are used for customer segmentation in order to improve the effectiveness of marketing and sales forces [119], as well as the type, number and quality of service offerings. In other words, BA can be used to improve customer experience [120]. In addition, sensors on products allow for real-time monitoring of usage patterns and customization of after-sales services to successfully target different customer segments [4]. Data from firm-customer-interaction is revolutionizing traditional commercial relationships: the manufacturing industry is transforming from a product to a service-oriented industry through the monetization of insights derived from data by means of innovative business models [121].

3.4.1. After-sales services

The notion of "servitization" was firstly introduced in the late 1980s as a way to gain an edge on competitors, engage customers and increase the level of differentiation in markets of homogeneous performance, price and quality [122].

A more current definition describes servitization as "the innovation of an organizations capabilities and processes to better create mutual value through a shift from selling products to selling product-service systems" [123, 124]. In addition, servitization has economic advantages for manufacturers and consumers: it increases sales revenues and makes maintenance and support costs more predictable [125]. As a consequene of this process, the manufacturing sector is steadily evolving from producing assets to delivering value to customers through servicing those products. After-sales services are seen as a high margin business with low associated risks that generate revenue throughout the life span of the asset, which account for a large percentage of corporate returns (24% of revenues and 45% of gross profits, according to [126]). Furthermore, when effectively delivered, they improve firm-customer relationship increasing customer loyalty and intent of repurchase. Moreover, after-sales services help gain valuable knowledge about customers' technologies, processes and plans that can, in turn, be used as feedback to customize new offerings.

Most organizations do not perceive the profitability of after-sales services and they fail at delivering value to customers by managing the offerings as a mere afterthought. These inefficient after-sales services do not generate profits. In fact, studies show that while servitized firms are generally larger in terms of sales revenues, they are also collectively less profitable than pure manufacturing firms [127]. This is because servitized firms have higher costs per employee, as well as higher working capital and net asset base. Successful management of after-sales services is cumbersome and requires the timely allocation of parts, people and equipment to the appropriate locations while minimizing costs and optimizing fill-rates. Simultaneously, successful after-sales services must satisfy customer needs in terms of acceptable delivery times and price [126]. BA can be the differentiating factor to optimize after-sales services management. Data from product failure rates, customers, business strategies and product technologies can be harnessed to train analytic models capable of forecasting after-sales services demand probability distributions and therefore facilitate resource allocation. In addition, customer segmentation can be applied to design a portfolio of attractive service offerings considering parameters such as waiting time and cost of service leading to premium, gold and silver service plans to satisfy different customer segments.

Example: Rolls-Royce product oriented product-service system. With the advent of new technologies such as the IoT and big data analytics, the development of after-sales services has been facilitated by incorporating sensors on products that inform the manufacturer about performance, defects and usage patterns while in hands of the customer. This translates into a business model shift in which the manufacturing company transitions from "doer" to "problem solver" [128]. An illustrating example is that of Rolls-Royce aerospace engines business unit whose business model changed from merely selling engines to "power-by-the-hour". As part of this offering, customers pay an hourly fee for the power generated by the engine and receive continuous support and maintenance from Rolls-Royce to ensure their correct functioning [127]. A challenge associated with these types of offerings is that of defining appropriate data access rights and privacy since manufacturers' oversight of usage patterns may not be always welcomed by the average customer.

3.5. End-of-life or reverse logistics

Although not discussed in [22], a fifth domain can potentially profit from the use of BA. This domain is concerned with what is known as *end-of-life* or *reverse logistics*, i.e. "the process of planning, implementing, and controlling backwards flows of raw materials, in process inventory, packaging and finished goods, from a manufacturing, distribution or use point, to a point of recovery or point of proper disposal" [129]. Reverse logistics involves recycling and remanufacturing as well as product returns, reuse of materials, waste disposal, refurbishing and repairing [130]; and it developed as a response to product-oriented policies that oblige manufacturers to guarantee and finance product take-back and recycling given growing environmental concerns [131, 132]. In this regard, sensors on products could accurately predict the end-of-life of a good based on analytics of usage patterns, and wireless connection could be used to inform the appropriate stakeholders in order to coordinate efficient reverse logistics. Research [133] suggests that forecasting the rate of return of products and their demand will help design and construct reliable and profitable reverse supply chains. In fact, integrating data from all the players within the reverse supply chain can guarantee higher profitability [134]. Furthermore, companies could use this information to target marketing campaigns to improve re-sales and customer experience.

4. Challenges

Top and bottom performing companies differ in their use of BA. Cao and Duan [135] conducted a study among 117 UK manufacturing companies and found that "compared with bottom-performing companies, top-performing companies were 2.86 times more likely to have developed organizational structure to enable analytical activities, 3.56 times more likely to have developed process to embed analytical activities, 3.06 times more likely to have developed strategy to guide analytical activities, 3.60 times more likely to use statistical analysis, 12.00 times more likely to use business reporting, 7.24 times more likely to use query and analysis, 6.53 times more likely to use spreadsheet, 5.9 times more likely to use forecasting, 7.56 times more likely to make data-driven decisions, and 5.31 times more likely to create new service or product using data-based insights." Then, it is fair to ask what are the aspects hindering BA adoption?

Five years after their 2011 report [22], the McKinsey Global Institute looked into the adoption and accomplishments of data analytics within the manufacturing industry [136]. Results showed that, besides digital native organizations and a few early adopters, most companies were lagging behind in terms of exploiting the potential value of their business data. Interviewed executives indicated that lacking senior management involvement and the appropriate organizational structure to aid the use of data and analytics were the major barriers that hindered value creation. In addition, the inability to outgrow legacy IT infras-

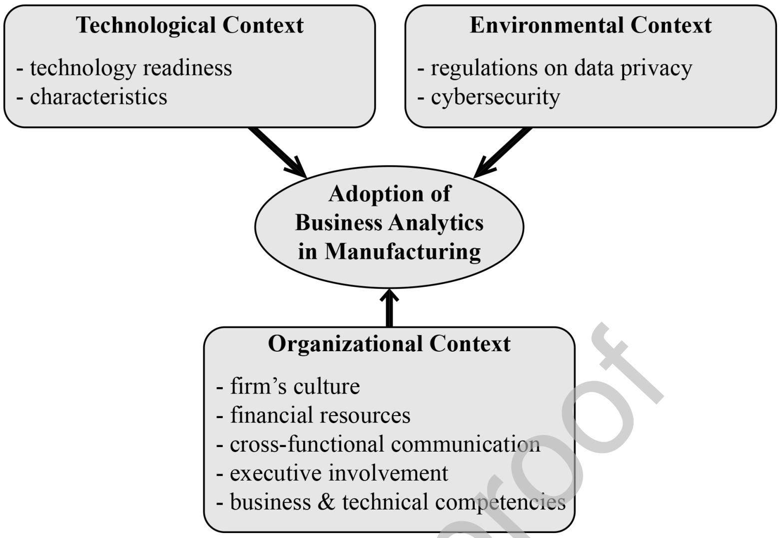

Figure 3: The technology-organization-environment framework associated with the adoption of business analytics in the manufacturing industry.

tructure that impede data aggregation arrested wide adoption. In this Section, the challenges that hinder the adoption of business analytics in the manufacturing sector are explored and then summarized in terms of the Technology-Organization-Environment (TOE) framework [137, 138], an organization-level theory that explains how these three elements of a firm's context influence innovation such as the adoption of business analytics. A summary of the aspects discussed here is shown in Figure 3.

A considerable percentage of organizations within the traditional manufacturing industry perceive analytics as a complex and costly undertaking whose results outweigh potential gains. In fact, over 20% of the more than 3000 business executives surveyed for a MIT Sloan Management Review article perceived that costs outweighed projected benefits [139]. In the same lines, Brinch *et. al.* [40] found that the need for analytics is higher than current investments and that is the result of analytics not being part of the industry digital strategy. And indeed, the path to extracting profitable insights from data is arduous, since quantitative technology investments need to be accompanied by cultural change within the organization and its approach towards data [109]. Profitable business insights are the result of enterprise (as opposed to business unit) approaches towards BA, in which quantitative techniques are utilized to improve all business functions concurrently. In addition, successful BA initiatives must be centralized, i.e. managed under common leadership and technologies, and the extracted knowledge must be seamlessly shared with all departments using consistent formats, common definitions and standards. Making use of the TOE framework, the organizational context with respect to a "firm's culture", "cross-functional communication" and "financial resources" are relevant when determining the extent of BA adoption.

Leadership is often cited as a BA management challenge [140]. Top management support is crucial to secure the necessary funding and ensure that the organizational culture supports analytics [116]. Senior executive involvement must lead the necessary organizational change to incorporate analytics into the core strategic vision of the organization. In fact, an effective sponsor of BA initiatives must [141]:

- define business needs to increase the likelihood of delivering value,
- be the primary beneficiary of such initiative to guarantee the necessary commitment (since more than 1 in 3 business executives cite "lack of management bandwidth due to competing priorities" as a challenge for analytics adoption [139]),
- prioritize data-driven decision-making over intuition or gut-feeling, given that in practice, a large proportion of decisions are made based on domain knowledge or past experience rather than grounded on data [44],
- have demonstrated influence and authority to successfully align the necessary resources, as well as cross-functional scope to change the organizational culture in a transformative way,

- be interested in implementing a long-term BA program as opposed to managing a single project.

In terms of the TOE framework, this means that the organizational context also includes "executive involvement" and, once again, points to the importance of "cross-functional communication".

Decision makers must be savvy enough to understand analytic model's underlying assumptions to make use of insights only where applicable [142]. Thus, successful implementation requires the development of executives and managers' capabilities to take advantage of such insights and integrate them into the workflow. In fact, "lack of understanding of how to use analytics to improve the business" [139] or as phrased by Vidgen *et. al.* [143], the challenge of "using analytics for improved decision making", is the most cited impediment faced by organizations in the quest of becoming more data-driven. As Flath and Stein put it [87], "the recent influx of machine learning research has brought forward a host of capable algorithms and tools but has not equipped operators and decision makers with the necessary work-flows and tools. Consequently, there is an urgent need for tool-kits and templates which assist manufacturing decision makers navigate through a world of new opportunities". This challenge points to the organizational context of the TOE framework, making "business and technical competencies" a key aspect when analyzing the likelihood of BA adoption. In addition, it points to the necessary "characteristics" of new technological solutions.

On the other hand, decision makers should be wary of falling into "the illusion of explanatory depth", i.e. the overconfident belief of understanding complex phenomena with greater precision, coherence and depth than they actually do [144, 145]. In fact, it has been proposed that *scio me nescire*, which translates to "I know that I know nothing", may in fact serve as a source of enhanced organizational performance [86]. Awareness of nescience, i.e. the lack of knowledge when knowledge is not there [146, p. 35], is central to an organization's success since it sets the direction for further inquiry and thus managers could use nescience as the criteria to set priorities for complex problem solving. Problems whose solutions appear to reduce nescience the most should be embarked on first [86].

Users of BA applications expect responsiveness, so the areas in which BA projects are deployed should react rapidly to user interaction [142]. Thus, process responsiveness needs to be improved to timely accommodate BA recommendations. In the TOE framework presented in Figure 3, responsiveness can be considered part of a "firm's culture" and thus, it belongs to the organizational context. In addition, rigorous assessment of the value delivered by BA projects is necessary to quantify ROI [147], measure customer value impact [143] and properly redefine project objectives. Successful BA projects understand key business objectives and have impact in meeting them [116]. Therefore, an experimentation-based approach where metrics to evaluate performance are developed and the impact of the project on the business bottom-line is quantified increases the chances of success. In brief, analytics must produce results and recommendations that are actionable and driven by business value, along with methods to quantify the effects caused by adopting such recommendations since this is generally tied to stakeholder buy-in [93].

An appropriate technology infrastructure is still a prerequisite [140, 143] and thus, "technology readiness" must be determined within the technological context of the TOE framework in order to determine the likelihood of adoption of BA. After all, data cannot be analyzed unless it is collected first. For many organizations that translates in substantial investments to upgrade existing systems (again pointing to the need for "financial resources" within the organizational context of the TOE framework). However, the main concern within the manufacturing industry is not investing at scale but deciding on the most adequate system for the needs of the organization [136]. More specifically, IT solutions should close the gap between the problem-specific view of analytic tasks in an industrial setting and the method-specific view of data analysis tools available in the market [148]. In this regard, information technology solutions must be simple and easy to use, suitable to the needs of the users, contain all relevant data and make use of standarized terminology [149, 150]. In addition, the selected IT solution must be robust and flexible to adapt to disparate manufacturing enterprises and should make use of open standards and clear specification of interfaces to ensure interoperability, i.e. support the exchange of information among different business units and across enterprises along the supply chain while ensuring data, information and knowledge integration [151]. Finally, since IT solutions and infrastructure are a long-term investment, they must be adequate to attend to the present requirements of BA projects, while remaining flexible to evolve with the business [142]. All these important "characteristics" that the technological solution must have should be considered within the technological context of the TOE framework.

The successful deployment of BA is tied to access to the right talented personnel with analytical, business and relationship skills. In TOE framework language, the organizational context must accrue the right "business and technical competencies". This means that typical analytical skills must be complemented with the flexibility and sense of urgency characteristic of business, in addition to outstanding communication skills to collaborate with different actors [142]. Wilder and Ozgur [152] list three career paths associated with BA:

- The data scientist whose skill set includes a solid foundation in math, statistics and computer science. They are capable of using advanced statistical methodologies and construct complex models on data.
- The business analyst, also described as data-savvy managers, who hold positions that allow them to identify and exploit opportunities. Thus, they need a solid foundation in business complemented with analytical capabilities. Their analytics needs are related to the ability to frame and interpret BA results in an effective way.
- The business user whose primary knowledge is in a business discipline complemented with basic statistics for simple descriptive data analysis. Their technical needs focus on accessing data and basic analysis.

Finding these profiles is challenging and thus, it leads companies to initiate recruiting activities up to 18 months before the position is expected to be filled [109]. Furthermore, demand for these profiles increases faster than the offer, resulting in skyrocketing salaries. However, there are opportunities to bridge the gap. Henke *et. al.* [136] proposed the new role of "business translator" who acts as a liaison between analytic experts and executives. In the words of a newly appointed business translator at a small manufacturer, "the disconnect between the IT department and the end user is so huge that it can be so greatly benefited by a translator" [153]. Business translators reconcile the language of analytics with that of other business functions to explain findings in business terms to executives and decision makers. In addition, companies are investing in training activities for existing personnel to develop analytical skills, while universities are launching new programs, boot-camps, certifications and massive open online courses to fill the gap [152, 154].

Finally, the IoT and mass collection of data are plagued with concerns about data privacy, cybersecurity and liability [155, 147], which speak to the environmental context of the TOE framework. Manufacturers should consider these issues from the onset of the design phase and make sure to disclose any security defects to customers, since failure to do so exposes enterprises to liability. In fact, cyber attacks have consequences beyond the financial value of the incident: health, safety, operations and environmental incidents impact the business reputation and are detrimental to the brand image [156]. Security breaches that compromise customers data may have major ramifications, not only from a legal perspective but also with respect to their relationship and trust on the company. Furthermore, breaches related to enterprises proprietary data put intellectual property and manufacturing secrets at risk of getting in the hands of competitors resulting in long-lasting economic losses [157].

5. Completing the Definition of BA in Manufacturing

In Section 2, a general definition of BA proposed by Holsapple *et. al.* was presented as starting point for this work. That definition indicated that business analytics is "concerned with evidence-based problem recognition and solving that happen within the context of business situations" [24]. While this remains true for the manufacturing sector, it is important to complete this definition by identifying the building blocks and actors that differentiate manufacturing from other sectors.

5.1. Building Blocks of BA in Manufacturing

While there is some research into the constituent elements of the information infrastructure of a digital enterprise [158], the literature fails to list the building blocks that enable the BA ecosystem. Given the definition of business analytics introduced in Section 2 and the challenges listed in Section 4, it is posed that BA endeavors are composed of a dynamic set of building blocks:

- Culture: an entity's culture and philosophy ingrained with a mindset of evidence-based problem recognition and solving is necessary to out-grow intuition, secure management buy-in and guarantee responsiveness to BA insights.
- Practices and technologies: this building block focuses on the way in which analytic tasks are performed. It recognizes technology-based and practice-based analytic techniques, as well as, qualitative, quantitative and hybrid techniques. Thus, this building block goes beyond commonly understood technology infrastructure (normally thought of being composed of hardware and software) to include mathematical tools such as statistical analysis, data mining, machine learning, etc.
- Capabilities: A set of competencies held by different actors within the evidence-based problem recognition and solving culture. This refers to the appropriate combination of analytical, business and relationship skills

held by each person involved in the BA project which is inherently different for different roles within the organization.

- Data: this building block contains all structured, semi-structured and unstructured data produced within the organization and by the organization's interaction with external entities such as suppliers and customers. It also includes the process of data acquisition, cleaning and storage.

5.2. Actors of BA in Manufacturing

The actors of BA are debated in literature with diverging views. While Lee and Chen [159] model of the analytical process identified the actor (who initiates the analytical process) and the actant (who takes actions accordingly) as participants, Pappas *et. al.* [160] analysis of big data and business analytics ecosystems determined that data actors are those who generate and use data. In this sense, they listed academia, industry/private organizations, government/public organizations, civil society, and individuals/entrepreneurs as BA actors whose capabilities (analytical competencies) are developed in their respective contexts leading to value creation, business and societal change. Furthermore, as discussed in Section 4, Wilder and Ozgur [152] analyze three career paths (the data scientist, the business analyst and the business user) and their skill set with respect to BA. Yet, while studying the adoption of BA for a telecom service provider, Gangotra and Shankar [161] considered as actors those that specifically interact with or can affect the product or service provided. According to their work, the BA actors and their roles are:

- Top management: sponsor the BA adoption program and monitor the business value created.
- IT project team: implement and maintain systems and tools.
- System integrators and consultancy firms: architect flexible IT systems and processes capable of adapting to changing internal and external business scenarios.

- Competency center managers: ensure agile processes and the availability of experts to use the tools to respond to market needs and regulatory demands.
- Competition: keep track of market movements and product offerings and counter propose.
- Business managers: use the insights and key performance indicators (KPIs) for fact-based decision-making in daily operational processes.
- External technology suppliers: produce user friendly tools for (big) data analytics.
- Consumers: evaluate and choose products to purchase.

While there is no clear consensus on who the actors of BA endeavors are and thus, more research on the matter is required, the work of Grangotra and Shankar [161] is in line with the actors evidenced in this work and summarized in Figure 4. Business units executives must recognize and solve problems based on evidence. This evidence is identified by personnel with analytical skills that apply statistical models to data. To bridge the work of analytical personnel and that of executives and managers, this study identified the figure of the "business translator". However, as discussed in Section 4, top management sponsorship and buy-in is necessary to guarantee success. Finally, an IT team and external technology suppliers are necessary to provide the tools and processes needed to create an ecosystem where BA can flourish leading the aforementioned actors to generate value and deliver it to customers.

6. Pathway to market leadership

Most companies looking into creating and capturing value from BA are probably already generating considerable volumes of data. In fact, only 20% to 25% of companies see data availability, ownership and governance as a barrier towards becoming more data-driven [139]. However, it is likely that proprietary

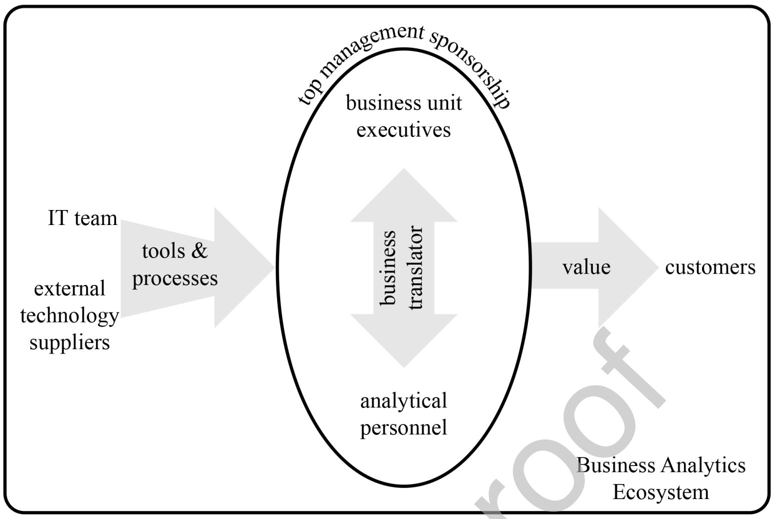

Figure 4: Actors in the manufacturing business analytics ecosystem. Business units executives must recognize and solve problems based on evidence. This evidence is identified by personnel with analytical skills that apply statistical models to data. To bridge the work of analytical personnel and that of executives and managers, there is the figure of the "business translator". Top management sponsorship and buy-in is necessary to guarantee success. Finally, an IT team and external technology suppliers are necessary to provide the tools and processes needed for the aforementioned actors to generate value and deliver it to customers.

data is segregated or "siloed" in outdated IT systems. Consequently, a technological barrier associated with upgrading such systems to guarantee centralized data collection, aggregation and storage must be overcome. Data must be collected from all business units and departments and aggregated using consistent terminology, open standards and clearly specified interfaces [151], and data storage must be centralized in order to improve accessibility and facilitate its analysis. This first barrier, hereafter referred to as "standardization", goes beyond a technological issue to include one of meaning. For data to be useful, it is crucial to ensure a shared understanding of terminology, interpretation and action [162]. This aspect of the standardization barrier is clear to business executives: "managing data quality" has been cited as a top concern [143].

Centralized, standarized data must be accessible to all stakeholders if they

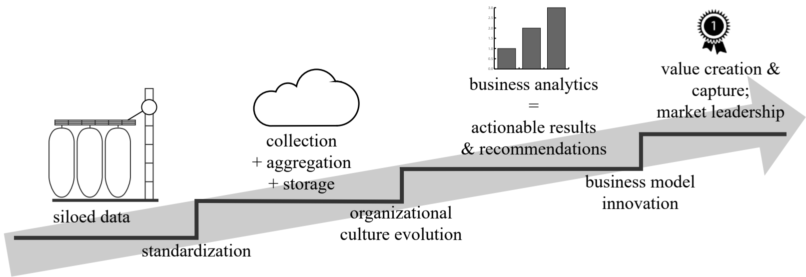

Figure 5: Pathway for the successful exploitation of business analytics.

are to extract value from it. In different terms, comprehensive interoperability driven by an enterprise cultural change that promotes information sharing represents the next barrier. Developing a culture that values evidence-based decisions and actions, encouraging data collection and analysis as well as information sharing is one of the hardest challenges faced by companies [109, 149, 140, 143]. Indeed, interviewed company representatives claim that a culture of departmental silo-thinking, lack of communication and failure to share information are impediments to the sucess of BA projects [139]. Therefore, it can be inferred that in order to leverage BA to the extent described in literature [22, 55] and in Section 3, technological investments must be accompanied by cultural change. Traditional silo-thinking within companies must evolve to a networked organizational culture that prizes information sharing across departmental and organizational boundaries. As discussed in Section 4, securing senior executive involvement to guide the necessary cultural change within the organization [141], and procuring the essential analytical talent [109, 142] are imperative for success.

In Figure 5, the first two barriers are represented as “standardization”, giving rise to a transition from siloed to integrated data, and “organizational culture evolution”, resulting in the appropriate evidence-based ecosystem for BA in a networked organization. At this stage, the ubiquitous use of BA should produce actionable results and recommendations to business questions and, as a result, guide decision-making and actions to improve operational and business performance. To unleash BA full potential, however, a third barrier concerning the development of new business models (BMs) must be overcome. After all, today's BA must be understood as the "era of data-enriched offerings" [3, 116]. BMs need to evolve to harness the creation, delivery and capture of currently unexploited forms of value. According to [121], BMs in the era of Industry 4.0 must "be designed around customer centricity, value creation networks and [...] the data that is generated".

It must be noted though, that adding technological features to manufactured products in the form of software, connectivity and data, generally marketed as "having an app" that allows the customer to track usage patterns, does not represent an innovative business model and does not affect the product market [163]. The value delivered to the customer is mostly unchanged and revenues are still the result of one-time sales. Another popular but weak approach is to open the product to developers that create innovative applications that generate brand engagement and are difficult to replicate by competitors. But again, value capture continues to be the result of one-time product sales and therefore, the BM is hardly changed. A new BM must create value to customers beyond the product itself and generate profits throughout its life-cycle. An example of successful business model innovation is presented in [163] which describes a company called Beam. Beam produces and sells smart toothbrushes but generates revenue through comprehensive dental health care by providing dental insurance and continuous supply of toothbrush heads and toothpaste to customers at a monthly fee. In this example, product sales (the smart toothbrush) represent a customer acquisition cost rather than a source of profits, and revenues are the result of consumable sales or service offerings accessory to the one-time-sales product (like dental insurance, toothbrush heads and toothpaste). Consequently, the market and the competitors of the company change (from the toothbrush to the insurance market, in the example above). In addition, advantageous customer data obtained through the product connectivity features can be exploited to tailor offering prices (e.g. insurance premiums) and marketing campaigns to satisfy various customer segments.

7. Conclusions

This work furthers the understanding of BA in manufacturing by upholding a general definition of BA and extending it to account for the unique building blocks and actors within the manufacturing sector. In addition, multiple manufacturing domains in which BA has the potential of being a differentiating factor were discussed highlighting successful examples when available. It was evidenced that its adoption is sporadic and concentrated on departmental efforts, instead of an enterprise endeavor. This shortcoming was associated with challenges such as data isolated in incompatible, legacy IT systems, poor interdepartmental communication and lack of senior executive involvement, which are key to lead a transition to evidence-based decision-making and actions. It is concluded that the pathway to market leadership through the effective use of BA is the result of overcoming three barriers. The first is a technological barrier, associated with the standardization of data collection, aggregation and storage to outgrow legacy IT systems and siloed data. The second barrier tackles enterprise culture regarding evidence-based decision making and actions, and information sharing. It also aims to procure seamless interoperability within and across organizational boundaries. This creates the perfect ecosystem to answer business questions through BA that deliver actionable results and recommendations. The third barrier is concerned with monetizing data and BA through business model innovation to create value and capture shares on a previously unexploited market. This enables differentiation in otherwise equivalent offerings and secure market leadership.

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