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The impact of data analytics on continuous improvement in business processes and talent management: an analysis of the European context

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Abstract

This study explores the role of business analytics (BA) in driving continuous improvement across business and human resources (HR) domains. Drawing on a multidisciplinary framework, the research examines how organisations leverage analytics to enhance innovation, profitability, and employee performance. The study employs data from the 2019 European Company Survey, encompassing over 21,000 firms across the EU, and applies logistic regression models to assess the relationship between the adoption of BA and various organisational outcomes. The results show that BA adoption is strongly associated with innovation practices, digitalisation, and human capital strategies, particularly performance monitoring, skill alignment, and employee involvement in decision-making. However, the study also reveals that certain expected correlations, such as between BA and pay-for-performance systems or teamwork, were not empirically supported. The findings highlight the need to understand BA adoption as a context-dependent, multi-dimensional process shaped by both organisational structure and strategic priorities. The study concludes with recommendations for both policymakers and business leaders, emphasising the importance of integrating analytics into HR and innovation frameworks to foster sustainable, data-driven transformation.

Key words: Business analytics, Human resources management, continuous improvement, business outcomes, human resources management outcomes.

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1. Introduction

In an era defined by rapid technological advancement and intensified global competition, continuous improvement has become a central pillar of organisational strategy. No longer confined to isolated process enhancements, it now reflects a broader commitment to adaptability, organisational learning, and sustained performance optimisation (Tayade, Ubale & Ubale, 2023; Pupulin, 2023). Traditionally rooted in manufacturing environments and exemplified by methodologies such as Lean and Six Sigma (Felizzola Jiménez & Luna Amaya, 2014; Hinojosa Macías, Gisbert Soler & Pérez Bernabeu, 2016), the concept has since expanded across sectors and functional areas, increasingly shaped by data-informed approaches.

As firms face mounting pressure to innovate, manage risk, and remain agile, the ability to continuously refine operations and align internal processes with strategic objectives has become a source of long-term competitive advantage (Aydiner et al., 2019; Shabbir & Gardezi, 2020). In parallel, the proliferation of organisational data and the growing accessibility of analytical tools have opened new pathways for embedding continuous improvement into decision-making structures (Saxena, John, & Deshpande, 2021; Ekka, Singh & Ranjan, 2022). Technologies such as business analytics (BA), artificial intelligence, and big data are now central to efforts to improve performance, anticipate change, and foster innovation (Chaudhuri et al., 2024; Wamba et al., 2017; Garmaki, Gharib, & Boughzala 2023).

Understanding the role of BA in continuous improvement is therefore essential for organisations seeking to enhance responsiveness, resilience, and sustainable value creation. BA enables firms to derive insights from large volumes of structured and unstructured data, facilitating evidence-based decisions across both operational and strategic domains (Trkman et al., 2010; Mucci, 2024). As research increasingly highlights the impact of BA is not only on business outcomes but also on human resource management (HRM), enabling talent optimisation, performance monitoring, and employee engagement (Belizón, Majarín & Aguado, 2024; Ameer, Garg & Singh, 2023), becoming its integration into continuous improvement frameworks a critical area of inquiry.

This research investigates the extent to which BA supports continuous improvement within contemporary organisations, with a specific focus on both business performance and human resources (HR) outcomes. Drawing on a representative European dataset including over 21,000 firms across the EU the study examines whether the adoption of BA is associated with indicators such as innovation, profitability, talent optimisation, and participatory management. By employing a multivariate modelling approach, the analysis aims to identify the organisational characteristics and practices most closely linked to the use of BA for process enhancement. In doing so, it contributes to a deeper understanding of how data-driven capabilities shape strategic and operational practices in dynamic environments, offering insights into the conditions under which BA can act as a driver of sustained improvement and competitive advantage.

2. Literature review on the use of business analytics in continuous improvement

2.1 Continuous improvement

Continuous improvement is a foundational concept in modern operational management, defined as the ongoing effort to refine processes in order to reduce waste, enhance quality, and maximize human potential (Tayade, Ubale & Ubale, 2023). This approach emerged in the manufacturing sector as companies transitioned from prioritizing capital equipment to fostering an efficient operational culture.

In the post-World War II era, manufacturers initially met rising production demands through rapid equipment purchases, which inadvertently introduced system inefficiencies. Toyota was among the first to challenge this capital-heavy model, developing lean manufacturing to achieve scalability through process optimization rather than equipment investment. This shift paved the way for methodologies such as Six Sigma, Lean, Business Process Reengineering, and Total Productive Maintenance, all designed to improve productivity and quality by empowering frontline workers to make critical decisions. Today, aligning continuous improvement efforts with business strategy has become essential to ensure these initiatives support organizational goals effectively (Pupulin, 2023).

As mentioned before, one of the methodologies that emerged from this shift was Six Sigma, a structured, results-driven methodology developed to enhance process quality by reducing variability and minimizing defects. Building on the foundations of earlier quality management theories, such as Statistical Process Control and Total Quality Management (TQM), Six Sigma integrates these concepts into a cohesive approach that prioritizes customer satisfaction. By employing data-intensive analysis and statistical tools, Six Sigma delivers measurable improvements across operational and financial metrics, allowing organizations to achieve consistent, high-quality results. The methodology’s effectiveness relies on specialized, trained personnel who lead improvement projects and foster a culture of operational excellence throughout the organization. Guided by the DMAIC cycle (Define, Measure, Analyse, Improve, and Control), Six Sigma projects systematically enhance process capabilities, targeting a defect rate as low as 3.4 defects per million opportunities, which makes errors almost imperceptible to customers. This rigorous focus on precision and alignment with strategic goals creates a sustainable commitment to quality from both management and employees (Felizzola Jiménez & Luna Amaya, 2014).

Lean manufacturing complements Six Sigma by focusing on systematically eliminating non-value-adding activities, or "waste," within the production process. Through tools like 5S (organization and cleanliness), SMED (quick changeovers), Kaizen (continuous improvement), and Kanban (visual workflow management), Lean seeks to streamline operations to meet customer demands efficiently while minimizing resource use. This approach helps organizations reduce costs, enhance productivity, and adapt more flexibly to market needs (Hinojosa Macías, Gisbert Soler, & Pérez Bernabeu, 2016).

While Lean is often implemented as a standalone methodology focused on waste elimination, it can also function as an integral part of Six Sigma. Lean's emphasis on streamlining processes and removing non-value-adding activities complements Six Sigma's structured, data-driven approach to reducing variability and defects. Within the Six Sigma framework, Lean tools and principles can be applied to identify inefficiencies that contribute to process variability, providing a foundation for Six Sigma projects to build upon. This integration, commonly referred to as Lean Sigma, enhances Six Sigma's capabilities by ensuring that waste reduction efforts align with the overarching goal of process optimisation and quality improvement.

In this way, Lean becomes a subset of the broader Six Sigma methodology, offering quick wins that pave the way for Six Sigma's more rigorous and comprehensive improvements. By incorporating Lean into Six Sigma, organisations can address both short-term operational inefficiencies and long-term quality goals, creating a unified approach that fosters continuous improvement and sustainable excellence (Hinojosa Macías, Gisbert Soler, & Pérez Bernabeu, 2016).

To conclude, continuous improvement is a vital strategy for organizations striving for success in today's fast-paced and competitive market. By adopting methodologies such as Lean manufacturing and Six Sigma, companies can systematically eliminate waste and reduce defects, thereby enhancing their responsiveness to changing market demands and technological advancements. This ongoing commitment not only cultivates a culture of operational excellence but also aligns processes with strategic goals, ensuring agility and competitiveness.

As Tayade, Ubale, and Ubale note:

> The reach of continuous improvement approaches has increased as a result of substantial technology discoveries, contemporary inventions, and rapidly changing market demands. Organizations began using the Six-Sigma methodology as a continuous improvement strategy in the late 1970s, and it is today recognized as the most dominant and productive utility in the Lean tool approach. (2023, p.30)

Furthermore, continuous improvement initiatives engage employees by empowering them to participate in problem-solving and innovation, fostering a sense of ownership and accountability. Thus, embracing continuous improvement is essential for driving sustained excellence and achieving long-term organizational success.

2.2 The use of data analytics in continuous improvement and its impact on business outcomes

In today's competitive landscape, organizations increasingly recognize the importance of BA as a critical instrument for developing effective strategies and managing diverse risks (Saxena, John, & Deshpande, 2021). When implemented effectively, it offers substantial advantages and reveals numerous growth opportunities, driven by the vast amounts of data generated in contemporary business environments. Emerging technologies such as big data and blockchain are transforming operations, providing a promising outlook for how analytics can prepare businesses for the future while minimizing risks (Mamakou & Manaras, 2024).

Building on this potential, BA also acts as a catalyst for technological integration, facilitating the adoption of Artificial Intelligence (AI) and Internet of Things (IoT) solutions. These capabilities allow organisations to enhance demand forecasting, optimise supply chain efficiency, and respond more effectively to dynamic market conditions (Wamba et al., 2017; Chaudhuri et al., 2024). While often used interchangeably with business intelligence, BA typically involves working with raw data that must be processed and transformed to yield meaningful insights, unlike business intelligence, which deals with pre-formatted data. To conduct these analyses, BA utilizes various statistical tools and software, with popular options including SPSS, R, and Python (Saxena, John, & Deshpande, 2021). Ultimately, the integration of BA is essential for organizations looking to harness data-driven insights for strategic decision-making and operational improvement. Beyond efficiency gains, BA plays a central role in fostering innovation by enabling organisations to develop new products and enhance existing ones through informed analysis and environmental scanning. A study by Chaudhuri et al. (2024) demonstrates that, when embedded within a strong data-driven culture, BA not only supports process optimisation but also acts as a catalyst for product innovation, linking internal capabilities with evolving external demands to generate greater business value. Therefore, the first hypothesis reads as follows:

H1: *The use of data analytics for continuous improvement will be correlated with greater innovation in organizations.*

BA is vital for improving overall business performance by equipping organizations with the tools to make data-informed decisions. By systematically analysing extensive internal and external data, companies can pinpoint inefficiencies and optimize their operations. For instance, BA aids in forecasting market trends and customer demand accurately, enabling organizations to allocate resources effectively and enhance customer satisfaction. It also plays a significant role in measuring performance across various functions, such as supply chain management and marketing strategies, ultimately resulting in cost savings and increased profitability (Trkman et al., 2010).

In addition, embedding BA into organisational workflows not only elevates performance but also strengthens market positioning. By leveraging data-driven insights into their operations, companies can make informed strategic decisions, optimise operations, and respond adeptly to market changes, factors that enhance competitiveness and create long-term value (Laguir et al., 2022).

H2: *The use of data analytics for continuous improvement will be associated with greater industry competitiveness in organizations.*

Furthermore, as businesses mature in their analytical capabilities, they not only see immediate performance improvements but also cultivate a culture of continuous improvement, where employees are empowered to engage in strategic initiatives (Trkman et al., 2010). According to the study conducted by Accenture and General Electric, 89% of firms believe that they might lose their market if they do not adopt big data and BA" (Columbus, 2014).

Crucial to enhancing organizational performance, BA significantly contributes to improving business process performance (BPER). In the fast-evolving global marketplace, companies must harness the extensive data produced by their operations to maintain a competitive edge (Mucci, 2024). By incorporating analytics tools and techniques, organizations can effectively analyse both structured and unstructured data, resulting in improved decision-making, operational efficiency, and more agile business operations (Aydiner et al., 2019). Integrating BA into business processes enhances firms' operational effectiveness and planning capabilities, enabling swift and adaptive responses to dynamic market conditions and continuous performance improvement (Bayraktar et al., 2019). This integration underscores the strategic importance of BA as a core organisational resource, allowing companies to leverage data insights to optimise internal processes, better meet customer needs, and secure a sustainable competitive advantage (Garmaki, Gharib, & Boughzala, 2023).

These operational benefits often translate into measurable financial outcomes. As organisations become more data-driven, they are better positioned to reduce costs, optimise resource allocation, and improve customer targeting, factors that directly influence profitability. A study by Wamba et al. (2017) empirically confirmed the positive impact of BA on firm performance, demonstrating improvements in profitability, return on investment, and overall financial outcomes when analytics capabilities are effectively deployed. In a separate large-scale survey conducted by Accenture and General Electric, data-driven companies were found to be "23 times more likely top their competitors in customer acquisition, about 19 times more likely to stay profitable and nearly seven times more likely to retain customers" (Loew, n.d.).

H3: *Therefore, the use of data analytics for continuous improvement will be correlated to higher profitability levels in organisations.*

Beyond profitability, BA also plays a pivotal role in driving long-term organisational growth. High-performing organisations increasingly regard BA as a strategic lever for growth and differentiation. By enabling the extraction of actionable insights from large and complex datasets, BA supports more agile decision-making, fosters innovation, and strengthens the organisation's ability to scale effectively. This enhanced analytical capability not only improves operational efficiency but also unlocks new opportunities for expansion and value creation. As noted by Shabbir & Gardezi (2020), many leading firms view BA as a key driver of sustained organisational growth in an evolving business landscape. This view is reinforced by a study conducted by Aydiner et al. (2019), which highlights that organisations with mature analytics capabilities are significantly more adept at reconfiguring internal resources and adapting to shifting market demands. By integrating predictive and prescriptive analytics, BA facilitates the continuous renewal of operational capacities, enabling firms to identify strategic opportunities and pursue new growth trajectories. The ability to transform complex data into actionable insights enhances responsiveness, supports informed decision-making, and reinforces competitive positioning. As such, embedding analytics into core business processes is not only critical for optimising performance but also for enabling sustainable and scalable organisational growth.

H4: *As well, the use of data analytics for continuous improvement with be associated with greater growth in organisations.*

2.3 The use of data analytics in continuous improvement and its impact on human resources outcomes

In addition to this, BA also plays an important role in transforming HRM by facilitating informed, data-driven decisions that enhance overall organisational performance (Ameer, Garg, & Singh, 2023). Over time, HR has evolved from basic administrative functions to a strategic role that leverages analytics to assess employee performance and productivity. For instance, Simón and Ferreiro (2018) present a case study of a large multinational retailer, Inditex, which implemented a workforce analytics initiative to better understand patterns of employee turnover and improve the alignment between store performance and HR practices. By integrating data from internal systems, productivity indicators, and workforce metrics, the company identified key areas for improvement, implemented targeted strategies, and enhanced the strategic positioning of the HR function.

Beyond individual cases, HR Analytics is being applied across a diverse set of domains such as talent acquisition, skills allocation, retention strategies, workforce scheduling, compensation planning, and employee engagement. These applications, although not always evaluated through formal causal analyses, reflect how analytics is being used in practice to address strategic HR challenges (Belizón, Majarín & Aguado, 2024). This growing use underscores the necessity for HR professionals to develop robust analytical skills to influence business strategies effectively, enabling performance tracking, improving employee outcomes, and aligning incentives, laying the groundwork for the following hypotheses:

H5a: *The use of data analytics for continuous improvement will be associated with a control-based management approach in organizations.*

H5b: *The use of data analytics for continuous improvement will be associated with the use of data analytics to improve employee performance.*

H5c: *The use of data analytics for continuous improvement will be correlated with the use of pay-for-performance systems in organisations.*

Understanding how these dynamics unfold requires a closer look at the types of analytics that shape HR practices today. The primary types of HR analytics are descriptive, diagnostic, predictive, and prescriptive analytics, each play a unique role in enhancing HR functions. Descriptive analytics reviews historical data to clarify past performance, while diagnostic analytics investigates the reasons for certain outcomes. Predictive analytics anticipates future trends, such as employee turnover, and prescriptive analytics offers actionable recommendations for staffing and development (Kale, Aher, & Anute, 2022). Despite the advantages, many organizations still face challenges in fully utilizing HR analytics, indicating a need for stronger analytical capabilities within HR teams.

Building on this typology, the integration of BA within HR has become a strategic imperative. BA empowers HR departments to move from intuition-driven to evidence-based decision-making, enhancing the strategic alignment between workforce capabilities and business objectives. The integration of BA into HR practices not only improves human capital management but also leads to enhanced business outcomes and a competitive edge in the marketplace (Ameer, Garg, & Singh, 2023).

Talent management is increasingly recognised as a strategic process aimed at attracting, developing, and retaining high-potential employees to sustain organisational competitiveness. Within this framework, data analytics has emerged as a critical enabler for optimising the alignment between employee skills and organisational needs. At the individual level, analytics facilitates more accurate job matching and predictive insights into performance and turnover, allowing for better-informed talent decisions (Belizón, Majarín & Aguado, 2024). One of the most impactful areas where data analytics drives continuous improvement is talent management itself. The rise of talent-related big data and AI-powered techniques, such as deep learning, has further enhanced this capability, enabling real-time, data-driven decision-making in areas like recruitment, team formation, and employee development. Notably, companies such as IBM have demonstrated the power of such tools, using AI to predict attrition with 95% accuracy and saving millions in retention costs. These developments underscore the role of analytics not only in responding to talent needs but also in continuously improving how organisations manage and develop their workforce (Qin et al., 2023). These developments highlight the potential of analytics not only to respond to talent needs but also to embed a system of continuous enhancement in how organizations manage their workforce.

H6: *The use of data analytics for continuous improvement will be positively correlated to a greater optimization of talent in relation to skillset and abilities needed in the organization.*

Analytics has been recognized as an essential capability within HR, offering the potential to create value from human capital and to broaden the strategic influence of HR departments. However, reaching this potential depends on addressing certain barriers. Research by Edwards et al. (2022) highlights that the growth of HR analytics is hindered by a limited grasp of analytical thinking in the HR field, which may prevent it from achieving its full strategic impact.

HR analytics enables organizations to systematically analyse employee data, enhancing key functions such as recruitment, training, and retention while helping align HR initiatives with broader organizational objectives (Ameer, Garg, & Singh, 2023). It has been shown to contribute significantly to talent retention and leadership quality, which are crucial drivers of business performance (Edwards et al., 2022). However, Simón and Ferreiro (2017) caution that an overemphasis on data quantity, rather than strategic application, can hinder its effectiveness, underscoring the need for analytics to generate actionable insights tailored to organizational goals. Despite these promising benefits, many organizations struggle to move beyond basic operational reporting, limiting the strategic potential of HR analytics (Angrave et al., 2016). This challenge is further compounded by gaps within the HR profession, such as insufficient analytical expertise, which hinder the full realization of HR analytics' advantages (Huselid & Minbaeva, 2018).

Moreover, "the use of BA aids a knowledge enterprise by promoting efficiency within an organization, particularly by using analytical methods to provide valuable decision-making knowledge to minimize operating costs and accurately forecast market trends" (Trkman et al., 2010, p. 319). This capability enhances the overall effectiveness of an organization, ensuring that resources are allocated wisely, and processes are refined for maximum impact. By embedding analytics into HR and operational strategies, businesses can foster a proactive environment where continuous improvement becomes ingrained in organisational culture.

The integration of BA within organizations is essential for driving continuous improvement and enhancing overall performance. By utilizing BA, companies can effectively analyse large volumes of internal and external data, identifying inefficiencies and optimizing their operations. This analytical approach not only leads to immediate performance gains but also lays the groundwork for sustained development and innovation, which are vital for adapting to changing market conditions (Ekka, Singh, & Ranjan, 2022).

Moreover, continuous improvement methodologies benefit from the insights provided by analytics, enabling organizations to streamline processes and reduce waste. This combination fosters a culture of accountability and proactive problem-solving among employees, ultimately resulting in better business outcomes and a competitive advantage in the marketplace (Ekka, Singh, & Ranjan, 2022). For instance, Experian implemented predictive workforce analytics to address employee turnover challenges, using tools like Visier to identify employee needs and streamline reporting processes. This initiative not only reduced reporting time by 70% but also aligned HR strategies with retention goals, fostering collaboration across departments and ensuring efforts were targeted towards organisational priorities (Kale, Aher,

& Anute, 2022). Such examples highlight how analytics tools can help teams align efforts more effectively, improving the overall cohesion of continuous improvement initiatives and ensuring that departments work toward shared organisational goals. Such examples illustrate how analytics facilitates coordination and strategic alignment across functions, reinforcing collective efforts.

H7: *The use of data analytics for continuous improvement will be positively associated with higher teamwork and collaboration in organisations.*

In addition to these operational benefits, analytics may also enhance employee motivation and engagement. Integrating BA into HR practices is crucial for fostering a culture of continuous improvement within organizations. By enabling data-driven decisions that align with strategic goals, BA contributes to more effective human capital management (Kale, Aher, & Anute, 2022). It also promotes timely feedback, personalised development plans, and adaptive goal-setting mechanisms, elements that encourage individual growth and collective performance (Bahrami & Shokouhyar, 2021). Furthermore, by aligning individual objectives with organisational priorities and granting employees greater autonomy over their work processes, BA fosters a deeper sense of ownership and engagement. As Belizón, Majarín & Aguado (2024) highlight, BA can also inform initiatives such as engagement tracking, well-being monitoring, and employee voice channels, contributing to a workplace where people feel heard, supported, and empowered. In doing so, BA helps cultivate a more meaningful and collaborative relationship between employees and their organisation.

H8: *The use of data analytics for continuous improvement will be positively correlated to a greater optimization of talent in relation to skillset and abilities needed in the organization.*

This data-driven approach not only facilitates immediate improvements in performance but also creates a framework for ongoing development and innovation, enabling organizations to adapt to changing market demands continuously (Kale, Aher, & Anute, 2022). While institutionalised forms of employee representation, such as unions or works councils, often resist the individualising tendencies of data-driven decision-making (Moore et al., 2018; Pulignano & Doerflinger, 2020), direct employee voice mechanisms appear to operate in the opposite direction. Rather than constraining the adoption of analytics, tools such as pulse surveys, team consultations or internal feedback platforms can enhance its effectiveness by providing real-time input that guides personalised, adaptive interventions. According to Belizón, Majarín & Aguado (2024), organisations increasingly use HR analytics to track engagement and well-being, translating individual feedback into targeted action. These cases illustrate that direct employee voice, when supported by analytics, enables more participatory and differentiated approaches to workforce management. In this sense, far from undermining fairness or cohesion, the integration of BA with direct voice mechanisms fosters a responsive, inclusive culture where employees can influence business processes and organisational development. This perspective underpins:

H9: *The use of data analytics for continuous improvement will be positively correlated with for the use of direct employee voice as a means to grant a say in business processes decision-making in organisations.*

3. Methodology

3.1 Description of the database: European Company Survey 2019

The European Company Survey (ECS) 2019 is a comprehensive dataset collected by Eurofound to examine workplace practices, innovation, and employee relations across European Union companies. Conducted through online questionnaires directed at employee representatives, the survey captures diverse aspects of organisational functioning, including innovation, organisational structure, the use of technological tools (such as analytics), and employee representation.

The dataset encompasses responses from 21,869 companies across all EU member states, offering a robust and representative cross-section of organisations from various industries and sizes. It consists of 160 columns, representing a wide range of variables relevant to business processes, HR, and organisational strategies.

This dataset is particularly valuable for analysing the role of BA in enhancing continuous improvement initiatives, with a focus on improving business processes and HR. While its comprehensive scope is a significant strength, it is essential to consider potential limitations, such as response biases and data quality variations across countries. Despite these challenges, the ECS 2019 provides a strong foundation for predictive modelling and actionable insights into the role of analytics in modern organisations.

Given the objective of this study, to examine relationships between organisational variables and the use of BA in continuous improvement processes, a quantitative methodology is particularly appropriate. This approach enables the identification of patterns and statistical correlations across a large and diverse sample. By allowing the testing of hypotheses and the measurement of associations between variables, it provides a structured framework for drawing generalisable conclusions (Saunders, Lewis, & Thornhill, 2023). The European Company Survey 2019, with its broad scope and standardised responses, supports this approach by offering reliable data suitable for statistical modelling and inferential analysis.

3.2 Data processing

To ensure data integrity and reliability, a comprehensive preprocessing strategy was implemented, encompassing data cleaning, transformation, and classification. Given the challenges associated with survey-based datasets, such as skewed distributions and categorical variables with limited variability, several preprocessing steps were applied to enhance the dataset's representativeness and analytical robustness.

Many variables in the dataset were categorical and required conversion into numerical formats to facilitate model interpretation. Binary variables (e.g., “Yes”/“No” responses) were transformed into 1 and 0, respectively. Ordinal variables, such as motivation levels and perceived competition, were encoded using numerical ranks to preserve their hierarchical structure.

For categorical attributes with multiple textual responses (e.g., industry sector, company size, ownership structure, and competitive environment), label encoding was employed. This transformation ensured that these attributes could be compared numerically without introducing bias.

Survey-based datasets often contain missing responses, particularly in optional questions. To mitigate the impact of missing data, a mode imputation strategy was applied, replacing missing values with the most frequently occurring response in each respective column. This approach maintained the distributional integrity of the dataset while minimizing data loss.

To provide a structured framework for analysing business environments, this study classifies countries into distinct economic models based on institutional characteristics. Since economic structures influence corporate decision-making, labour markets, and innovation strategies, this classification is crucial for interpreting the model’s results accurately. The classification follows widely accepted frameworks from Hall and Soskice (2001) and the European Commission (2008), which distinguish between different types of market coordination and governance models. Based on these classifications, countries in the dataset are grouped into four categories:

1. **Coordinated Market Economies (CMEs)**: These economies rely on strong coordination between firms, labour unions, and financial institutions. They are characterized by long-term employment relationships, extensive vocational training, and collaborative decision-making in industrial policies. Countries classified as CMEs in this

study include: Austria, Belgium, Denmark, Finland, Germany, the Netherlands, and Sweden.

2. **Liberal Market Economies (LMEs)**: LMEs depend primarily on market-driven mechanisms, where firms operate in flexible labour markets, short-term employment contracts, and rely heavily on financial markets for corporate governance. These economies are characterized by low state intervention and strong competitive dynamics. The countries classified as LMEs are: United Kingdom, Ireland, Malta, and Cyprus.

3. **Statist Market Economies**: This group consists of countries where the state plays a significant role in economic activity, industrial policies, and labour market regulations. These economies combine elements of both coordinated and market-driven approaches but exhibit greater government intervention. The countries in this category include: Greece, Spain, France, Italy, and Portugal.

4. **Central and Eastern European Countries (CEECs)**: CEECs have undergone significant economic transformations since the 1990s, transitioning from centrally planned economies to market-oriented systems. While they share some characteristics with LMEs, particularly in financial liberalization and labour flexibility, they exhibit distinct post-socialist institutional arrangements. The countries classified as CEECs include: Bulgaria, Croatia, Estonia, Hungary, Latvia, Lithuania, Romania, Slovakia, and Slovenia.

While some scholars argue that CEECs may align more closely with LMEs, others highlight their institutional legacies and transitional challenges, which justify treating them as a separate category (European Commission, 2008).

Ultimately, the combination of data preprocessing and economic classification enhances the interpretability and reliability of the model, ensuring an optimal foundation for modelling and analysis in our study.

3.3 Variables and sample's preliminary descriptive statistics

This section outlines the dependent, independent, and control variables used to examine the role of BA in driving continuous improvement across multiple dimensions of organisational performance. Each variable has been selected to align with the hypotheses developed for this study and to address the research objectives comprehensively. The description given for each variable follows the definitions established in the survey design codebook to ensure consistency and clarity in the analysis except for the variable **'country_group'**.

Dependent variable:

The dependent variable measures the central focus of the study: the use of BA for continuous improvement.

itprodimp: Does this establishment use data analytics to improve the processes of production or service delivery?

This variable serves as the key outcome of interest, reflecting whether organisations employ BA to enhance their production or service delivery processes. It provides a direct measure of the implementation of BA for continuous improvement, which is foundational for evaluating the relationships proposed in the hypotheses.

Control variables:

The control variables account for organisational characteristics that may influence the relationship between BA and continuous improvement, controlling for structural and operational differences that could confound the analysis.

Table 1. Control Variables' definition and descriptive values

Variable	Definition	Values	Descriptive (N = 21,869) in %	VIF
subsorhq	Is the establishment at this address the company headquarters?	Headquarters - [0]	55	1.174045
		Subsidiary site - [1]	45	
mm_sector_grp	MM sector Group	Construction - [0]	6	1.196162
		Production - [1]	29	
		Services - [2]	65	
mm_size_grp	MM size Group	Large - [0]	30	1.616520
		Medium - [1]	39	
		Small - [2]	31	
est_size	Establishment size in number of employees	10 to 49 employees - [0]	31	1.430084
		250 employees or more - [1]	26	
		50 to 249 employees - [2]	42	
est_age	Age of the establishment in categories	10 years or less	10	1.128095
		11 to 20 years	19	
		21 to 30 years	18	
		more than 30 years	51	
chowner	Since 2016, has there been any change in the ownership of the company to which this establishment belongs?	No - [0]	78	1.056278
		Yes, and it involved a change of management - [1]	22	
		Yes, but management remained the same - [1]		
actprod	Is this establishment engaged in the production of goods, assembly of parts or delivery of services?	No - [0]	32	1.248965
		Yes, this is mainly carried out in collaboration with one or more other companies - [1]	8	
		Yes, this is mainly carried out in collaboration with one or more other establishments within our company - [2]	21	
		Yes, this is mainly carried out internally - [3]	37	
		Yes, this is mainly contracted out - [4]	2	
actdede	Is this establishment engaged in the design or development of new products or services?	No - [0]	62	1.422592
		Yes, this is mainly contracted out - [1]	38	
country_group	Groups in which countries have been classified following widely accepted frameworks from Hall and Soskice (2001) and the European Commission	CEEC - [0]	13	1.153390
		CME - [1]	53	
		LME - [2]	5	
		Statist Market Economy - [3]	29	
ecommerce	Does this establishment buy or sell goods or services on the internet? E.g business-to-business portals, e-commerce etc.	No - [0]	62	1.151397
		Yes - [1]	38	
salesint	Since 2016, what percentage of this establishment's sales were to customers in other countries?	1% to 24% - [0]	23	1.154774
		25% to 49% - [1]	7	
		50% or more - [2]	15	
		Not applicable - our establishment does not engage in sales - [3]	15	
		We do not engage in export (0%) - [4]	40	

Independent variables:

The independent variables are grouped into business and HR categories, reflecting different aspects of organisational operations that are hypothesised to be influenced by BA for continuous improvement. Each category aligns with specific hypotheses, offering a structured approach to addressing the research question.

3.3.1 *Business outcome variables*

Table 2. Independent Variables' definition and descriptive values

Variable	Definition	Values	Descriptive (N = 21,869) in %	VIF
innoprod	Since 2016, has this establishment introduced any new or significantly changed products or services?	No - [0]	59	1.495057
		Yes, new to the market - [1]		
		Yes, new to the market - [1]	41	
innoproc	Since 2016, has this establishment introduced any new/changed processes either for producing goods or supplying services?	No - [0]	56	1.468705
		Yes, new to the market - [1]	44	
		Yes, new to the market - [1]		
innomark	Since 2016, has this establishment introduced any new or significantly changed marketing methods?	No - [0]	63	1.253092
		Yes, new to the market - [1]	37	
		Yes, new to the market - [1]		
pmstratnps	Regularly developing products, services or processes that are new to the market - important for the competitive success	1	13	1.206928
		2	20	
		3	34	
		4	32	
pmstratlp	Offering products or services at lower prices than the competition - important for the competitive success	1	14	1.204556
		2	16	
		3	22	
		4	49	
pmstratbq	Offering products or services that are of better quality than those offered by the competition - important for the competitive success	1	44	1.110345
		2	30	
		3	18	
		4	7	
competmark	How competitive would you say the market for the main products or services provided by this establishment is?	Not very competitive - [0]	46	1.048091
		Not at all competitive - [1]	4	
		Fairly competitive - [2]	10	
		Very competitive - [3]	40	
profit	In 2018, did this establishment make a profit?	No, we made loss - [0]	11	1.455874
		Not applicable, our company is a not-for-profit organisation - [1]	8	
		We broke even - [2]	10	
		Yes, we made a profit - [3]	71	
profplan	Did this establishment expect to make a profit in 2018?	No - [0]	12	1.354601
		Yes - [1]	88	
chemp	How has the total number of employees in this establishment changed since the beginning of 2016?	Decreased by more than 10% - [0]	6	1.293045
		Decreased by up to 10% - [1]	10	
		Stayed about the same - [2]	43	
		Increased by up to 10% - [3]	22	
		Increased by more than 10% - [4]	19	
chempfut	In the next three years, how do you expect the total number of employees in this establishment to change?	It will decrease - [0]	13	1.248318
		It will stay about the same - [1]	50	
		It will increase - [2]	37	
prodvol	Since 2016, how has the amount of goods or services produced by this establishment changed?	It has decreased - [0]	9	1.043481
		It has increased - [1]	53	
		It has stayed about the same - [2]	38	

3.3.2 *Human resources variables*

Table 3. Independent Variables' definition and descriptive values

Variable	Definition	Values	Descriptive (N = 21,869) in %	VIF
supchek	Which of these two statements best describes the general approach to management at this establishment?	Managers control whether employees follow the tasks assigned to them - [0]	20	1.119946
		Managers create an environment in which employees can autonomously carry out their tasks - [1]	80	
dischelp	Helping colleagues without being asked - to be evaluated positively	Fairly important - [0]		1.132708
		Not at all important - [0]	42	
		Not very important - [0]		
		Very important - [1]	58	
motimon	Offering monetary rewards - to motivate and retain employees	Never - [0]	10	1.338983
		Not very often - [1]	50	
		Fairly often - [2]	33	
		Very often [3]	8	
motilearn	Providing opportunities for training and development - to motivate and retain employees	Never - [0]	21	1.234383
		Not very often - [0]		
		Fairly often - [1]	51	
		Very often [2]	28	
lowmot	Overall, how motivated do you think employees in this establishment are?	Not at all motivated - [0]		1.139879
		Not very motivated - [0]	81	
		Fairly motivated - [0]		
		Very motivated - [1]	19	
itperfmon	Does this establishment use data analytics to monitor employee performance?	No - [0]	59	1.172747
		Yes - [1]	41	
vpbres_d	Payment by results, for example piece rates, provisions, brokerages - employees received variable pay	None at all - [0]	39	1.534079
		Less than 20% - [1]	25	
		20% to 39% - [2]	8	
		40% to 59% - [3]	6	
		60% to 79% - [4]	5	
		80% to 99% - [5]	6	
		All - [6]	12	
vpinper_d	Variable extra pay linked to individual performance - employees received variable pay	None at all - [0]	34	1.556705
		Less than 20% - [1]	31	
		20% to 39% - [2]	10	
		40% to 59% - [3]	6	
		60% to 79% - [4]	5	
		80% to 99% - [5]	6	
		All - [6]	9	
vpgrpe_d	Variable extra pay linked to the performance of the team, working group - employees received variable pay	None at all - [0]	45	1.645916
		Less than 20% - [1]	25	
		20% to 39% - [2]	7	
		40% to 59% - [3]	5	
		60% to 79% - [4]	4	
		80% to 99% - [5]	5	
		All - [6]	9	
vpprsh_d	Variable extra pay linked to the results of the company - employees received variable pay	None at all - [0]	46	1.307017
		Less than 20% - [1]	19	
		20% to 39% - [2]	4	
		40% to 59% - [3]	3	
		60% to 79% - [4]	3	
		80% to 99% - [5]	6	
		All - [6]	19	
teasin	With regard to the employees doing teamwork, do most of them work in a single team or in more than one team?	Most of them work in a single team - [0]	66	1.038771
		Most of them work in more than one team - [1]	34	
tauton	Who usually decides how the tasks are distributed within the team?	Tasks are distributed by a superior - [0]	81	1.099470
		Team members decide among themselves - [1]	19	
trski	Ensuring that employees have the skills they need to do their current job - important for providing training to employees	Fairly important - [0]		1.181405
		Not at all important - [0]	28	
		Not very important - [0]		
		Very important - [1]	72	
skillsmatch_d	What percentage of employees have the skills that are about right to do the job?	Continous variable [0-100]	71.66 (Mean)	1.746516
overskill_d	What percentage of employees have a higher level of skills than is needed in their job?	Continous variable [0-100]	15.97 (Mean)	1.738717
training	Participating in training - way employees can become more skilled at their jobs	1	22	1.092391
		2	29	
		3	49	
hirready_d	How many of these newly recruited employees did not have the skills to do their job to the required level?	20% to 39% - [0]	16	1.052307
		40% to 59% - [1]	12	
		60% to 79% - [2]	10	
		80% to 99% - [3]	5	
		All - [4]	7	
		Less than 20% - [5]	32	
		None at all - [6]	18	
indir	Management prefers to consult with the employee representation or directly with employees?	Management prefers not to consult with employees or their representatives - [0]	2	1.051868
		Management prefers to consult with employees directly - [1]	21	
		Management prefers to consult with the employee representation - [2]	24	
		Management prefers to consult with the employee representation and with employees directly - [3]	53	

4. Results

Following the initial descriptive analysis of the dataset, this section shifts focus to examining the relationships between key variables, aiming to identify relevant patterns and interactions that contribute to the analytical framework of the study.

4.1 Spearman Correlation Analysis for the dependent variable

Figure 1. Control & Dependent variables

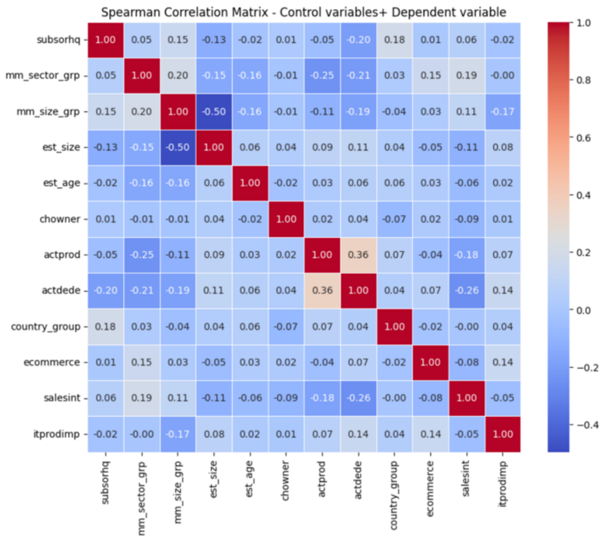

Figure 2. HR & Dependent variables

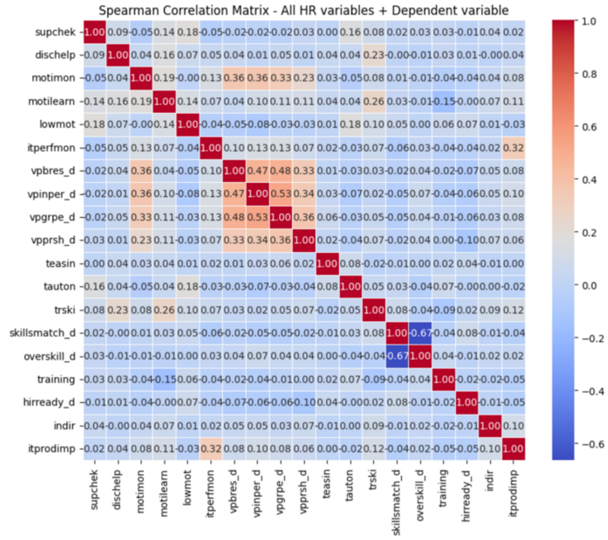

Figure 3. Business & Dependent variables

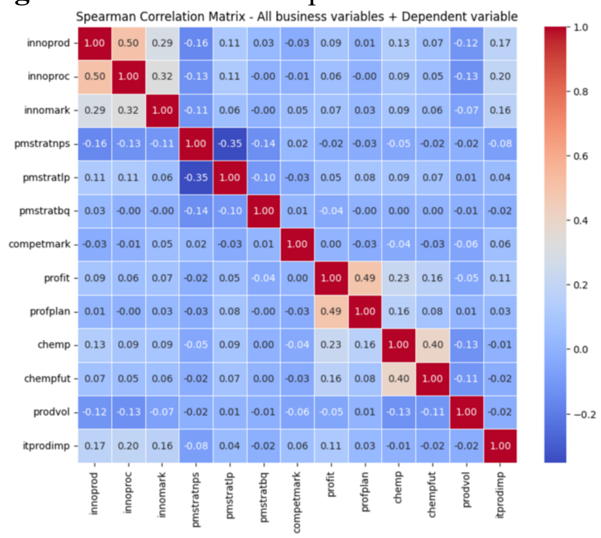

Figure 1. presents the Spearman correlation matrix between the dependent variable (**itprodimp**, indicating whether the establishment has introduced new or improved products/services) and the designated control variables. Among these, **actdede** (engagement in design/development activities) and **ecommerce** (buying/selling goods or services online) each

register a positive correlation of approximately 0.14, which can be regarded as weak. No control variable in this figure attains a moderate or strong correlation with **itprodimp**.

Figure 2., on the other hand, addresses the HR variables. The variable **employee performance monitoring** exhibits the strongest positive association with the dependent variable, at around 0.32, generally viewed as moderate. Meanwhile, the variables **variable pay individual performance, development opportunities**, and **training needs** each display weaker positive correlations, ranging from 0.10 to 0.12.

Lastly, *Figure 3.* focuses on the business variables, including **new processes**, **new product or services**, and **new marketing methods**. Here, **new processes** emerge with the highest correlation (about 0.20), placing it in the weak-to-moderate category. The correlations for **new product or services** and **new marketing methods** lie around 0.16 to 0.17, whereas **profit** stands near 0.11, reflecting a comparatively weaker positive relationship. Comparing all three figures reveals that HR variables and specifically **employee performance monitoring** exhibits the strongest overall correlation with **itprodimp,** whereas the control and business variables generally display weaker associations.

4.2 Predictive model – Logistic model

Logistic regression is a widely used statistical method for modelling the relationship between a binary dependent variable and one or more independent variables. By applying the logit function, it estimates the probability of an event occurring while ensuring values remain between 0 and 1. This approach is essential for classification tasks, allowing researchers to analyse patterns, assess risks, and make informed decisions across disciplines such as healthcare, BA, and social sciences. (LaValley, 2008).

This study employs a logistic regression model as a supervised machine learning algorithm to analyse the factors influencing the adoption of BA for continuous improvement. Specifically, the model predicts the likelihood of BA adoption in driving innovation, enhancing industry competitiveness, increasing profitability, improving employee performance monitoring, optimising pay-for-performance systems, fostering teamwork and collaboration, aligning talent management with organisational needs, and strengthening employee involvement in decision-making. By leveraging Python’s computational capabilities, this model provides probabilistic insights, enabling organisations to align BA-driven strategies with key operational objectives, ultimately promoting sustained improvement and organisational success.

4.3 <u>Results *and analysis*</u>

Table 4. Logistic regression models (coefficients and *p*-values)

	Independent and control variables	Model 1		Model 2		Model 3	
Control variables	Headquarters	0.1359	(0.205)	0.0369	(0.753)	0.0969	(0.425)
	Industry sector	0.1619	(0.063)*	0.0922	(0.325)	0.0951	(0.323)
	Size	-0.5045	(0.000)***	-0.5072	(0.000)***	-0.4946	(0.000)***
	Size in number of employees	-0.0043	(0.952)	-0.0266	(0.728)	0.0098	(0.900)
	Age of the establishment	-0.0168	(0.731)	0.0478	(0.376)	0.0250	(0.655)
	Changes in ownership	-0.0033	(0.979)	0.0503	(0.706)	-0.0581	(0.674)
	Production activity	0.0843	(0.044)**	0.0669	(0.139)	0.0639	(0.167)
	Innovation activity	0.1707	(0.000)***	0.1485	(0.001)***	0.0824	(0.095)*
	Country classification	0.0595	(0.234)	0.0680	(0.225)	0.0903	(0.119)
	Ecommerce	0.5980	(0.000)***	0.5877	(0.000)***	0.4349	(0.000)***
	Percentage of international sales	0.0281	(0.398)	0.0344	(0.337)	0.0532	(0.151)
HR variables	Management style			0.1970	(0.165)	0.1783	(0.216)
	Prosocial behaviour			0.0440	(0.708)	-0.0004	(0.998)
	Monetary incentives			-0.0412	(0.611)	-0.1015	(0.222)
	Development opportunities			0.1706	(0.044)**	0.1211	(0.167)
	Employee motivation level			-0.1059	(0.467)	-0.0053	(0.972)
	Employee performance			1.5551	(0.000)***	1.5085	(0.000)***
	Payment by results			0.0007	(0.983)	-0.0026	(0.938)
	Variable pay individual			-0.0053	(0.880)	-0.0130	(0.718)
	Variable pay team performance			0.0318	(0.390)	0.0216	(0.569)
	Variable pay company results			0.0025	(0.924)	0.0002	(0.994)
	Teamwork			-0.0020	(0.987)	-0.0057	(0.962)
	Task distribution			0.0680	(0.639)	0.0905	(0.543)
	Training needs			0.3190	(0.012)**	0.2991	(0.021)**
	Skill job match			-0.0030	(0.405)	-0.0027	(0.476)
	Overqualification level			-0.0046	(0.335)	-0.0054	(0.267)
	Training participation			-0.0674	(0.342)	-0.0289	(0.694)
	Recruitment skill gap			-0.0110	(0.664)	-0.0029	(0.912)
	Employee consultation structures			0.2097	(0.001)***	0.2339	(0.000)***
Business variables	New product or services					0.3368	(0.017)**
	New processes					0.3962	(0.004)***
	New marketing methods					0.4392	(0.001)***
	Innovation strategy					-0.1096	(0.074)*
	Low price strategy					-0.0685	(0.228)
	High quality strategy					-0.0852	(0.160)
	Perceived market competitiveness					0.0410	(0.315)
	Profit					0.2387	(0.000)***
	Expected profit					-0.0554	(0.773)
	Employment change					-0.1075	(0.067)*
	Expected employment change					-0.0642	(0.491)
	Production volume change					0.0293	(0.749)

Statistical significance: *p* -value < 0.005 (***); *p* -value < 0.050 (**); *p* -value < 0.100 (*)

The results of the logistic regression models provide a comprehensive understanding of the factors associated with the adoption of BA for continuous improvement in organisations. The dependent variable (**itprodimp**) captures whether an establishment employs BA to enhance its production or service delivery processes. To assess the determinants of BA adoption, a stepwise approach was employed, beginning with a baseline model incorporating control variables, followed by an extended model that introduced HR-related predictors, and culminating in a full model encompassing both business and HR-related variables. A final model was then developed using Recursive Feature Elimination (RFE) to identify the most influential predictors.

Model 1, which included only control variables, provided initial insights into the structural and organisational characteristics associated with BA adoption. The results indicated that the organisational **size** ($p < 0.001$), **ecommerce** ($p < 0.001$), and **innovation activity** ($p < 0.001$) significantly correlated with the likelihood of using BA for continuous improvement.

As we can see in *Table 4* from the negative coefficient of firm **size**, larger organisations were less likely to report adopting BA. As firms moved from one size category to the next (e.g., from small to medium or from medium to large), their likelihood of implementing BA decreased. In contrast, engagement in product or service design was positively associated with BA adoption, reinforcing the strong link between innovation and data-driven decision-making. This suggests that organisations focused on developing new products or services tend to be more likely to leverage analytics to optimise processes, improve efficiency, and maintain a competitive edge.

On the other hand, the variables **industry sector** and **innovation activity** were both positively and significantly correlated with BA adoption. Firms in services and production sectors showed a higher likelihood of adopting analytics compared to those in construction. Similarly, firms involved in product or service design activities were more inclined to implement BA, suggesting a closer alignment between innovation processes and data-driven practices.

Additionally, the large positive coefficient for **ecommerce** stands out, indicating that organisations engaging in online transactions tend to be substantially more likely to adopt BA. This may reflect the extensive digital data streams generated in e-commerce environments, which in turn are associated with stronger incentives to employ analytics for process optimisation and better-informed decision-making. This underscores the interdependence between digitalisation and data analytics, as companies that adopt e-commerce solutions also tend to leverage data-driven strategies for process optimisation.

While these initial findings were informative, the explanatory power of the control variables alone was relatively modest, as indicated by a pseudo-R^2 of 0.054. This required the inclusion of additional independent variables to better capture the organisational dynamics linked to BA adoption. Model 2 expanded upon the baseline specification by incorporating HR-related predictors, significantly enhancing the model's explanatory power, as indicated by an increase in pseudo-R^2 to 0.152. The results highlighted the critical role of HR practices in being associated with firms' adoption of BA for continuous improvement.

Several control variables that were statistically significant in Model 1 remain so in this expanded specification. Specifically, firm **size, innovation activity** and **ecommerce** all maintain their significance. These findings reinforce the earlier observation that smaller firms, those engaged in innovation through design and development, and firms with digitalised commercial activity are more inclined to adopt BA. At the same time, certain control variables that were initially significant in Model 1 lose statistical relevance in Model 2. For instance, **industry sector**, which previously showed a marginally significant positive association with BA adoption, no longer reaches conventional significance levels once HR factors are included. This suggests that the initial effect of sectoral variation may be partly explained by its correlation with differences in HR practices across industries.

Among the most significant variables in Model 2 is the use of BA for **employee performance monitoring**, which exhibited a strong and statistically significant positive association with analytics adoption as we can see from its coefficient and p_value in Table 4. This result offers robust support for **H5b**, confirming that organisations leveraging analytics to assess employee performance also tend to extend these practices to broader continuous improvement initiatives. Additionally, the variables **training needs** and **employee consultation structures** emerged as significant predictors, reinforcing the idea that both talent optimisation and participatory decision-making are integral components of a data-driven organisational strategy. These findings validate **H6** and **H9**, respectively, as they highlight the relevance of aligning workforce capabilities with organisational needs and the value placed on employee voice in shaping business processes.

The findings further underscore the role of employee development practices. The variable **development opportunities**, was positively associated with BA adoption, providing empirical support for **H8**. This suggests that firms prioritising continuous learning and skill enhancement are more likely to adopt BA as part of a broader effort to motivate and engage employees.

However, other components of the HR framework yielded more limited evidence of support. No evidence was found in support of **H5a**, as the variable **management style** intended which intended to capture a control-based management style did not reach significance in any model specification. Similarly, variables designed to capture pay-for-performance systems (**payment by results**, **variable pay company results** and **variable pay team performance)** were not statistically significant in any model, leading to the conclusion that **H5c** is not supported. Lastly, the variables of **teamwork** and **task distribution** failed to reach significance, indicating that **H7** is not validated within the scope of this analysis.

Building on these findings, the Model 3 incorporated business-related independent variables to provide a more holistic understanding of BA adoption. The inclusion of these variables further improved the model's predictive capacity, raising the pseudo-R^2 to 0.182. Notably, the results reinforced the strong association between innovation and BA adoption.

Among the most significant predictors, firms that had introduced new or significantly changed products (**new product or services**), processes (**new processes)** or marketing methods (**new marketing methods)** exhibited a higher likelihood of using BA for continuous improvement. These findings provide empirical support for **H1**, as they indicate that firms engaging in innovation also tend to be adopters of analytics in order to enhance their operational capabilities. In contrast, strategic positioning and industry competitiveness, proxied by **innovation strategy** did not exhibit statistical significance, the absence of significance suggests limited empirical backing for **H2** failing to validate this hypothesis.

Moreover, financial performance was a key determinant, with **profit** emerging as a significant positive correlate of BA adoption. This validates **H3**, indicating that financially stable firms are more likely to invest in the infrastructure and talent required for effective use of BA. Conversely, the results reveal that firms that had increased their employee count since 2016 (**employment change**) were less likely to adopt BA. The negative relationship may indicate that firms undergoing workforce expansion face operational constraints that delay or deprioritise investments in analytics adoption. As such, **H4** is not supported, suggesting that workforce expansion may coincide with operational complexities that may inhibit immediate investment in BA.

Lastly, it is interesting to note that several HR and control-related variables from Model 2 remained significant in this final specification. These include **employee performance monitoring**, **training needs**, and **employee consultation structures**, each of which continued to show a positive association with BA adoption. The persistence of these variables across models underscores the enduring link between workforce management and participatory structures in shaping data-driven transformation.

To refine the model and identify the most influential predictors, Recursive Feature Elimination (RFE) was applied, reducing the number of variables to a subset of fifteen key features. The final model achieved an accuracy of 73.0%, representing a substantial improvement over previous specification. The selected predictors provided valuable insights into the factors associated with BA adoption. Among the most critical variables, firm **size** and **industry sector** remained important, confirming that structural characteristics continue to correlate with analytics adoption even when controlling for business and HR factors. Additionally, **innovation activity**, which captures engagement in design and development activities, reaffirmed its significance, further validating the link between innovation and data-driven decision-making. The presence of innovation-related variables (**new product or services, new processes, new marketing methods**) in the final model reinforced the centrality of innovation in being associated with BA adoption. Similarly, **ecommerce** remained a strong predictor, underscoring the role of digital transformation in enabling data-driven business processes.

HR-related factors continued to play a prominent role, with **management style**, **development opportunities**, and **employee performance monitoring** emerging as key predictors. The significance of these variables highlights the extent to which HR strategies and analytics-driven workforce management contribute to broader BA adoption. Additionally, the variable **training needs**, which measures the emphasis on ensuring that employees possess the necessary skills for their roles, was retained in the final model, further reinforcing the idea that firms investing in talent development are more likely to integrate BA into their operations. The inclusion of **employee consultation structures**, which reflects employee consultation practices, suggests that firms fostering inclusive decision-making processes are more likely to adopt BA as part of their continuous improvement efforts.

Overall, the results of the final model confirm that BA adoption is driven by a combination of innovation, HR management, digital transformation, and financial performance. Firms that actively engage in innovation, whether through new product development, process improvements, or digitalisation, tend to be more likely to integrate BA into their operations. Additionally, organisations that prioritise employee training, structured supervision, and performance monitoring exhibit a higher likelihood of BA adoption, highlighting the strategic importance of HR practices in facilitating data-driven decision-making.

Although we cannot infer causality from these results, we can establish that the use of BA for continuous improvement is positively correlated with greater innovation, enhanced business performance, and stronger HR-related outcomes.

Despite the strong predictive performance of the model, certain limitations must be acknowledged. The relatively lower recall for the negative class suggests that the model may be somewhat biased toward predicting BA adoption, potentially underestimating the barriers faced by firms that have not yet implemented analytics-driven continuous improvement strategies. Future research could explore additional contextual factors, such as organisational culture, leadership support, and regulatory environments, to further refine the understanding of BA adoption dynamics.

In conclusion, the findings underscore the multifaceted nature of BA adoption, illustrating how innovation, HR practices, digitalisation, and financial stability collectively correlate with firms' propensity to integrate analytics into their continuous improvement strategies. By leveraging these insights, organisations can develop targeted interventions to enhance their data-driven capabilities, fostering greater efficiency, competitiveness, and long-term sustainability.

5. Discussion

The findings of this study provide empirical insights into how BA supports continuous improvement in organisations, while also offering a nuanced perspective on the strategic and operational conditions that shape its adoption. In doing so, this research contributes to the broader discourse on the interplay between analytics, organisational learning, and performance optimisation, as outlined in the literature on Lean, Six Sigma, and broader continuous improvement frameworks.

The results support the widely held view that the adoption of BA is closely aligned with innovation-oriented practices. This reinforces the historical trajectory of continuous improvement, which has evolved from early manufacturing philosophies to increasingly data-driven strategies. As previously highlighted by scholars such as Tayade, Ubale & Ubale (2023) and Pupulin (2023), continuous improvement has shifted from reactive quality control to proactive, strategically embedded methodologies. The use of analytics appears to be a natural extension of this evolution, enabling firms to measure, monitor, and refine their processes with greater precision. The current findings confirm that firms engaged in improvement and transformation efforts are more likely to embed analytics into their operational models, suggesting that data-driven decision-making is becoming central to modern interpretations of continuous improvement. This is consistent with the arguments made by Aydiner et al. (2019), who underscore that analytics maturity enables firms to reconfigure processes in alignment with changing market conditions.

In parallel, this study adds weight to the growing literature on the role of analytics in shaping HRM. Prior contributions have underscored that BA has the potential to transform HR functions from administrative units into strategic partners capable of driving performance and workforce alignment (Ameer, Garg, & Singh, 2023; Edwards et al., 2022). The present results partially align with these claims, indicating that organisations committed to skill alignment, performance monitoring, and participatory practices are more inclined to adopt data-driven systems. Belizón, Majarín & Aguado (2024) also stress that HR analytics is increasingly used to translate engagement and well-being data into targeted development strategies, allowing organisations to act on individual needs while aligning with broader goals. These findings contribute to the broader understanding of how analytics may facilitate human capital optimisation, reinforcing its potential role as a strategic tool and a key enabler of organisational agility and adaptability

However, not all theoretical expectations were fully reflected in the empirical evidence. While much of the literature assumes a comprehensive and immediate impact of BA across organisational domains, the data suggests a more selective and context-dependent pattern of adoption. Some organisational practices traditionally associated with structured management or collaborative work environments do not appear to be systematically linked to analytics use, highlighting a gap between theoretical potential and current implementation. This may be due to the varying degrees of analytics maturity across firms, or to cultural and structural barriers that limit the integration of BA into certain decision-making domains. As suggested by Angrave et al. (2016), the potential of analytics is often constrained by capability gaps, resistance to change, or a lack of strategic coherence in its application.

These findings call for a more differentiated understanding of analytics adoption, not as a linear or uniform process, but as one shaped by organisational context, strategic priorities, and resource availability. This perspective aligns with the insights of Trkman et al. (2010) and Mucci (2024), who contend that while analytics can significantly enhance cost efficiency, planning, and competitiveness, its impact depends on the organisation's capacity to align tools, culture, and goals. Moreover, as Simón and Ferreiro (2017) caution, a focus on data alone, without clear strategic purpose or implementation capacity, can limit the effectiveness of analytics initiatives.

The results also suggest directions for future research. In particular, longitudinal studies could help clarify the causal pathways between analytics adoption and continuous improvement outcomes, especially in relation to organisational growth or innovation cycles. Additionally, further qualitative research could explore the cultural and leadership factors that facilitate or hinder the strategic embedding of analytics. It may also be valuable to investigate the role of BA in sectors not traditionally associated with high analytics adoption, in order to understand whether barriers are technical, perceptual, or institutional in nature.

Taken together, these findings reinforce the view that BA acts as a strategic enabler of continuous improvement, particularly when integrated with innovation initiatives, digital transformation, and HR development practices. At the same time, they highlight the importance of interpreting analytics adoption not as a uniform trajectory, but as one shaped by specific organisational characteristics such as firm size, employee skill alignment, and digital engagement. By grounding the analysis in these contextual determinants, this study offers a more differentiated understanding of how analytics can drive sustainable performance and long-term competitiveness.

While the findings of this study offer valuable insights into the organisational factors associated with the adoption of BA for continuous improvement, several limitations must be acknowledged.

First, the cross-sectional and observational nature of the data restricts the capacity to infer causality. Although the models identify significant associations between BA adoption and various organisational characteristics, they do not account for potential mediating or moderating variables that may shape these relationships. For instance, factors such as leadership style, digital maturity, or organisational culture, well established in the literature as influential in technological implementation, were not included in the model. As such, the pathways through which BA affects or is affected by organisational practices remain underexplored. Future research would benefit from incorporating these intermediate variables, potentially through longitudinal or mixed methods approach, to clarify the causal mechanisms and conditions under which analytics drives continuous improvement.

Second, the methodological and geographical scope of the study imposes further constraints. Many of the variables included in the analysis, particularly those measuring organisational practices and perceptions, were captured using dichotomous or ordinal categories, which may limit the granularity and nuance of interpretation. The dependent variable itself, whether firms use BA to improve the processes of production or service delivery, relies on a relatively narrow and self-reported survey item that may not fully reflect the complexity or maturity of BA integration. Additionally, the survey was conducted exclusively in the European context, which, while diverse in institutional arrangements, does not capture practices in other advanced economies such as the United States, Japan, or South Korea. Finally, although this paper adopts a quantitative lens to identify generalisable patterns, it does not capture the lived experiences or strategic rationales that underpin BA adoption. These dimensions could be more fully understood through complementary qualitative research, which would allow for a deeper exploration of organisational contexts, decision-making dynamics, and the perceived value of analytics from the perspective of practitioners

Despite these limitations, this study makes a meaningful contribution to the growing body of research on BA and organisational transformation. By systematically identifying the factors most closely associated with BA adoption, through sequential modelling and feature selection, this study offers an empirically grounded framework that can inform both scholarly debate and managerial practice. The findings reinforce the importance of innovation, digital readiness, and human capital development as enablers of data-driven transformation. In doing so, this paper not only advances our understanding of the conditions under which analytics can thrive but also underscores its potential as a strategic catalyst for sustainable, performance-oriented change across organisations.

6. Recommendations

Based on the findings of this study, a number of actionable and strategically relevant recommendations can be formulated for both policy makers and organisational leaders who aim to strengthen the integration of BA as a catalyst for continuous improvement and innovation.

For policy makers, the results highlight the importance of supporting innovation ecosystems, particularly among small and medium-sized enterprises (SMEs). Given the significant positive correlation between innovation activity and the use of BA for continuous improvement, public policy should focus on enabling innovation-led digital transformation. This could include targeted subsidies for the adoption of analytics tools, funding for training programmes in data capabilities, and support for collaborative platforms that connect firms with analytics providers and academic institutions. Moreover, investing in digital infrastructure, especially in sectors or regions with lower e-commerce adoption, could help reduce structural barriers to the implementation of BA.

From a managerial perspective, organisations should prioritise the integration of analytics into HRM and innovation processes. Although we cannot infer causality, the results indicate a significant positive correlation between the use of BA for continuous improvement and HR practices such as employee performance monitoring, training, and employee consultation. This suggests that organisations aiming to adopt analytics more broadly may benefit from first embedding it into workforce-related decision-making. Investing in HR analytics not only improves talent management but also creates the internal capability to scale data-driven decision-making across business functions. Likewise, companies should view BA not simply as a technological investment but as part of a broader organisational transformation that aligns people, processes, and digital tools around strategic goals.

Taken together, these recommendations point to the need for a dual approach: public support mechanisms that create favourable external conditions, and internal leadership that prioritises data capabilities, talent development, and innovation culture. By acting on both fronts, stakeholders can better position their organisations, and economies, to harness the full potential of BA as a driver of sustainable, continuous improvement. Ultimately, the successful adoption of BA depends not only on technological readiness, but also on a shared vision that embeds data-driven thinking into the strategic and cultural fabric of organisations.

7. Declaration of the use of AI

Declaration of Use of Generative Artificial Intelligence Tools in Final Degree Projects

I, Catalina María Marto Garzón, student of E6 Analytics at Universidad Pontificia Comillas, upon submitting my Final Degree Project titled "The impact of data analytics on continuous improvement in business processes and talent management: an analysis of the European context", declare that I have used the Generative Artificial Intelligence tool ChatGPT or similar code-based GAI tools **only** in the context of the activities described below:

1. **Critical perspective**: Used to find counterarguments to a specific thesis I intended to defend.
2. **References**: Used alongside other tools, such as Science, to identify preliminary references that I later cross-checked and validated.
3. **Code interpreter**: Used to perform preliminary data analysis.
4. **Multidisciplinary studies**: Used to understand perspectives from other communities on topics of a multidisciplinary nature.
5. **Literary and language style editor**: Used to improve the linguistic and stylistic quality of the text.
6. **Summarizer and explainer of complex books**: Used to summarize and understand complex literature.
7. **Reviewer**: Used to receive suggestions on how to improve and refine the work with different levels of rigor.
8. **Translator**: Used to translate texts from one language to another.

I affirm that all information and content presented in this work are the result of my individual research and effort, except where otherwise indicated and proper credit has been given (I have included appropriate references in the Final Degree Project and explicitly stated how ChatGPT or similar tools were used). I am aware of the academic and ethical implications of submitting non-original work and accept the consequences of any violation of this declaration.

Date: 08/04/2025
Signature: Catalina María Marti Garzón

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