International journal of applied management and economics
Vol : 02 , N° 14, June 2025
ISSN : 2509-0720

Bert And The Strategic Reinvention Of Morocco's Agri-Food Industry.

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Conflict of interest: The author reports no conflict of interest.

To quote this article: LAKHLIFI .Fz & ABDELLAOUI .M (2025) « Bert And The Strategic Reinvention Of Morocco's Agri-Food Industry »,

IJAME : Volume 02, N° 14 | Pp: 110 – 126.

Submission date : May 2025
Publication date : June 2025

DOI : 10.5281/zenodo.15551963

Abstract

This article explores how the BERT learning model in artificial intelligence improves the personalization of products and services in the industry by leveraging customer data to better adjust the offerings and increase consumer satisfaction. The literature review shows that BERT goes beyond traditional methods by detecting weak signals and analyzing natural language more precisely. Nevertheless, its concrete application in the industrial sector remains underexplored. To fill this gap, our study is based on seven semi-structured interviews conducted with marketing, supply chain, production, data, and quality experts. We conducted this study in the Casablanca-Settat region, part of the agri-food sector. The results highlight four key levers through which BERT optimizes personalization: early trend detection, facilitating the anticipation of customer expectations; better analysis of consumer feedback, offering finer and more relevant segmentation; improved demand forecasting, allowing for the limitation of unnecessary stocks and the avoidance of shortages; and more tailored and flexible recommendations, aligning the offer with the real needs of different customer segments. However, this study has limitations regarding the generalization of the results due to the small sample size. Future research should delve into the economic and operational impact of BERT and identify best practices for its gradual integration.

Keywords: Morocco, Strategy, Industry, AI, Qualitative Study, Algorithm.

1 Introduction

Innovation is one of the key directives that are part of the current Moroccan industrial policy, particularly the Industrialization Strategy 2023-2030, which aims to strengthen the companies competitiveness and accelerate the emerging technologies (Chebab, 2022). Innovation, therefore, plays, like the other directives, a central place in the country's growth (Tchékémian, 2022), of which artificial intelligence makes it a real precursor and stimulator (Bertolucci, 2024). We find deep learning among the most suitable technologies, which stands out for its ability to process massive volumes of data and extract sensitive information to strengthen organizational decision-making (Shinde & Shah, 2018). Its application in industry makes it possible to improve the value chain, optimize production processes, and increase product customization according to consumer expectations. Based on deep learning, the BERT (Bidirectional Encoder Representations from Transformers) model is establishing itself as a lever for exploiting customer data to refine the match between supply and demand (Ghojogh & Ghodsi, 2020).

1.1 Background

Industrial customization represents a major strategic transformation (Chandra et al., 2022), enabling companies to respond precisely to consumer expectations while optimizing their internal processes (Guo et al., 2020). Unlike traditional approaches based on standardization (Bonvoisin et al., 2020), customization relies on the advanced exploitation of data and emerging technologies such as artificial intelligence and predictive analytics (Leonard, 2024).

According to several scientific studies, the integration of intelligent systems in the production chain and inventory management allows for increased flexibility, thus reducing surplus costs and improving resource efficiency (Antomarchi et al., 2020). At the same time, personalization improves customer satisfaction by offering products and services tailored to individual preferences (Banda et al., 2023), which translates into increased loyalty and better brand value (Fikre et al., 2021). The strategic challenge is not limited to adapting the offer, but also extends to reconfiguring business models, promoting more agile production that is responsive to market trends (Khudhair et al., 2020). Recent research highlights that companies that are able to effectively exploit customer data and transform it into precise operational adjustments benefit from a sustainable competitive advantage (Sari et al., 2021). By combining predictive models and deep learning algorithms, personalization becomes not only a lever for differentiation, but also a driver of industrial performance (Moradi & al., 2022; Mellado & al., 2020), making it possible to reconcile innovation (Imane & al., 2024), efficiency and customer satisfaction. Thus, personalization is not limited to a simple adaptation of products, but profoundly redefines the relationship between industry and the consumer, establishing a new paradigm where flexibility and competitiveness are inseparable (Talmenssour, 2022).

Along the same lines, industrial personalization oscillates between two strategic approaches: mass customization, which optimizes efficiency without sacrificing flexibility, and individualized personalization, which maximizes the fit between the offer and the specific needs of customers (Ambada, 2015). The challenge is not to choose one over the other, but to find a balance between economies of scale and customer precision (Gi et al., 2021). Too broad customization dilutes perceived value, while too specific an adaptation burdens production and reduces profitability (Kedi et al., 2024). The most successful companies use data to intelligently segment their markets and deploy targeted flexibility, thus ensuring high-impact customization without compromising industrial efficiency (Iyelolu et al., 2024). Companies are leveraging purchase histories, feedback, and other data sources to refine their personalization strategies and maximize customer value (Taherdoost, 2023). Analyzing past purchases helps identify consumption patterns and anticipate individual preferences (de Jong et al., 2024). Customer feedback, whether from online reviews, surveys, or after-sales service, reveals latent expectations and specific dissatisfactions (Ghazouani & Samah, 2021). Integrating this data into predictive models improves the relevance of recommendations and optimizes the product offering (Scarano et al., 2023). Learning algorithms analyze purchasing behaviors in real-time and adjust proposals based on emerging trends (Bashar et al;, 2023). Unstructured data from social networks and customer interactions enrich these analyses by capturing weak signals (Halvadia & Menon, 2021; Budiyanto et al., 2022). Effective personalization relies on the ability of companies to transform this information into targeted actions (Kohtamaki et al., 2022). The exploitation of transactional and behavioral data is not limited to the optimization of recommendations but also influences inventory management and the adaptation of industrial processes (Tawse & Tabesh, 2021). Decision-making based on these insights helps reduce unsold items, improve the user experience, and increase loyalty (Oumaima et al., 2023). Thus, the strategic exploitation of customer data is not limited to classic segmentation but becomes a lever for differentiation and competitiveness (Maoulainine et al., 2024).

BERT is revolutionizing customer data analytics by capturing the nuances of language and interpreting implicit information often overlooked by traditional models (Aftan & Shah, 2023). Unlike traditional rule-based and keyword-based approaches, BERT understands context and relationships between terms. This ability enables more precise insights to be extracted from customer reviews (Korootev, 2021), social media interactions, and customer service requests (Asheampong et al., 2021). The algorithm identifies emerging trends and detects latent expectations without requiring direct human intervention (Asheampong et al., 2021). By leveraging unstructured data, BERT goes beyond the limitations of quantitative analytics by integrating a qualitative understanding of consumer preferences and frustrations (Catelli et al., 2022). This approach transforms personalization into a dynamic and proactive process, capable of adapting the offer in real-time. Optimization is not limited to product recommendations but extends to inventory management and marketing campaign adjustment (Haleem et al;, 2022). Integrating BERT into personalization systems reduces interpretation errors and improves the relevance of strategic decisions (Liu, 2023). The company no longer simply segments its customers, it anticipates their needs before they even express them explicitly (Zim et al., 2023). Despite its potential, studies on the concrete application of BERT in industry remain limited, particularly in the agri-food sector.

1.2 Research gap

According to the existing literature on our topic, current research on industrial personalization largely exploits machine learning models and predictive analytics to optimize the adequacy between supply and demand (Guo et al., 2020; Banda et al., 2023). However, these approaches mainly focus on segmentation and algorithmic optimization without really capturing the complexity of customer expectations and industrial dynamics (Khudhair et al., 2020).

Customer data integration still relies on rigid models, where the adaptation of the offer is limited to gradual adjustments rather than proactive anticipation of emerging needs (Tawse & Tabesh, 2021). Moreover, most studies treat personalization from a quantitative perspective, evaluating measurable performances such as increased sales or reduced logistics costs, without delving into the strategic and organizational implications of these transformations (Sari et al., 2021; Fikre et al., 2021).

The application of BERT in the industrial sector suffers from a clear lack of specific investigation. Current research demonstrates its effectiveness in analyzing customer data and interpreting weak signals, but it remains essentially limited to the fields of marketing and e-commerce (Catelli et al., 2022; Korootev, 2021). Few studies explore how BERT could transform industrial process management, supply chain decision-making, or production cycle optimization (Haleem et al., 2022). The impact of BERT on the qualitative understanding of customer expectations and its integration into production management systems remains largely underexplored, leaving a gap in the scientific literature (Asheampong et al., 2021).

This lack of a holistic approach limits the ability of companies to fully exploit BERT's capabilities to improve personalization, considering industrial constraints and organizational resistance (Zim et al., 2023). It then becomes imperative to develop applied research that does not simply evaluate the algorithmic performance of BERT but analyzes its real impact on industrial strategies, product innovation, and company competitiveness.

1.3 Problem statement

We aim to grasp the mechanisms of the BERT model, seeking an answer to the following problem: *How does the application of the Transformer BERT model optimize the personalization strategy of products and services in the industrial sector, by exploiting customer data to improve the adequacy of offers and customer satisfaction?* To answer this question, we adopted a qualitative approach. First, we analyzed the gaps in the existing literature to grasp the limits of current methods. Then, we conducted seven semi-directed interviews with experts from the agri-food sector, based in the Casablanca-Settat region, to identify the levers and obstacles related to the BERT adoption for industrial personalization. The results of this study shed light on the organizational, technical, and strategic challenges of this transformation and open the way to new optimization perspectives. Existing quantitative approaches evaluate algorithmic performance and the effectiveness of personalization models, but they don't explain enough how and under what conditions BERT transforms customer data management and the adequacy of offers to consumer expectations. This is why a qualitative approach allows us to build a more nuanced understanding of the mechanisms by which BERT influences decision-making, the flexibility of industrial processes, and the customer experience.

2 Methodology

To properly address our problem, we opt for a qualitative study. This study analyzes feedback from companies that integrate this technology to identify the levers and limits of its adoption and highlight the necessary developments in data management and industrial personalization. We have chosen to analyze the application of BERT in the agri-food sector, a strategic area for the Moroccan economy, due to its strong potential for innovation and digital transformation. The Casablanca-Settat region was chosen as a study area due to its central role in the national agri-food industry, bringing together numerous companies in the sector, from producers to distributors. This industrial concentration offers an ideal setting to observe the impact of new technologies on customer data management and the optimization of industrial processes. To ensure the relevance of our qualitative insights, we adopted a purposive sampling strategy, selecting interviewees based on their direct involvement with AI adoption or data-driven personalization within the agri-food sector. Profiles included production managers, data analysts, supply chain coordinators, and IT specialists from both large firms and SMEs. The selection aimed to capture a variety of organizational contexts and levels of technological maturity. However, this non-probabilistic approach introduces certain limitations. First, the findings may reflect the perspectives of more innovation-friendly actors, potentially overlooking resistance or skepticism from less digitized companies. Second, the geographic concentration in Casablanca-Settat—while strategic—might limit generalizability to other Moroccan regions with different infrastructural realities. Lastly, conducting interviews in French and dialectal Arabic, then translating them into English, may carry a risk of semantic distortion, despite our careful attention to preserving meaning during translation.

We conducted ten semi-structured interviews with various profiles to collect diverse points of view on the BERT application in industrial customization. Our interviews are structured as a dialogue in French and dialectical Arabic, which allowed us to translate the results into English. As the analysis progressed, we noticed that the answers were becoming redundant, which indicates that we had reached the data saturation threshold. Since the last three interviews have redundant answers, we analyzed seven interviews. We therefore stopped the collection, considering that the data collected was sufficient to answer the problem studied. This saturation prevents us from accumulating repetitive information, which would not have further enriched the results.

Table 1. Summary of the profiles interviewed

Interviewee	Experience	Key Expertise	Main Concerns	Duration
Chief Data & AI Officer	10 years	AI strategy & data-driven transformation	Cultural shift for AI adoption	1H13
Marketing Manager	5 years	Consumer behavior & market segmentation	Identifying implicit consumer needs	50 min
Production Manager	3 years	Industrial optimization & production efficiency	Balancing standardization & personalization	45 min
Customer Data Manager	6 years	Customer data analytics & predictive modeling	Merging qualitative & quantitative data	48 min
IT Director	19 years	IT infrastructure & AI integration	Ensuring AI scalability & security	1H
Supply Chain Director	18 years	Supply chain optimization & demand forecasting	Managing stock levels & logistics	1H02
Quality Manager	15 years	Product quality & regulatory compliance	Ensuring product consistency & sustainability	57 min

Source: Authors

We also performed sentiment analysis using the TextBlob library, a natural language processing (NLP) tool that measures the emotional polarity of a text. This approach is based on a lexical evaluation, assigning each word a sentiment value between -1 (negative) and +1 (positive), while a score closes to 0 indicates emotional neutrality. The overall sentiment of a text is evaluated using the following formula:

$$S = \frac{\sum_{i=1}^{n} Pi}{n}$$

→ S represents the overall sentiment score of the text,

→ P_i denotes the polarity of the i-th word,

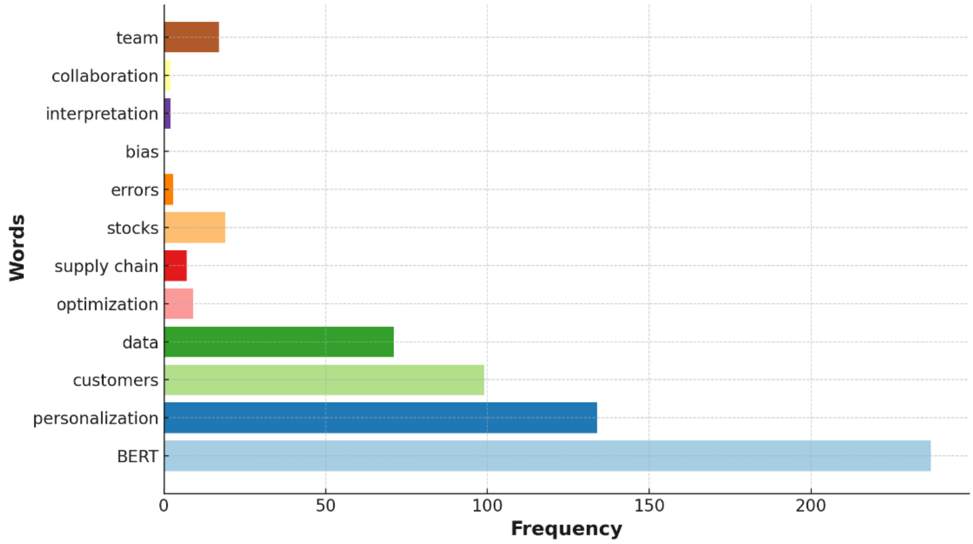
→ n corresponds to the total number of words analyzed.

3 Results analysis

3.1 Sentiment analysis

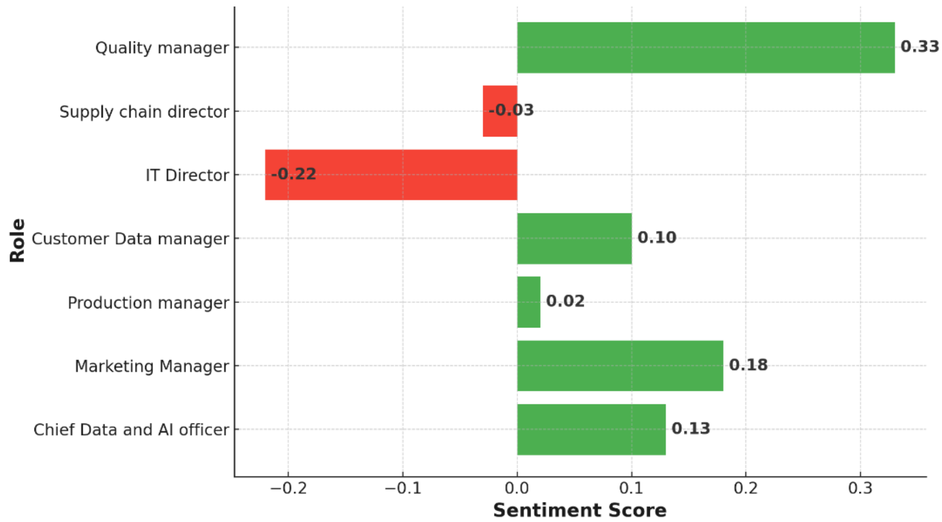
The word frequency (Figure 1) highlights BERT, personalization, customers, and data, confirming the importance of AI in adapting the offer to expectations.

Figure 1. Word frequency analysis



The word frequency (Figure 1) highlights BERT, personalization, customers, and data, confirming the importance of AI in adapting the offer to expectations. The terms optimization, supply chain, and stocks show their impact on logistics and resource management. However, errors, biases, and interpretations highlight the risks associated with excessive automation. Finally, the words collaboration and team remind us that AI must be integrated with a human and strategic approach to maximize its effectiveness.

Figure 2. Sentiment analysis score



This figure highlights the differences in interviewees' perceptions of BERT. There are marked differences between professions. Data and AI profiles (Chief Data & AI Officer, IT Director) show higher sentiment scores, reflecting enthusiasm for AI's personalization and analysis capabilities. Conversely, operational professions (Production, Supply Chain, Quality) show more moderate or neutral scores, revealing concerns about the limits of automation and industrial constraints. The red line indicating the neutrality threshold highlights an interesting trend: no profile shows a total rejection of BERT, but confidence levels vary. Professions related to customer relations and marketing seem to see strong potential, while supply chain and production players insist on the need for human supervision to avoid errors in data interpretation.

3.2 Content analysis

The vertical analysis of the seven interviews highlights varied perspectives on the implementation of BERT in the industrial sector, each influenced by the respondents' field of expertise and experience. A strategic and transformational approach is adopted by the Chief Data & AI Officer, who sees BERT as a fundamental lever for organizational intelligence and advanced personalization of offers. However, it is emphasized that the effectiveness of this technology relies on a cultural transformation within companies, requiring increased cooperation between departments. The Marketing Manager, on the other hand, emphasizes consumer behaviour and BERT's ability to detect implicit trends through natural language analysis. His point of view, although enthusiastic, remains exploratory, with rigorous quantification of the results still required.

A more operational perspective is adopted by the Production Manager, who raises the conflict between customization and standardization of industrial processes. A balance is sought between flexibility and efficiency, although some reservations remain regarding the ability of AI to adapt to specific production constraints. In the same vein, the Supply Chain Director highlights the opportunities offered by BERT in terms of inventory optimization and waste reduction, while insisting on the need for fine anticipation of consumer trends to avoid unnecessary shortages or surpluses. For his part, the Customer Data Manager adopts an analytical vision focused on data governance, highlighting the fusion of structured and unstructured data to better understand consumer expectations. A more technical perspective is provided by the IT Director, who addresses the challenges of integration, scalability, and fine-tuning of AI models, emphasizing the need for a robust and secure infrastructure.

Finally, the Quality Manager focuses his analysis on the management of standards and product compliance, seeing BERT as a tool for detecting anomalies more quickly and improving the quality perceived by consumers. However, concerns are expressed regarding the potential impact of excessive customization on the stability of formulations and product durability. Thus, although diverse approaches are observed, a consensus is reached on the usefulness of BERT to transform decision-making and refine customization. However, a gradual and thoughtful integration seems required to optimize its adoption and minimize internal resistance, while ensuring coherence between marketing, industrial and technological issues.

The horizontal analysis of interviews reveals common dynamics as well as significant divergences in the perception of BERT according to the roles and specific challenges of each respondent. A consensus emerges regarding the capacity of AI to capture weak signals and transform the analysis of customer expectations. It is recognized that traditional approaches based on purchase histories and surveys do not allow to accurately identify the deep motivations of consumers. As the Marketing Manager pointed out, “Our classic tools tell us what customers did, but not why they did it”. However, nuances appear in the way this technology should be integrated and exploited. A clear distinction is observed between data and marketing professionals, who see BERT as a standalone and scalable solution, and those from the manufacturing and supply chain sectors, who insist on the need for human control and gradual adoption. The IT Director, for example, believes that AI can be seamlessly integrated into existing systems, while the Supply Chain Director warns against a hasty deployment that could disrupt inventory management and logistics flows.

A notable tension is also identified between personalization and standardization. While the marketing and data teams defend the idea of advanced and continuous personalization, the Production Manager insists on industrial constraints, recalling that "we cannot afford to have 50 variants of the same product in the factory". Measured and industrializable personalization therefore seems to be the preferred path to avoid excessive complexity of the production chain. On the organizational level, it is widely accepted that BERT will only be able to deploy its full potential if it promotes increased collaboration between the different departments. Currently, data remains fragmented, and as the Customer Data Manager specified, "artificial intelligence must not be an isolated tool in the hands of a single department, but rather a transverse lever allowing more informed decision-making".

The impact of BERT on sustainability and resource optimization is also unanimously addressed. All respondents agree that improved consumption forecasts thanks to BERT could reduce unsold items and waste. The Quality Manager adds an interesting perspective by specifying that "better understanding customer expectations upstream would not only limit surpluses but also improve satisfaction and product perception". However, a debate persists on the risks linked to the overexploitation of data and algorithmic biases that could distort certain strategic decisions. The importance of a human interpretation of the analyses produced by BERT is therefore widely emphasized, to avoid pitfalls linked to decontextualized automatic recommendations. In conclusion, it emerges from this horizontal analysis that if BERT is unanimously perceived as a powerful and transformative tool, its integration can only be successful by respecting certain essential conditions: progressive adoption, reinforced inter-service collaboration, balanced management between customization and standardization and continuous human supervision to guarantee the relevance and reliability of the insights generated.

3.3 Discussion

The analysis of the interviews highlights the limitations of traditional personalization approaches and the growing interest in integrating BERT into the industry (Guo et al., 2020; Banda et al., 2023). However, its adoption does not follow a uniform trajectory. Perceptions vary depending on expertise and business challenges. On the one hand, data and marketing professionals see BERT as a strategic accelerator, capable of deciphering weak signals and refining product recommendations with unprecedented precision (Fikre et al., 2021; Asheampong et al., 2021). On the other hand, production and supply chain managers are more cautious. Their main fear? Excessive complexity of industrial processes. Too much flexibility in the offer can lead to a loss of operational efficiency, which raises a dilemma already highlighted in the literature: should we favor personalization or standardization? (Khudhair & al., 2020; Gi & al., 2021). The study confirms that this balance remains a major challenge for the successful adoption of BERT. In addition, another structural obstacle emerges: data fragmentation and departmental silos. Currently, information systems and customer databases remain dispersed across multiple departments, which hinders the optimal exploitation of BERT (Sari & al., 2021). As the Customer Data Officer pointed out, AI should not be an isolated tool, but a transversal lever promoting centralized and informed decision-making. This observation is consistent with the recommendations of Tawse & Tabesh (2021), who emphasize the importance of integrated data governance to avoid organizational silos and ensure consistency between marketing and industrial strategies. On an operational level, BERT transforms customer data analysis into a dynamic and predictive process. Unlike traditional systems, which rely mainly on static and reactive models, BERT identifies emerging trends, interprets implicit signals, and adjusts supply accordingly (Guo et al., 2020; Banda et al., 2023). This ability to capture non-explicit insights not only improves the personalization of recommendations but also strengthens the adequacy between supply and demand. The impact is direct: better inventory management, optimization of logistics flows, and reduction of unsold items. However, the adoption of BERT is not without challenges. While its benefits are clear, its integration raises organizational and technical questions. How can effective personalization be guaranteed without sacrificing industrial scale? How can algorithmic biases that could distort recommendations be avoided (Zim et al., 2023)? For BERT to be fully exploited, three essential conditions must be met: robust data governance increased interdepartmental collaboration, and continuous human control. Without these elements, strategic decisions risk being biased or misaligned with the realities on the ground. Ultimately, BERT is a powerful lever for industrial personalization, but its effectiveness depends on a delicate balance between technological innovation and operational constraints. Its adoption should not be seen as a simple transition to more advanced automation. It requires a redesign of organizational models, a redefinition of responsibilities, and a clear strategic vision. Only companies capable of navigating between flexibility and standardization, while maintaining rigorous control of data and AI, will derive a sustainable competitive advantage from this transformation.

4 Conclusion

This study highlighted the key role of BERT in optimizing industrial personalization, demonstrating its ability to detect weak signals in customer data and refine the match between supply and demand. Unlike traditional approaches, which rely mainly on static models and quantitative analyses, BERT introduces a new dynamic by capturing emerging trends and implicit expectations, often ignored by conventional tools. Its adoption transforms personalization into an intelligent and adaptive process, where decision-making is based on an in-depth analysis of consumer behaviours and more refined management of industrial resources.

However, the integration of BERT is not without challenges. Its effectiveness relies on rigorous data governance, a phased deployment strategy, and a delicate balance between personalization and standardization. Too much flexibility can compromise the efficiency of production lines, while an overly rigid approach limits the impact of personalization. This paradox is a central issue, to which companies must respond by adjusting their organizational model and technological capabilities. Despite these advances, this research has significant limitations. The limited number of interviews and the qualitative approach limit the generalization of the results. Future research should explore three major areas: the impact of BERT on industrial performance and competitiveness of companies, organizational resistance, and success factors for large-scale adoption, and interoperability between BERT and other AI tools to maximize its potential. Without a clear strategy and an integrated vision, the BERT adoption risks encountering resistance and not delivering all the expected gains. Ultimately, BERT represents a powerful lever, but its success does not rely solely on its technological capabilities. It is not simply a question of integrating AI into the value chain, but of redefining how industrial companies exploit data to anticipate, personalize, and optimize their processes.

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