Powering management control with Business Analytics: An institutional perspective to uncover the enablers of adoption

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Received: 24 August 2024
Accepted: 10 June 2025

Abstract

Despite the widely recognized potential of Business Analytics (BA) in enhancing decision-making and boosting business performance, organizations struggle to extract strategically valuable insights from data. The focus tends to be on data collection, cleansing, and storage, with less attention given to evaluating organizational, human, and cultural factors that can impact the successful adoption and institutionalization of these approaches. In light of this, the present research aims to examine how Business Analytics (BA) is incorporated into decision-making processes and to comprehend the institutional factors that influence their effective implementation. The study applies the theoretical framework developed by terBogt and Scapens (2019) to understand how the general archetype of BA is institutionalised through varied situated rationalities.

The study utilizes an action research approach in a case where the company's objective was to determine how BA could assist in forecasting the costs of spare parts and maintenance. The findings show that the institutionalization of BA is linked to the presence of an "institutional entrepreneur" and institutional "conflicts", a deep understanding of the company's performance management model, an institutional environment ready for innovation, and an appropriate internal communication model.

This study contributes to the existing literature by highlighting the need for a holistic approach to integrate BA into management control systems, and offers practical recommendations for organizations seeking to leverage BA for performance management.

Keywords: Business Analytics, Management Control, Institutional Perspective, Situated Rationalities

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Management Control (ISSN 2239-0391, ISSNe 2239-4397), 2025, 1 – Special Issue
Doi: 10.3280/MACO2025-001-S1005

1. Introduction

In today's digital landscape, organizations can rely on a vast amount of data, providing opportunities to enhance decision-making and strategic management. Business Analytics (BA) – the application of mathematical, statistical, and computational techniques to business data – has gained prominence as a critical tool for improving performance and fostering innovation (Davenport and Harris, 2007). Recent research emphasizes the transformative potential of BA in driving business model innovation, creating competitive advantages, and enhancing agility (Ciampi *et al.*, 2021; Kraus *et al.*, 2020).

Despite these advancements, organizations often encounter significant challenges in realizing BA's potential. These challenges are not merely technical but are deeply rooted in organizational, cultural, and human factors. The failure rate of analytics projects remains high, with research indicating that up to 80% of business intelligence (BI) initiatives fail to deliver expected returns (Al-Okaily *et al.*, 2023). Contributing factors include poor data governance, inadequate training, and resistance to organizational change, which collectively hinder the effective integration of BA into decision-making processes (Rana *et al.*, 2022).

Theoretical perspectives, such as the Resource-Based View (RBV) and Dynamic Capabilities View (DCV), underscore the importance of aligning BA with an organization's strategic objectives and operational processes to derive actionable insights (Ciampi *et al.*, 2021; Loureiro *et al.*, 2021). However, the institutional and cultural dimensions of BA adoption remain underexplored. Research has shown that factors such as entrepreneurial orientation, leadership commitment, and communication structures significantly influence the success of analytics initiatives (Kraus *et al.*, 2020; Al-Okaily *et al.*, 2023).

This study aims to address these gaps by examining the institutional dynamics that underpin the adoption and institutionalization of BA. Utilizing the framework of terBogt and Scapens (2019), this research explores how different organizational rationalities interact to shape the institutionalization of BA. Through an action-research approach in the wood processing machinery sector, the study investigates how BA can be leveraged to improve forecasting and enhance commercial processes.

Findings suggest that the successful institutionalization of BA hinges on key factors: a) the presence of an institutional entrepreneur driving change, b) institutional conflict exposing inadequacies in existing practices, c) alignment with performance management systems, d) readiness for technical and cultural innovation, and e) robust internal communication mechanisms.

This research contributes to the literature by highlighting the interplay between technical capabilities and organizational factors in BA adoption. Practical implications include strategies for fostering a data-driven culture, improving governance, and integrating BA into strategic decision-making.

The paper is structured as follows: Sections 2 and 3 present the theoretical background and the specific theoretical approach applied. In Section 4 the methodology is described in detail. Section 5 highlights the main findings of the research that are discussed in Section 6.

2. Theoretical background: the growing relevance of Business Analytics

In the modern digital era, businesses worldwide have access to an unparalleled amount of data and fresh opportunities to analyze it. Amid the so-called "data race," there is often a strong focus on the collection, cleaning, and storage of all available data (Zhang *et al.*, 2015). However, less attention is given to understanding the potential insights that data can provide and identifying which data is truly relevant for supporting the management of organizational performance (Klatt *et al.*, 2011). This recognition has led to the emergence of the BA phenomenon, which involves the iterative and methodical exploration of analytical data for both operational and strategic purposes (Davenport *et al.*, 2010). The process of transforming data into actionable knowledge follows four key steps: data acquisition from various sources; data access, including indexing, storage, sharing, and archiving, facilitated by integrated IT systems; data analytics, involving analysis and manipulation; and application in decision-making.

Advancements in tools like Online Analytical Processing (OLAP), Business Intelligence (BI), and social media Competitive Intelligence solutions have significantly expanded the capabilities for data analysis, visualization, and reporting (Mancini *et al.*, 2018; He *et al.*, 2015). Despite these advancements, organizations frequently encounter challenges in extracting strategically valuable insights from data, as many IT systems are limited in their ability to provide sufficient information flows for performance measurement and management (Del Gobbo, 2023; Badia and Donato, 2022). Data silos, inconsistencies, and poor governance further complicate efforts, often making it difficult to translate analytics outputs into actionable decisions (Visani, 2017; Bititci *et al.*, 2012; Visani *et al.*, 2012;). Additionally, skill gaps in data analytics and machine learning persist, with up to 80% of business intelligence and analytics projects failing to meet expectations (Al-Okaily *et al.*, 2023). Moreover, the opacity of AI-powered models – stemming from their complexity – frequently undermines trust and interpretability, reducing the effectiveness of analytics in supporting strategic decision-making (Rana *et al.*, 2022). Organizational resistance to adopting data-driven decision-making processes exacerbates these issues, highlighting the need for a concerted effort to build a culture that embraces analytics.

Against this backdrop, the integration of artificial intelligence (AI) into BA has unlocked unprecedented opportunities for innovation and strategic transformation. AI-powered systems enable organizations to process unstructured data such as text, images, and videos, offering deeper insights into customer behavior, market trends, and operational inefficiencies (Loureiro *et al.*, 2021). The Internet of Things (IoT) has further enhanced BA by generating real-time data streams that facilitate predictive maintenance, supply chain optimization, and personalized marketing campaigns (Kraus *et al.*, 2020). These developments align with the Dynamic Capabilities View (DCV), which emphasizes the need for organizations to continuously adapt their analytics initiatives to dynamic environments, ensuring long-term competitiveness (Ciampi *et al.*, 2021). However, while technical advancements have expanded the scope of BA, ensuring alignment with organizational objectives and strategic goals remains a persistent challenge.

In recent years, there has been a growing interest in how organizational capabilities and specific contextual conditions shape the effective use of BA (Horani *et al*., 2023). Bayraktar *et al.* (2024), for instance, show that a company's level of technological intensity has a strong influence on how efficiently it can benefit from BA. Similarly, Maroufkhani *et al.* (2023) highlight the importance of factors like internal readiness, data quality, and the active support of top management to successfully implement BA projects, especially in SMEs where data governance is usually less formalised. Other recent contributions emphasize that analytics can only deliver long-term value if it becomes part of everyday decision-making processes, reinforcing the idea that organizations don’t just need the right technology, but also flexible institutional frameworks that can adapt to new tools and ways of thinking (Chaudhuri *et al.*, 2024).

As a result of the above, it is clear that implementing new practices in Management Accounting requires more than technological upgrades; it demands a shift in organizational processes, mindsets, and culture. Burns and Scapens (2000) argue that embedding new practices into routines is crucial for achieving sustained change.

Additionally, it's worth reflecting on how today's rapidly evolving technological context is reshaping the way BA becomes embedded in organizations. The widespread adoption of Big Data platforms and AI-driven tools is speeding up not only the development of analytics solutions but also their implementation across business functions (Ciampi *et al.,* 2021; Loureiro *et al.,* 2021). As a result, the institutionalization of BA may no longer follow gradual or predictable paths. Instead, we may increasingly see fast-tracked or uneven adoption processes, where the usual time for reflection, negotiation, and adjustment among stakeholders is significantly compressed. At the same time, as AI models become more powerful, they also become more complex and difficult to interpret. This can create barriers to trust and shared understanding, especially when analytics tools are developed by technical teams, with limited involvement of people from other departments (Rana *et al.,* 2022). In many cases, this shift increases the influence of data scientists and IT specialists in shaping strategic decisions, sometimes at the expense of more traditional roles like financial controllers or operational managers (Rudko *et al.,* 2024).

Taken together, these trends suggest that the institutionalization of BA is not a one-size-fits-all process, but it evolves alongside the technologies themselves and the shifting roles and power dynamics they bring. For this reason, future research should pay closer attention to how BA is adopted in AI-rich environments, exploring whether new forms of rationality or leadership emerge to help translate complex technical outputs into meaningful action and organizational learning (El Malki and Touate, 2024; Horani *et al.,* 2023).

In this context, the ability to institutionalize BA practices is critical for unlocking their full potential. While substantial progress has been made in advancing analytics capabilities, gaps remain in understanding the organizational and human dimensions of BA adoption. These gaps present an opportunity for further research into the interplay between technology, culture, and institutional frameworks, advancing the integration of data-driven approaches into the fabric of decision-making and performance management.

The future of BA lies in its ability to drive augmented analytics, where AI automates data preparation, insight generation, and visualization, enabling organizations to focus on strategy rather than process (Loureiro *et al.*, 2021). Ethical concerns, such as data privacy, algorithmic bias, and transparency, are becoming increasingly significant, necessitating the development of governance structures that ensure fairness and accountability. As the adoption of BA continues to grow, addressing these challenges and exploring new methodologies to institutionalize analytics capabilities will be critical to ensuring their transformative impact on businesses across industries.

3. Theoretical framework: the evolution of Burns and Scapens Frameworks

The Burns and Scapens framework provides a detailed understanding of management accounting change and stability through its focus on four key concepts: institutions, actions, rules, and routines.

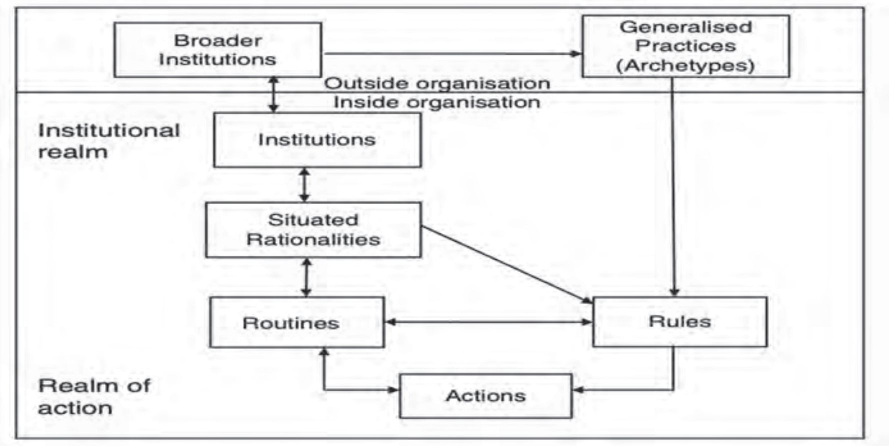
According to Scapens (1994), management accounting practices become routinized, making behaviors predictable and stable even in complex organizations.

Burns and Scapens (2000) developed a model to illustrate how rules and routines evolve over time. The process begins with encoding institutional principles into rules and routines, which are enacted through individual actions. Over time, repeated behaviors lead to the reproduction of these rules and routines, ultimately resulting in their institutionalization and making them taken for granted. Changes in these practices may occur gradually, following path-dependent trajectories, or rapidly, driven by external events that challenge ingrained assumptions. Scholars such as Lukka (2007), and Oliveira and Quinn (2015) have expanded on the framework by distinguishing between ostensive routines (generalized ideas) and performative routines (specific actions), as well as formal and informal rules embedded in systems. Despite its contributions, the original framework has been critiqued for its limited consideration of broader institutional influences, power dynamics, and trust.

In response to feedback on the original framework, terBogt and Scapens (2019) introduced an extended version that includes new concepts and process flows (refer to Figure 1).

This framework builds on the original model by Burns and Scapens but incorporates additional layers to account for both external influences and internal processes. The process begins with broader institutions, which include field-level norms, societal expectations, and industry-wide practices. These institutions exert influence on organizations by establishing generalized practices or archetypes, such as performance measurement systems or reporting frameworks. These generalized practices act as templates that organizations may choose to adopt, adapt, or resist depending on their context.

Figure 1 - The extended framework of terBogt and Scapens (2019) (p. 1810)



In a given time, generalized practices derived from broader institutions are introduced into the organization. At this stage, influential actors or stakeholders within or outside the organization may advocate for the adoption of these practices. For instance, regulatory bodies or industry leaders may mandate specific accounting standards that align with these generalized practices. Once generalized practices enter the organizational context, they interact with the organization's internal institutions, including its existing rules, routines, and institutional logics. These internal institutions represent the embedded norms and practices that have evolved historically within the organization. This interaction often creates tension between the external expectations embodied in the generalized practices and the entrenched internal ways of doing things.

At the heart of the framework is the concept of situated rationalities, which refers to the localized, context-specific reasoning employed by individuals and groups within the organization. Different groups interpret and enact generalized practices based on their professional backgrounds, experiences, and organizational roles. Situated rationalities influence how organizational members perceive the relevance, feasibility, and desirability of the new practices. These rationalities can lead to varying levels of acceptance, adaptation, or resistance to the proposed changes.

As generalized practices are interpreted through the lens of situated rationalities, they begin to influence the organization's rules and routines. This step involves the encoding of new practices into formal rules or informal routines. Encoding occurs when principles and norms from generalized practices are translated into specific actions or behaviors. Repeated enactment of these actions by individuals contributes to the gradual institutionalization of new rules and routines within the organization. Over time, repeated actions and the stabilization of routines lead to institutionalization. New rules and routines become embedded in the organization, shaping future behaviors and decision-making processes. However, the process does not end here. The framework highlights the presence of recursive feedback loops, where institutionalized practices and routines can influence the organization's situated rationalities, further shaping how future changes are perceived and enacted.

The framework also accounts for instances where contradictions or misalignments arise. If broader institutions or generalized practices conflict significantly with local rationalities or internal institutions, resistance may occur. This resistance can lead to modifications in the way generalized practices are implemented or, in some cases, outright rejection. On the other hand, such conflicts may also trigger significant organizational change, breaking established routines and prompting the organization to develop new rules and practices. Throughout the process, the framework recognizes the role of power and agency. Certain individuals or groups – termed institutional entrepreneurs – may actively promote or resist the adoption of new practices. Their influence depends on their ability to shape situated rationalities and mobilize resources to align broader institutional demands with local practices. Finally, as organizations adopt and adapt generalized practices, their new routines and behaviors may influence broader institutions. This step highlights the recursive nature of the framework, where organizational actions can contribute to the evolution of field-level norms and practices over time.

In conclusion, the extended Burns and Scapens framework provides a more detailed understanding of management accounting practices. It emphasizes the significance of specific rationalities and the influence of broader institutional contexts. This extension not only enhances the foundational concepts of the original framework but also fills critical gaps, offering a strong tool for analyzing the intricacies of organizational change.

4. Methodology

4.1 The action research approach

The research employed an action research (AR) approach, which can be defined as “a participatory, democratic process concerned with developing practical knowledge in the pursuit of worthwhile human purposes.” The main goal of AR is “to integrate action and reflection, theory and practice, in collaboration with others, to find practical solutions to issues” (Reason and Bradbury, 2001, p. 1). AR involves the researcher's active participation in the phenomenon under investigation (Jönsson and Lukka, 2006), in partnership with the client system, thereby providing a more comprehensive insight (Parker, 2012).

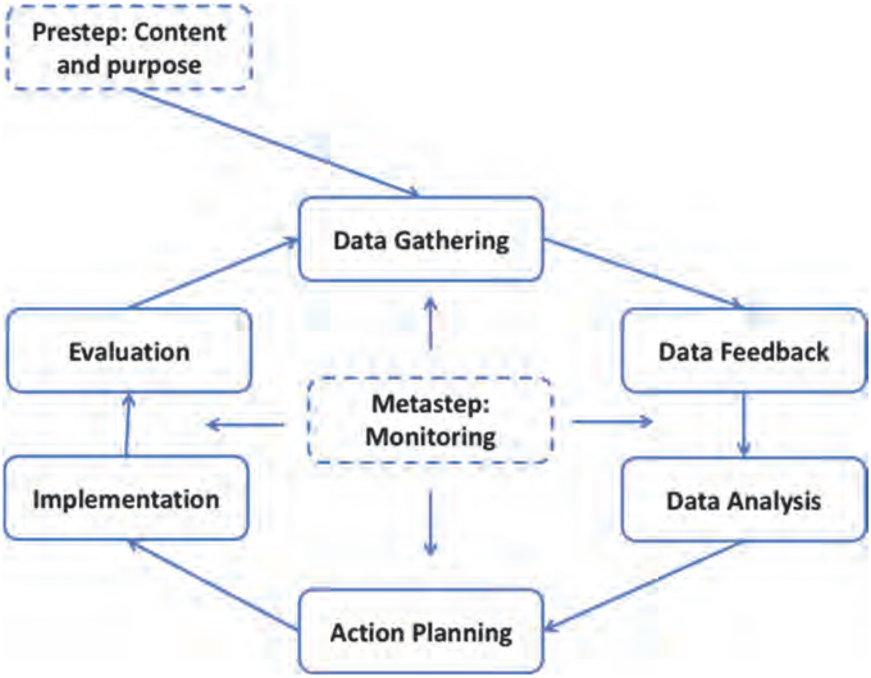
AR research involves a continuous movement between theory and practice. This approach allows researchers to test practical solutions in collaboration with the host organization and analyze outcomes using relevant literature (Jönsson and Lukka, 2006; Van Aken, 2004).

Fundamentally, action research (AR) is centred on change (Coughlan and Coghlan, 2002). Engaging in action aids in understanding the dynamic processes associated with organizational change. AR has two primary objectives: addressing a specific practical problem and contributing to scientific knowledge (Gummersson, 2000). This dual focus makes AR particularly suitable for situations where companies encounter specific managerial issues during a change process, and resolving these issues can lead to broader theoretical contributions. This study provides an example of such a scenario: the company encountered a management accounting problem related to the development of a new pricing system for spare parts and maintenance based on analytical data, while there was a clear gap in the literature on this specific topic. Furthermore, there was a lack of research on evaluating organizational, human, and cultural factors that can influence the successful adoption and institutionalisation of BA tools and approaches. AR was thus chosen to gain a holistic understanding of the phenomenon through direct interaction with the organization and its members (Anderson and Widener, 2007).

Specifically, we applied the operational framework for AR developed by Coughlan and Coghlan (2002), which consists of a pre-step, six operational steps, and one meta-step (see Figure 2).

The first step involves understanding the context in which the company operates, including its markets, supply chain, and technologies, as well as its strategy, business model, and organizational structure. Additionally, it aims to comprehend the specific issue the company is addressing, such as targets, constraints, deadlines, and key stakeholders.

Figure 2 - The AR operational framework of Coughlan and Coghlan (2002)



Right after this, the initial operational cycle consists of three steps for data collection and evaluation: a1) collecting data through various methods such as interviews, databases, surveys, original data, etc.; a2) providing the collected data to the client system for discussion regarding their reliability and the need for additional data collection; a3) analyzing the data in alignment with the primary research objectives.

In the second operational cycle, there are three additional steps: 1) action planning: the research team and the organization's management involved in the project define clear objectives, determine tasks, assign responsibilities, and set a timeline; 2) implementation: the host organization executes the planned action; 3) evaluation: both the outcomes and the process are analyzed to design the next cycle of planning and action.

This iterative approach, comprising cycles of data analysis and action, is particularly valuable for Action Research (AR). It ensures that the research implementation is not a one-off process but a continuous cycle that builds on previous iterations to generate insights on the researched topic.

During the development of the case study, we realized that the specific nature of the research necessitated a modification of the AR cycle approach. Since the action required was specifically focused on data analysis, the 3-step data cycle could not be merely considered a preliminary to action planning and implementation. Instead, each of the two action steps was based on the data cycle. The research team had to collect, scrutinize, and analyze data within each of these steps: both during the planning of the action and its implementation. Therefore, the specific AR model applied can be represented as a three-step process with a data sub-cycle integrated into the first two steps.

While the research did not follow a classic longitudinal case design, the project spanned 13 months and involved continuous engagement with the organization. This extended involvement allowed us to observe not only the development of a practical solution, but also the evolving institutional dynamics around the adoption of the BA tool. The iterative nature of data collection, planning, and reflection created a process that, in many ways, mirrored the temporal and adaptive qualities of a longitudinal study.

4.2 Case selection, data collection and data analysis

Alpha Ltd (the company's real name has been anonymized for confidentiality purposes) is an Italian company engaged in the manufacturing industry. Established in 1945 in Northern Italy, the company specializes in producing stand-alone and integrated woodworking machinery.

The choice of Alpha Ltd as a case study was driven by both theoretical and practical considerations:

- The company operates in a well-established, globally competitive industry, making it a suitable setting to explore how external pressures influence the adoption of BA;
- Its CEO (aged 47, with a background in industrial engineering and previous involvement in digital transformation projects) played a key role in promoting a more data-driven approach across the organization;
- At the time of the study, Alpha could be considered moderately digitally mature: it had implemented ERP and CRM systems but had not yet adopted structured predictive analytics;
- Communication within the company followed a hybrid model: while decisions were generally top-down, cross-functional initiatives encouraged open collaboration and informal exchanges among departments.

Consequently, the company was a good candidate to study for improving our understanding of the factors affecting BA implementation.

In 2022, Alpha Ltd recorded revenues of €125 million, with an EBITDA exceeding €15 million. The market was growing, profitability was robust, and the company's financial condition was sound. Since its founding, Alpha's revenue model has remained consistent, distinctly separating the sales of machinery from after-sales services, such as maintenance and spare parts, which customers could procure post-warranty.

At the end of 2022, two prominent clients approached Alpha's Sales Director, requesting a proposal for a single flat leasing fee that would encompass the product cost, maintenance services, and spare parts necessary to maintain the machine's operational performance at the desired level for 5 years after the warranty period. This inquiry was not merely a singular customer request but represented a new business delivery model.

In response, the Sales Director promptly conveyed the clients' request to the CEO, who subsequently launched a project to develop a new pricing system. Historically, the company had included estimates of future maintenance and spare parts costs within its commercial offers; however, these estimates were based solely on subjective judgment and lacked empirical data or rigorous analysis. The CEO faced challenges in promoting a cultural shift towards a more data-driven organization, and this external stimulus offered an opportunity to accelerate that process. The Director of the Management Control Department was appointed to oversee this new initiative, and he quickly recognized that the organization lacked the necessary competencies and knowledge to address this undertaking effectively. Consequently, Alpha sought the assistance of two researchers with complementary expertise – one in performance measurement and business analytics, and the other in finance and management accounting – to join the project team.

The research was conducted from January 2023 to February 2024. The CEO, aiming to implement a series of algorithms to support various organizational functions over time, assumed the roles of project sponsor and gatekeeper. The project team initially comprised the researchers, the company's controller, and the Sales Director.

Data were collected utilizing multiple methods within the framework of action research. Throughout the project, the research team frequently visited Alpha, gathering qualitative data through direct observation, focus groups, review of company documents, and participation in management meetings (Denzin and Lincoln, 2008; Yin, 2008). Interviews were conducted to identify the factors that should be considered in developing the new pricing model, capturing diverse perspectives.

Subsequently, some ideas generated during the interviews were presented to focus groups with a team of managers, including three members of the After Sales Department (the Director, the Vice Director and the Controller of the Department), the Sales Director and the Director of the Management Control Department. Data about the costs and revenues generated by maintenance services and spare parts were procured partially from existing databases and partially generated through ad hoc procedures. Focus groups were also utilized in the latter stages of the analysis to discuss both the preliminary and final outcomes of the project. Overall, the case study engaged the research team for over 250 hours and lasted around 13 months.

Researchers attended each meeting, during which the information gathered was immediately transcribed and analyzed. Similarly, the documents collected were independently coded by the researchers, and both inter-coder and intra-coder reliability checks were conducted. At various stages of the process, the results of the analyses were reported and discussed with the company's management team to validate the findings (see Table A in appendix for details of the different activities – www.sidrea.it/ powering-business-analytics).

5. Findings

5.1 The pre-step

According to the research model, the pre-step was aimed at understanding the strategic, organizational and technological context in which Alpha operates. To better understand operational practices and gather early insights from key stakeholders, we conducted a series of interviews and also administered a questionnaire during the first phase of the project (February-March 2023). The questionnaire was completed by ten employees reflecting different levels of experience and responsibility within the company, thus providing a well-rounded perspective.

The aim was i) to explore their expectations about the potential usefulness of BA tools, and ii) to test their intuitive understanding of cost variability across different machine models and markets. The questionnaire mixed open- and closed-ended questions. Examples include:

– "Which machine group do you expect to have the highest average maintenance cost over a 5-year horizon?"
– "How do you estimate the variability of service costs between North America and Europe?"

– "How confident are you that historical service data can support predictive pricing models?" (Likert scale 1–5)
– "What potential challenges do you foresee in implementing a data-driven pricing model in your department?"

The results revealed a mixed picture. While after-sales staff expressed concerns about the reliability of the data and the fragmented nature of existing databases, sales staff were more optimistic about using structured data to support negotiations. This early diagnostic activity helped shape the subsequent stages of the research and also laid the foundation for the final validation phase (see Section 5.3).

The initial interview was conducted with the Chief Executive Officer and the financial controller to gain an overarching understanding of the strategic and operational landscape. The wood machinery industry is notably advanced in Northern Italy, where several sector leaders are situated. Customers in this market tend to be highly profitable companies; consequently, they prioritize attributes such as flexibility, reliability, quality, and service over merely seeking low prices from their suppliers. Alpha manufactures a diverse array of products, including saws, planers, milling machines, sanders, and grinders.

Alpha operates three manufacturing plants located in various regions of Italy, where it assembles components designed by its engineers and sourced from over 250 external suppliers. The majority of these suppliers are based in Italy and Northern Europe, except for certain mechanical components procured from China and other regions in the Far East. In terms of commercial operations, more than 80% of the machines are exported, primarily to the United States (40%), Germany (22%), and Japan (9%).

Subsequent interviews were conducted with employees from various departments to gain deeper insights into specific issues. The machines sold by Alpha are utilized in varying capacities by different customers; some operate on three 8-hour shifts, resulting in increased operational stress and a higher demand for maintenance and spare parts, while others function for only two shifts per day. Another significant variable is the geographical location of the customer: in certain countries, there is a greater propensity to use unofficial spare parts, which consequently leads to reduced sales of services and spare parts. Furthermore, the requirement for after-sales services varies according to the type of machine: more complex machines necessitate frequent maintenance and costly spare parts, whereas simpler machines incur lower and less frequent maintenance expenses. Currently, the maintenance service operates entirely on an "on-demand" basis. After the first year of operation, during which a warranty contract is in effect, customers are free to procure maintenance services from Alpha or any other supplier in the open market. Should they choose to engage Alpha, they typically request a quotation and negotiate the price for the service as if it were a new sale.

5.2 The first action research "cycle"

Once understood the general competitive landscape and the main factors affecting pricing dynamics, the team was prepared to initiate the appropriate activity cycle, commencing with the "Action Planning" step. A meeting was convened to plan the activities to be undertaken. From a technical perspective, all participants reached a consensus to utilize the individual machine sold as the unit of analysis, while also determining the historical costs associated with maintenance and spare parts for various product models. This analysis would enable the establishment of differentiated lease rates for distinct models.

Once the primary objective was delineated, the first "data cycle" was activated. During the initial meeting, the researchers inquired about the available data concerning past interventions and spare parts sales for each machine. However, acquiring a response to this inquiry proved to be more time-consuming than anticipated, entailing considerable effort from the After Sales Department, which possessed the most comprehensive knowledge of maintenance and spare parts data, alongside associated issues, yet concurrently exhibited skepticism regarding the project's feasibility.

Initially, the company maintained two separate databases about maintenance interventions: one overseen by the Accounting Department and the other by the After Sales Department. These databases did not align perfectly; some interventions were documented in the Accounting database but not in the After Sales database, while others were recorded as sales of new products in the Accounting database. The reconciliation and comprehensive analysis of the two databases necessitated a considerable investment of time.

As a result of this step, the research team obtained comprehensive data on all revenues and costs associated with the sales of spare parts and maintenance interventions for 1,243 machines delivered over the past 15 years. The variability in the annual revenue data generated by maintenance and spare parts for each machine was substantial, with an abundance of data available for older machines and a relatively limited number of observations for more recently sold machines. On average, the dataset encompassed six years of operational relationships, yielding a total of 83,678 observations.

Following the definition of the target and the preparation of the dataset, the "Implementation" step of the AR model commenced. The data were cleaned from the effect of inflation and were subsequently reorganized from chronological order to a life-cycle-based order. The researchers recoded the data according to the year of delivery of the machines. For example, data pertaining to the year 2015 were recoded as representing the second year for machines sold in 2014, while being considered as the fifth year for machines sold in 2011. Although this technical adjustment was straightforward, it proved challenging to communicate effectively to the management team, as personnel at Alpha were not accustomed to this novel perspective on data analysis. However, once the After Sales Director grasped the concept, he expressed enthusiasm for this alternative approach to evaluating the margins generated by each machine.

During the analysis of the data, the researchers realized that, although the findings were intriguing, they remained insufficiently refined for the project's ultimate objectives. Primarily, the data exhibited a high variance, which undermined the reliability of the average values in accurately representing the projected profitability associated with the sale of a new machine. Upon inquiry regarding this concern, the Director of the After Sales Service acknowledged that the datasets encompassed all revenues derived from maintenance activities, irrespective of their nature. Specifically, it was not feasible to differentiate between routine maintenance activities aimed at sustaining operational efficiency and extraordinary interventions intended to enhance productivity or completely overhaul the machine's structure – activities that were not included in the lease rate charged to customers. The high variance in the data was largely attributed to these extraordinary interventions. Consequently, a second "data cycle" involving the collection, feedback, and analysis of data became necessary during the "Implementation" step.

Initially, a mathematical criterion was established to determine a threshold above which certain interventions warranted closer examination. Interventions exceeding the average plus three standard deviations were classified as potential extraordinary interventions, prompting the after-sales department to compile detailed data regarding these specific instances. Each intervention was meticulously reviewed against available documentation to ascertain whether it constituted a genuine extraordinary intervention or an exceptionally costly routine maintenance activity. Although this inspection process was time-intensive, it ultimately resulted in the exclusion of 8,467 interventions from the analysis, thereby contributing to a reduction in variance of over 50%. Following this refinement, 1,163 machines remained in the dataset.

Once the final values were obtained, the average costs of spare parts and maintenance for each year of the machines' life cycles were calculated as a percentage of the machines' industrial costs. These values were subsequently discounted, taking into account the company's cost of capital. The net present value of the costs associated with spare parts and maintenance was then divided by the industrial cost of each machine. Finally, the company computed the fixed yearly lease rate for years two through six as a percentage of the selling price, employing an internally developed formula based on the target profitability, as detailed in Table 2.

For instance, looking at Table 2, the machines of Model 1 on average generate a Total Cost of Ownership (TCO) related to maintenance and spare parts much higher than the machines of Model 2. The cumulated actual value is 16.80% of the industrial cost of the machine versus only 7.60%.

Once the actual value of the cumulated costs generated by the maintenance and the spare parts is available, the amount of the fixed service cost rate (FSCR) (from years 2 to 6) equivalent to the same actual value can be easily calculated by applying the following formula derived from basic financial knowledge:

$$Average\ TCO = \sum_{t=2}^{6} FSCR * (1 + WACC)^{-t} \qquad [1]$$

where:

Average TCO=Actual Value of the costs generated by the maintenance and the spare parts as a percentage of the industrial cost of the machine;

FSCR=Fixed Service Cost Rate incurred by the company from the second to the sixth year of the machine’s lifetime as a percentage of the industrial cost;

WACC= Weighted Average Cost of Capital of the company.

The last column of Table 2 presents the FLR calculated for Models 1 and 2, by applying the internally developed formula to the FSCR. Through the same approach, a fixed lease rate was calculated for each of the 68 machine models manufactured by the company.

Table 2 - The calculation of the average Total Cost of Ownership (TCO) and the Fixed Lease Rate (FLR)

	Average Machine Cost	**Average costs incurred by the company for maintenance and spare parts. Discounted to year 0 (Weighted Average Cost of Capital = 9.5%)**							**Total Cost of Ownership (TCO) incurred for maintenance and spare parts in periods 2-6 as a percentage of the industrial cost**	**Fixed yearly Service Cost Rate (FSCR) from year 2 to year 6 as a percentage of the industrial cost**	**Fixed yearly Lease Rate (FLR) from year 2 to year 6 as a percentage of the selling price**
		Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**	**Year 6**	**Total costs incurred for maintenance and spare parts in periods 2-6**			
Model 1	€ 83,465	Warranty period	€ 1,895	€ 2,727	€ 2,813	€ 3,260	€ 3,327	€ 14,023	16.80%	4.79%	7.54%
Model 2	€ 95,786	Warranty period	€ 1,341	€ 1,400	€ 1,467	€ 1,460	€ 1,607	€ 7,275	7.60%	2.17%	4.12%

Then the “Evaluation step” started, involving all the members of the project. Several limitations were identified in the proposed approach. Firstly, although the entirety of the data was pertinent, the number of observations for each machine model was frequently insufficient, leading to average values that lacked the reliability necessary to support the new pricing system. Secondly, the computed average values did not account for the varying behaviors of customers situated in different countries. As a result, the "average" percentage lease rate could be excessively high in certain countries while being disproportionately low in others. Lastly, the Sales Director indicated that the sales personnel, as the end users of the new pricing system, would likely not favor a single lease rate, as this would be perceived as a constraint on their negotiation power. A "one-size-fits-all" solution, which involves a unique leasing fee determined by an algorithm based on historical data, was deemed unappealing from their perspective. The new pricing system should furnish sales personnel with a range of values derived from historical data; however, the final determination of the "appropriate" lease rate should be entrusted to the account manager responsible for each customer. Furthermore, during the evaluation step, the team recognized that the final model should also exhibit flexibility in terms of time, enabling the definition of the leasing fee regardless of the contract duration and expiration date.

5.3 The second “action research” cycle

During the same meeting in which the first cycle of action research was evaluated, the second cycle commenced with the formulation of an action plan designed to address the principal issues identified from the assessment of the results. Subsequently, new data were collected, validated, and analyzed. The research team decided to categorize certain machine models with similar maintenance requirements to enhance the significance of each cluster. Two distinct courses of action were adopted. Initially, the Director of the After-Sales Department and the Directors of the Sales Department were tasked with grouping the machine models based on their maintenance needs. Concurrently, a hierarchical clustering analysis was conducted on the Total Cost of Ownership (TCO), expressed as a percentage of the machine's industrial cost, employing the Ward method. This clustering procedure suggested that an optimal number of clusters ranged between 10 and 12. The results corroborated the groupings proposed by the company, resulting in the classification of 1,163 machines into 12 homogeneous groups, as opposed to the initial 68 machine models.

During the third team meeting, the customers' features affecting the maintenance requests were investigated. The Director of After-Sales Service was very assertive in stating that customer behavior was not correlated with either the size or industry of the customer, but primarily with their geographical location. As previously mentioned, varying countries exhibited differing tendencies to purchase spare parts and maintenance services from the original equipment manufacturer. Given the extensive number of countries served, the team initiated an analysis to cluster these countries into a limited number of groups. Following this analysis, which included several t-tests to determine whether disparities existed in TCO percentages generated by identical machines across different countries, four primary geographical clusters were established: Italy, Europe, North America, and the Rest of the World.

In light of these preliminary findings, a two-way ANOVA was conducted to assess the individual and combined effects of machine group and customer geographical area on the dependent variable: the revenue generated from spare parts and maintenance services, calculated as a percentage of the machine's selling price over the five-year period following the warranty. While this figure represents income for the company, it also reflects the cost borne by the customer to maintain machine performance, making it conceptually equivalent to Total Cost of Ownership (TCO). As such, the same metric can be understood from two sides: as revenue for the manufacturer and as operational cost for the client.

The results of the ANOVA show that both machine type and location have a statistically significant effect on this revenue/TCO indicator (p-values < 0.005), supporting the logic behind the model's segmentation approach.

Moreover, the results confirm the relevance of the machine groups and geographical area, identified both as isolated drivers and for their joint effect. The p-values are well below 0.005. The adjusted R squared is above 0.7, showing a high capability of the model to represent what drives the TCO generated by spare parts and maintenance.

The researchers inquired whether the team members were completely satisfied with a model that incorporated only two variables, or if there was a need to further explore additional relevant factors. The Sales Director raised an interesting point on this argument. He needed a very synthetic approach, easy to apply and easy to explain to the account managers. The two variables taken into consideration, grouped in a few machine clusters and geographical areas were able to explain a huge part of the dependent variable and at the same time were easy to communicate to the Salespeople.

Further analyses would have certainly added more complexity than informative effectiveness.

The final model was then defined. It requests the operator to select the machine group and the customer's geographical area. As a result, Figure 3 provides the FLR that the customer should pay as a percentage of the machine's selling price, regarding the different duration of the contract.

Figure 3 - The FLR by contract time horizon suggested by the new pricing system

Geographical Area
Europe

Machine Group
5

Time horizon	FLR (% of selling price)			Reliability
	Average		Min	
1y contract	**1.7%**	-	**1.4%**	*A*
2y contract	**2.5%**	-	**2.1%**	*A*
Ny contract	**…**	-	**…**	…
10y contract	**13.3%**	-	**11.3%**	*B*

Table 3 - *The FLR by contract time horizon and machine subgroups suggested by the new pricing system*

7	Models	FLR (% of selling price) 1y contract			FLR (% of selling price) 2y contract			FLR (% of selling price) Ny contract			FLR (% of selling price) 10y contract			Reliability
		Average		Min	Average		Min	Average		Min	Average		Min	
Small planers	*SZ1200; SZ2530; SZ3880; SZ5670; SZ9090*	1.6%	-	1.4%	2.8%	-	2.4%	…	-	…	12.7%	-	10.8%	*A*
Large planers	*LS1230; LS1750; LS2310; LS5500; LS7000; LS9000*	1.9%	-	1.6%	2.2%	-	1.9%	…	-	…	14.5%	-	12.3%	*A/B*
Special planers	*MS4400; MS4440; MS4880*	2.6%	-	2.2%	3.9%	-	3.3%	…	-	…	n.a.	-	n.a.	*C*
…	…	…	-	…	…	-	…	…	-	…	…	-	…	…

Starting from the average value, the salespeople can apply a rate ranging from -15% (the value reported as the minimum) to +15% of the proposed value, according to specific features of the customer and the specific conditions included in the contract (for instance, the possibility to monitor the real usage of the machine). Higher discounts could be provided only with the consensus of the Director of the Sales Department.

Additionally, the last column reports on a scale from A to E the reliability of the values suggested by the system based on the number of observations, as required by the salespeople in the last meeting.

Moreover, the system enables salespeople to operate at the machine subgroup level when necessary (see Table 3). In fact, some sales representatives expressed dissatisfaction with the average metrics at the machine group level, requesting more granular measurements, particularly in instances where the reliability of the subgroups is relatively high (at least a grade of B).

In the final stage of the project (January 2024), we conducted a structured validation with the same participants involved at the beginning of the project. The questionnaire included 30 items per respondent and focused on their ability to estimate average service costs across machine types and geographical markets. For example:

– "Estimate the average maintenance cost for Machine Group X in Europe over a 5-year post-warranty period."
– "Which model is likely to generate higher after-sales revenues in North America: Model A or Model B?".

The responses were compared to the values generated by the proposed BA model. Out of a total of 300 answers, 266 (88.6%) aligned with the model's results, highlighting a strong match between participants' experiential judgment and the analytical insights provided by the new system.

Following this validation phase, the model and its logic were presented in a dedicated meeting with the CEO, general manager, and product line directors. During the session, the team reviewed actual customer cases and tested the tool's applicability in real commercial scenarios. The discussion confirmed the model's relevance and usability, and managers expressed support for its adoption, thus the approach was formally integrated into the company's sales processes.

5.4 Formal guidelines versus emergent practices

Although the original model was intended to produce a fixed leasing rate, sales teams quickly pushed back against this rigidity, arguing for the need to adapt pricing based on client-specific factors such as relationship history, risk, and market expectations. This feedback led to the introduction of a flexible "range-based" approach that allowed for contextual variation, shifting the model from a top-down structure to a more negotiable and user-responsive tool.

The After-Sales Department, initially skeptical about the model's ability to capture operational nuance, became progressively more engaged once the data had been cleaned and refined. What made the difference was not managerial pressure, but the growing perception that the tool was grounded in their own practical experience.

Another noteworthy shift emerged in how the model's logic was communicated internally. While the technical foundation rested on financial metrics like NPV and TCO, many users preferred to explain the results using heuristics or simplified narratives during meetings. This form of internal translation highlights how practical use often overrides formal structure when it comes to institutionalizing new tools. These patterns show that the adoption of BA is not a straightforward or uniform process, but rather a dynamic negotiation between standardized systems and the realities of daily work. The routines that took shape through this negotiation ultimately proved more influential than the formal guidelines in embedding the tool into the company's decision-making practices.

6. Discussion and conclusions

The objective of this research was to examine the introduction of the general archetype of Business Analytics (BA) within decision-making processes through the theoretical framework established by terBogt and Scapens (2019). The study aimed to elucidate the institutional dynamics that facilitate the successful adoption of such analytical tools. As hypothesized, the tangible success of Business Analytics solutions in supporting managerial processes is significantly influenced by institutional dynamics, independent of their technical efficacy.

Specifically, the first factor influencing the institutionalization of BA for management and control purposes is the presence of an "institutional entrepreneur." In the case under examination, this role was embodied by the CEO of the company, who sought to transition the organization from an experience-based model to a data-driven approach, thereby innovating decision-making processes and replacing historical routines grounded in personal judgment and experience.

This factor is closely related to a second aspect, namely the existence of an institutional "conflict," wherein prior practices are deemed inadequate for navigating a changing environment. In the case presented, two major clients requested that Alpha's Sales Director devise a new business delivery model that included a fixed leasing rate incorporating the machine, maintenance, and spare parts for a specified duration. Furthermore, in a situation where the CEO was struggling to promote the archetype of BA, this external stimulus provided the necessary trigger to facilitate the process, giving salespeople a glimpse of the potential of the tool to support them in managing the evolving business landscape.

A third factor influencing the institutionalization of BA for management and control purposes is a comprehensive understanding of the company's performance management model, ensuring that the tool is perceived as an integral component of the overall business strategy. In this context, both the After-sales Director and the Sales Director were tasked with creating long-term value and profitability, leading to the recognition that a transition to a new pricing system based on data and multiyear contracts was essential for effectively supporting the decision-making process of the stakeholders involved in the project. Moreover, mathematical statistical analysis is of limited utility unless it is aligned with key performance indicators, such as contract profitability in this instance.

Additionally, an institutional environment conducive to innovation – both technically and in terms of data, as well as a willingness to embrace such innovation – is imperative for the successful implementation of BA tools. In the case examined, significant efforts were made to collect data from diverse and inconsistent databases managed by various departments, providing the CEO with an opportunity to emphasize the importance of fostering a data-centric culture. Frequently, personnel represent one of the most formidable obstacles to the introduction and utilization of new tools, which is exacerbated by a lack of effective communication models that can clearly convey information and elucidate organizational benefits. Particularly in the realm of BA, it is essential for company personnel to comprehend and accept the underlying logic of the models. Those utilizing the tool must grasp and share this logic to apply it effectively, thereby mitigating the risk that users encounter analyses containing numerical data whose significance they do not understand or share.

This latter point is further connected to the notion that the general archetype of BA is institutionalized through various situated rationalities across different organizational groups. In the case analyzed, the CEO and the controller initially sought an algorithm that was highly precise and technically sophisticated; however, they soon recognized that the end users, specifically the Sales Department, would prefer a pricing system that was less complex yet more intuitive and accessible to support their daily operations. Furthermore, effective implementation was facilitated by the After-sales Department, which provided a balanced perspective. Given their familiarity with the company's data, they maintained a more pragmatic and realistic view of the potential design and contribution of the new pricing system compared to that of the CEO and the controller, while simultaneously offering a more rigorous perspective than that of the Sales Department.

From a theoretical standpoint, this study contributes to the existing literature by underscoring that the successful implementation of BA is contingent upon factors beyond merely designing the most suitable tool and the competencies of the individuals involved. It also relies on an understanding of the diverse rationalities at play. In this respect, the institutional entrepreneur serves a pivotal role as the driving force and coordinator of the process. Furthermore, the research enriches the institutional literature on management accounting by illustrating that the terBogt and Scapens model should be interpreted through a dynamic lens. Indeed, the interactions between the archetype and the situated rationalities are not static but rather represent a dynamic dialogue that influences routines, regulations, and actions.

In terms of practical contributions, this research emphasizes the necessity of evaluating the perspectives of all stakeholders involved before initiating a BA project. This encompasses individuals responsible for data provision, analysis, and the utilization of analytical outputs. Engaging each group appropriately and timely ensures that they comprehend the foundational logic and methodology, thereby enabling them to adapt the development and implementation process of BA accordingly.

Nonetheless, this study is not without limitations, which simultaneously present opportunities for future research. First, we recognize that our findings are drawn from a single case, which naturally limits their generalizability. Further research across different sectors and company sizes – particularly comparing large firms to SMEs – would help validate and expand upon our conclusions.

Second, while the duration of the project enabled us to observe early adoption and adaptation, the study did not include a formal post-implementation phase. Future work should consider longitudinal case designs that trace how BA tools become normalized in everyday routines over time, allowing for a more direct comparison between official policies and real-world usage.

Lastly, this study focused on a specific BA application with a relatively narrow scope. Exploring more complex or interdisciplinary analytics tools in future research could help determine whether different enablers and barriers emerge in those contexts, offering a more comprehensive view of what supports successful BA integration.

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