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Artificial Intelligence and Cross-Functional Integration: An Exploratory Study of the Convergence between Management Control and Supply Chain in Moroccan Industries

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Abstract:
In a constantly changing industrial context, characterized by growing uncertainty, accelerated digitalization and intensified competition, companies are forced to review their internal management methods. This research focuses on the role of artificial intelligence (AI) as a strategic lever for integration between two key functions, historically compartmentalized: management control (MC) and supply chain management (SC). The aim is to understand how AI affects cross-functional coordination, the shared construction of performance indicators, and the evolution of professional roles at the interface of these two functions.

The study adopts an exploratory qualitative approach, based on ten semi-directive interviews with Moroccan industrial managers from a variety of sectors. Moroccan companies present structural and technological specificities, such as centralized decision-making and limited cross-functional integration, which make the context particularly relevant for analyzing how AI can support organizational transformation. Thematic analysis of the data reveals three major dynamics: (1) the synchronization of decision-making processes between MC and SC, made possible by the automation of information flows and the generation of shared alerts; (2) the co-construction of hybrid performance indicators integrating both financial and operational dimensions, facilitated by the use of dynamic dashboards; (3) the transformation of professional roles, marked by a rise in analytical skills, acculturation to AI and a redefinition of functional boundaries.

The results confirm the contributions of strategic alignment and dynamic capabilities theories, showing that AI is a lever for orchestrating decisions, strengthening performance governance and organizational adaptation. The study also mobilizes recent work to update these theoretical frameworks in the age of intelligent technologies. Beyond its theoretical contribution, this research proposes concrete managerial implications for companies seeking more agile and integrated governance. It invites us to rethink the logic of collaboration between functions, through the implementation of technological devices that promote transparency, transversality and co-responsibility in performance management.

Keywords: Artificial intelligence (AI), cross-functional integration, management control, supply chain, performance governance, strategic alignment, organizational transformation

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1. Introduction

Faced with increasingly complex economic environments and intensifying competition, optimizing internal functions has become a major strategic challenge for industrial companies. In this context, artificial intelligence (AI) is emerging as a transformative technology with great potential, capable not only of automating complex tasks, but also of generating predictive analyses and supporting real-time decision-making (Zhang, 2024; Hendriksen, 2023). While the benefits of AI have been widely documented in fields such as production, logistics and finance (Wamba-Taguimdje et al., 2020), its role as a lever for cross-functional integration has yet to be fully explored in the academic literature (Hendriksen, 2023).

Yet the relationship between management control and the supply chain appears to be a particularly relevant field of strategic study. These two functions, traditionally compartmentalized, work together to steer the organization's overall performance: management control aims to direct resources and ensure the consistency of financial objectives, while the supply chain organizes the physical and informational flows that determine responsiveness, service quality and customer satisfaction (Trkman et al., 2016). However, tensions between budgetary constraints and operational requirements are frequent, exacerbated by tools, indicators and often disjointed time horizons (Moll and Yigitbasioglu, 2019).

Integrating AI into this cross-functional space opens up new perspectives. In particular, it enables the automation of forecasts, real-time variance analysis, the simulation of logistical and financial scenarios, the construction of cross-referenced indicators, and the harmonization of decision-making processes. (Chatterjee et al., 2021). In this sense, AI can be seen as a catalyst for strategic alignment, capable of fostering coordination, decompartmentalizing professional responsibilities and transforming steering routines.

This raises a central question:to what extent and in what ways can artificial intelligence foster strategic integration between management control and the supply chain in industrial companies, by reconfiguring roles, decision-making processes and performance management systems?

To answer this question, this research adopts an exploratory qualitative approach, based on the analysis of ten semi-directive interviews conducted with supply chain, management control and information systems professionals. The respondents come from a variety of industrial sectors (automotive, chemicals, energy, pharmaceuticals, textiles, construction and public works, etc.) and from companies of different sizes (SMEs, mid-sized companies and large corporations), all based in Morocco. This diversity makes it possible to cross sectoral and structural perspectives to gain a better understanding of the cross-functional dynamics observed.

The Moroccan industrial context presents a number of specific features that make it particularly relevant for this study. Compared to more digitally mature economies, Moroccan companies often face structural constraints such as centralized decision-making, limited integration between departments, and uneven technological adoption. These challenges can hinder the effectiveness of cross-functional collaboration and the deployment of advanced tools such as AI. Studying how AI contributes to overcoming these limitations offers valuable insights into the potential of digital technologies to transform performance management in emerging contexts.

Three sub-questions more specifically guide the survey:

- How does AI help to synchronize decision-making processes between the two functions?
- To what extent does it encourage the construction of shared indicators and common reference systems?
- How does it transform cross-functional practices, roles and modes of collaboration?

By shedding empirical light on these dimensions, this article aims to enrich academic thinking on the dynamics of organizational integration induced by artificial intelligence, while proposing operational avenues for strengthening performance governance in a rapidly transforming industrial context.

2. Framework of the Study

This section presents the framework of the study by articulating both the theoretical foundations and the conceptual model developed. The research is based on the interconnection between management control and supply chain management — two strategic functions whose interaction plays a key role in enhancing organizational performance. This relationship is complex and requires a deeper understanding of how these functions interact, align, and potentially reinforce each other. Particular attention is given to the transformative role of advanced technologies such as artificial intelligence (AI), which serves as a catalyst for integration, coordination, and performance optimization across these domains.

2.1. Management control and the supply chain: interdependent strategic functions

In an industrial environment characterized by intensifying competition and increasingly complex flows, the coordination of internal functions is a major strategic lever. Among these, management control and the supply chain appear to be two essential functions whose interdependence conditions the organization's overall performance. Management control, as defined by (Anthony, 1965) and enriched by (Bouquin, 2008), is designed to support the implementation of strategy through decision-making, planning and management tools. It relies on tools such as budgeting, dashboards and variance analysis, and is based on a financial rationale geared to optimizing resources.

The supply chain manages all physical, informational and financial flows through industrial, logistics and commercial processes. Its logic is systemic, emphasizing responsiveness, coordination of internal and external players, and customer satisfaction (Mentzer et al., 2001; Christopher, 2016). Whereas management control operates according to formal, predefined cycles, the supply chain evolves in uncertain environments, requiring greater decision-making flexibility. This time lag, combined with the often-distinct systems of indicators, creates tensions between budgetary constraints and operational imperatives.

This complementarity, while potentially generating synergies, is often hampered by persistent organizational and cognitive compartmentalization. The lack of coordination between strategic planning and logistical execution leads to inefficiencies, particularly in terms of risk management and resource allocation. Consequently, the construction of an integrated management system, based on common frames of reference, appears to be a strategic opportunity that has yet to be fully exploited.

2.2. Strategic alignment between functions: definitions and challenges

Strategic alignment between controlling and the supply chain is important to ensure that actions are consistent and that the company's overall objectives are met. This alignment maximizes synergies and optimizes resources. In this section, we explore the notion of strategic alignment, the associated challenges and the impact of function integration on organizational performance.

Strategic management literature has long stressed the importance of functional alignment to ensure coherent decisions and organizational efficiency. The model proposed by (Henderson and Venkatraman, 1993) links business strategy, organizational structure and information systems. This framework has been enriched by (Chan and Reich, 2007), which identify four fundamental dimensions of alignment: structural (distribution of roles), functional (common objectives), technological (interoperability of systems) and cognitive (shared vision).

Applied to the relationship between management control and the supply chain, this framework highlights the need to synchronize timeframes, unify indicators and build shared decision-making processes. In addition to tools, this means implementing cross-functional cooperation logics, supported by connected information systems and a cross-functional culture.

Convergence can take the form of integrated indicators (Simons, 1994), such as overall logistics costs or margins per channel, enabling a coherent assessment of performance. However, the reality shows that this convergence remains limited by silo structures and governance that are ill-suited to cross-functional decision-making.

More recently, several studies have highlighted the importance of dynamic, adaptive alignment between functions, particularly in complex, uncertain environments. According to (Tallon and Pinsonneault, 2011), effective alignment relies not only on organizational structure, but also on the ability of functions to share objectives, data and action logics on an ongoing basis. (Queiroz et al., 2018) emphasize that this dynamic alignment becomes critical in digital supply chains, where speed of adaptation to events and decision-making agility depend on real-time collaboration between departments. In addition (Yu et al., 2018) show that the vertical and horizontal integration of data between management control and the supply chain promotes greater strategic responsiveness, by enabling more integrated governance of performance. These recent contributions reinforce the idea that strategic alignment can only be achieved if functions share a common informational infrastructure and are part of a collaborative governance logic geared towards global value creation.

This study therefore formulates the following research proposition (RP):

RP1. It is proposed that artificial intelligence may foster greater functional integration between management control and supply chain management, particularly by supporting the synchronization of decision-making processes and enhancing coordination between their objectives.

This proposition is based both on the theory of contingency (Donaldson, 2001) which asserts that organizational effectiveness depends on structural adaptation to context - and on recent contributions concerning the potential of AI to harmonize decision-making processes.

Artificial intelligence enables decisions to be structured, automated and synchronized in real time. Machine learning models facilitate the co-analysis of budget and logistics data, offering integrated scenarios for shared anticipation. This catalytic role is all the more crucial in industrial contexts marked by market volatility and unstable supply chains.

Recent studies, such as those by Baryannis et al., (2019), Choi et al., (2018), or even Pech et al., (2021), emphasize that AI promotes transparency, traceability and fluidity in decision-making. These capabilities strengthen functional alignment by bringing a common basis of understanding and action to traditionally separate functions.

2.3. Artificial intelligence as a catalyst for cross-functional convergence

Artificial intelligence, as an advanced analysis technology, profoundly transforms performance governance processes. It offers an enhanced ability to integrate financial and operational dimensions, through forecasting, simulation and dynamic visualization tools (Mehta et al., 2025; Chen et al., 2024).

This cross-referencing of information flows gives rise to the construction of a shared repository between functions, enabling a common reading and joint interpretation of performance.

In the context of the digital transformation of supply chains, the integration of artificial intelligence (AI) plays a crucial role in improving organizational performance. According to (Shahzadi et al., 2024), the adoption of AI in supply chain management improves demand forecasting, inventory management and overall decision-making capabilities, contributing to better organizational performance. In addition, AI facilitates collaboration between different business functions, enabling better coordination and faster, more accurate decision-making. This integration of AI also promotes the creation of shared performance indicators, combining financial and operational data for a more comprehensive assessment of business performance. In this way, AI acts as a catalyst for convergence between management control and supply chain functions, facilitating the co-construction of shared performance indicators. This dynamic opens the way to a second research proposition:

RP2. It is suggested that artificial intelligence could support the co-construction of shared performance indicators between management control and the supply chain, by enabling cross-functional data integration and interpretation.

The research of (Kaplan and Norton, 1996) have shown that shared indicators are powerful tools for strategic coordination. AI, with its ability to aggregate data from multiple sources, makes it possible to go beyond fragmented readings of performance. It facilitates the emergence of hybrid indicators integrating costs, service quality and risk levels.

These indicators are not simply produced automatically; they are the fruit of a process of cross-functional collaboration, reinforcing mutual understanding and the legitimacy of trade-offs. This approach is in line with the theory of dynamic capabilities (Teece et al., 1997), where performance is based on adaptability, continuous reconfiguration and the development of in-house skills.

Recent work (Bhattacharya et al., 2024; Mehta et al., 2025) shows that AI makes it possible to design intelligent dashboards, co-powered by different functions. These devices enable us to structure a common performance language and create cross-functional regulation routines.

Integrating AI into supply chain management not only automates processes, but also transforms the roles and professional practices of the players involved. Hendriksen (2023) emphasizes that the integration of AI into supply chain management is a socio-technical process, influenced by the way human actors interpret and make sense of AI systems. This transformation requires an adaptation of skills and professional roles, with a shift towards more analytical and strategic functions. Thus, AI does not replace professionals, but accompanies them in the evolution of their practices, reinforcing cross-functional collaboration and fostering a culture of transversality.

RP3. It is proposed that the integration of artificial intelligence contributes to transforming professional roles and practices in both management control and supply chain functions, fostering a convergence toward more analytical, collaborative, and strategic profiles.

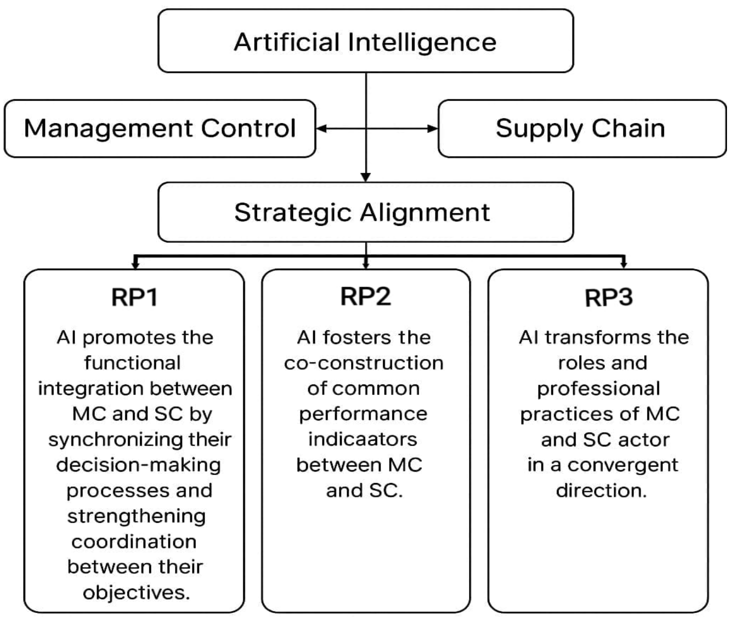
Finally, this last proposition is in line with the evolution of skills and professional identities. AI doesn't just automate; it reconfigures roles. The controller becomes a strategic analyst; the logistician, a budgetary partner. This functional hybridization is reinforced by collaborative tools, shared interfaces and increased expertise in data analytics.
Mehta et al. (2025), as well as Sethia (2024) emphasize that the introduction of cognitive technologies is leading to profound changes in practices and structures. Complementarity between professions is becoming a strategic issue, structured by the ability to build shared visions.

Artificial intelligence facilitates this transformation through its ability to make data intelligible, support collective decision-making processes, and decompartmentalize knowledge. From this perspective, it embodies a lever for organizational transformation based on cross-functionality, agility and the co-construction of performance in complex industrial environments.

In order to answer our research question, we formulate three research propositions concerning the role of artificial intelligence in the strategic alignment between management control and the supply chain. Figure 1 summarizes these propositions, highlighting the levers of functional integration, co-construction of performance indicators, and transformation of professional roles.

These research propositions are not intended to be statistically tested but rather serve as interpretive lenses guiding the qualitative analysis of the field data.

Figure 1: Conceptual model of strategic alignment between controlling and supply chain through artificial intelligence



3. Research methodology

This study adopts an exploratory qualitative approach, particularly suited to the analysis of an emerging and complex organizational phenomenon: the integration of artificial intelligence between management control and the supply chain. Conducted in the context of Moroccan industrial companies, this research aims to understand the cross-functional dynamics undergoing transformation. As emphasized by (Miles et al., 2019), qualitative research enables us to grasp the richness of social interactions, the logics of players, and institutional dynamics in context.

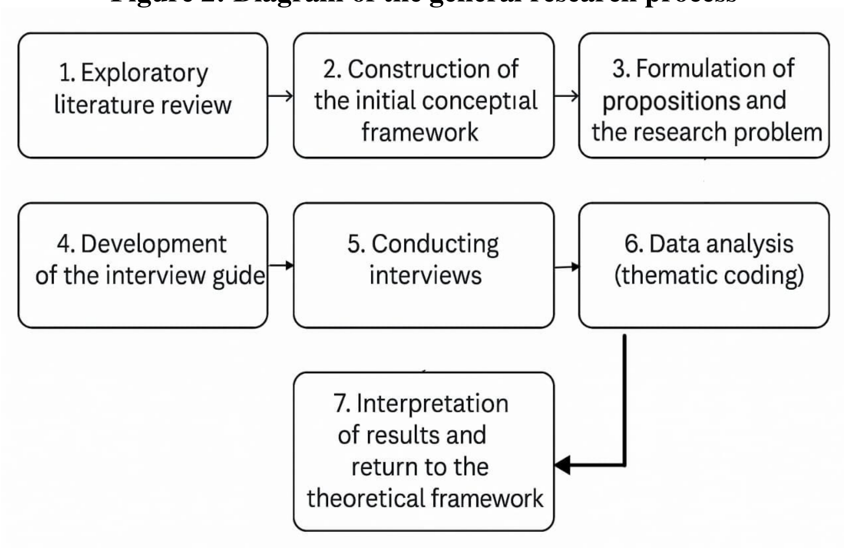
This methodological choice is also based on the recommendations of Yin (2017) and Gioia et al. (2013), that inductive approaches are relevant when conceptual frameworks are under construction. The aim of this research is therefore not to test pre-established causal relationships, but to explore the representations, practices and interpretative logics developed by actors confronted with a technology perceived as transformational.
Moreover, this methodological positioning responds to a central challenge: to understand the mechanisms of cross-functional coordination, professional evolution and cooperation logics in real industrial contexts, while taking into account sectoral, structural and cultural specificities.

3.2. The research process

The research was conducted using an inductive approach, focusing on the empirical observation of concrete practices. This choice is justified by the still unstable and little-theorized nature of the phenomenon studied: the use of AI in the dynamics of cross-steering between management control and the supply chain.

The process was divided into several phases as illustrated in Figure 2. Initially, an exploratory review of the literature identified three areas for investigation: concrete uses of AI, coordination practices between functions, and the transformation of roles and indicators. On this basis, an initial conceptual framework was developed to structure the data collection and analysis.

Figure 2: Diagram of the general research process



Research propositions were then developed, not for statistical validation, but as interpretive lenses to guide the understanding of the data collected. These research propositions structured the semi-directive interview guide, aiming to generate rich and reflective narratives around the identified conceptual dimensions. The interview guide was structured around four key dimensions: the uses of AI, coordination practices, the evolution of indicators, and the transformation of professional roles.

The field phase was conducted with ten Moroccan industrial companies that had embarked on a transformation process using artificial intelligence in their management functions. The Moroccan context offers a particularly rich setting for observation, given the structural and technological challenges companies face when integrating AI into traditionally compartmentalized functions. Participants were selected on the basis of their direct involvement in AI integration projects and their strategic role in the decision-making chain. Recruitment was based on direct solicitation, supported by professional networks and recommendations. The purposive sampling targeted profiles occupying key positions in management control, supply chain, data science or information systems functions. Interviews continued until theoretical saturation was reached (Glaser and Strauss, 2017). Interviews were conducted in compliance with ethical principles, with the informed consent of participants and the assurance of anonymity of responses.

Data triangulation was ensured by comparing points of view from different functions and by cross-sectoral comparison. Interviews lasted between 30 minutes and 1 hour, enabling in-depth exploration of the targeted dimensions. This approach guarantees consistency between the research question, the collection tools, the epistemological positioning and the analysis methods, thus ensuring the internal validity of the study and the relevance of the results obtained in their specific context.

3.3. Data collection and analysis

Data were collected using semi-structured interviews, a tried-and-tested method in management science for reconciling thematic structuring and openness to spontaneous discourse (Kvale and Brinkmann, 2008; Campenhoudt and Quivy, 2011). Respondents occupied strategic functions: management control, supply chain management, data science and information systems management, as illustrated in Table 1.

Table 1: Sample Description of Interviewees

Respondent	Role	Sector	Company Size	AI Maturity Level
R1	Management Controller	Automotive	Large Enterprise	Advanced
R2	Supply Chain Director	Agri-food	Medium Enterprise	Intermediate
R3	IT/AI Manager	Chemicals	Large Enterprise	High
R4	Data Analyst	Logistics	SME	Low
R5	Supply Chain Director	Energy	Large Enterprise	Advanced
R6	Management Controller	Electronics	Large Enterprise	Intermediate
R7	AI Manager	Construction	Medium Enterprise	Low
R8	Head of Management Control	Pharmaceutical	Large Enterprise	High
R9	Information Systems Lead	Plastics	Medium Enterprise	Intermediate
R10	Data Analyst	Textiles	SME	Low

Sectoral diversity, varying company sizes and levels of AI maturity were incorporated to ensure a plurality of perspectives, in line with the contextual sampling principles advocated by (Eisenhardt, 1989).

The thematic analysis of verbatims was based on the principles proposed by (Braun and and Clarke, 2006). A double level of reading was mobilized: a vertical analysis by actor, and a horizontal inter-case analysis to identify transversal recurrences. NVivo software was used to code the interviews, structure the emerging categories and cross-reference the data with the dimensions of the theoretical framework.

This approach was inspired by the research design of (Gioia et al., 2013), aimed at bringing the social constructs of the actors into dialogue with the theoretical frameworks of analysis, while ensuring interpretative rigor and fidelity to the statements collected.

4. Results

This section presents the main findings of the thematic analysis based on ten semi-structured interviews conducted with Moroccan industrial players, in relation to the three research propositions developed. The verbatims were coded and grouped into thematic categories using NVivo software. The results are presented along three axes corresponding to the dimensions explored: functional integration (RP1), co-construction of indicators (RP2) and transformation of professional roles (RP3).

4.1. Functional integration and process synchronization (RP1)

In all the interviews, respondents mentioned significant effects of AI, which appears to be a strong lever for coordination between supply chain (SC) and management control (MC) functions, irrespective of company size or business sector. In large Moroccan industrial companies—particularly in the automotive, energy, chemicals, electronics, and pharmaceuticals sectors—with a high or intermediate level of AI maturity, respondents report advanced synchronization between budgeting and logistics processes. AI tools are deployed to generate cross-planning scenarios, feed shared alerts, and coordinate operational and financial decisions in real time.

In Moroccan SMEs and mid-sized companies, such as those in the textile, construction, plastics or logistics sectors, respondents also mention a structuring effect of AI on functional exchanges, even with a lower level of technological maturity. The use of AI tools enables better anticipation of disruptions, increased coordination of logistics investment projects and greater transparency in arbitration.

All respondents point to a reduction in decision-making tensions, particularly in trade-offs related to logistics costs, stock levels, and joint planning. AI acts as a technical mediator, making data accessible and interpretable on a shared basis. Harmonized practices are also emerging, such as cross-validation of forecasts, alignment of reporting, and unified dashboard management. Respondents describe AI as a tool for streamlining exchanges between departments and better articulating decisions. Several interviews emphasize the ability of tools to generate common alerts, align planning schedules, and limit discrepancies between the budgetary vision and operational constraints.

These findings are confirmed by the analyses carried out in NVivo. Figure 3 below provides a visual illustration of the most frequent terms associated with coordination between SC and MC.

Figure 3: Word cloud on the theme of "AI Coordination"

Source: NVivo

Respondents describe AI as a tool for streamlining exchanges between departments and better articulating decisions. Several interviews emphasize the ability of tools to generate common alerts, align planning schedules and limit discrepancies between budgetary vision and operational constraints.

4.2. Shared performance indicators and steering tools (RP2)

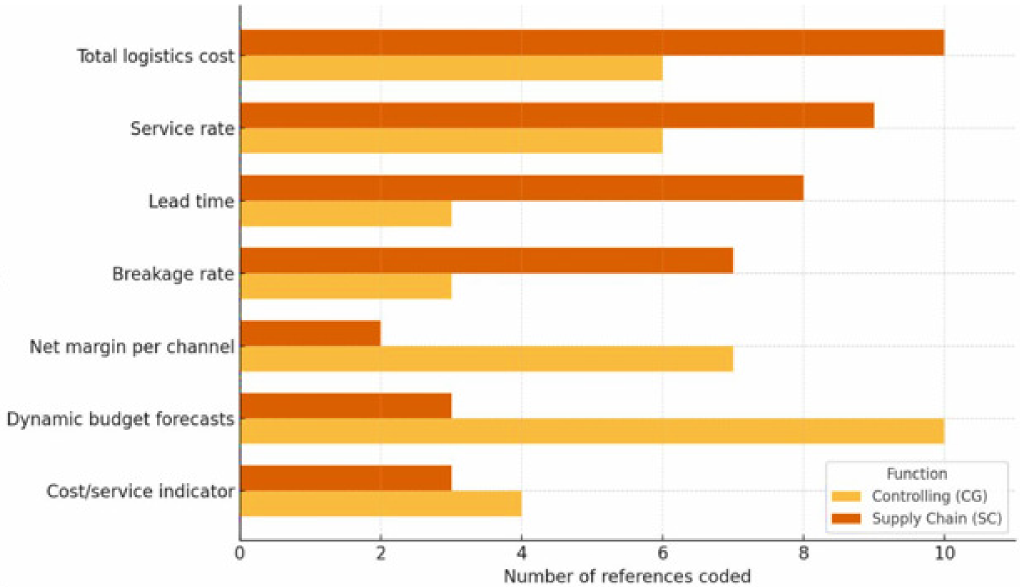
The results reveal that AI is enabling the emergence of hybrid and shared indicators, particularly in the automotive, chemical, pharmaceutical and electronics sectors. Large Moroccan companies with a high level of AI maturity use decision-support tools to cross-reference net margins, logistics costs, service rates and lead times. These integrated indicators are co-constructed by the MC and SC departments, often in conjunction with the IT department.

In medium-sized and smaller Moroccan companies, such as those in the agri-food, plastics, construction and logistics sectors, AI dashboards provide better visibility of the interdependencies between financial decisions and operational constraints. For example, the tool can be used to simulate the impact of logistics delays on budget forecasts, or to cross-reference service rates with unit margins.

Most respondents report that these common repositories have enabled them to move beyond siloed approaches. The unification of analytical platforms (Power BI, internal AI BI) and the development of jointly piloted tools have facilitated the adoption of cross-functional KPIs, adaptable to the specificities of each sector. The most frequently mentioned indicators are total logistics cost, service rate, and dynamic budget forecasts. Some respondents emphasize that AI enables shared visualizations to be produced, facilitating a joint reading of performance.

Coding extracts in NVivo show a high density around the themes of shared performance and joint indicators, as shown in Figure 4. The most frequently mentioned indicators are total logistics cost, service rate and dynamic budget forecasts. Some respondents emphasize that AI enables shared visualizations to be produced, facilitating a joint reading of performance.

Figure 4 : Thematic coding for "performance indicators"



Source : NVivo

4.3. Transforming professional roles and practices (RP3)

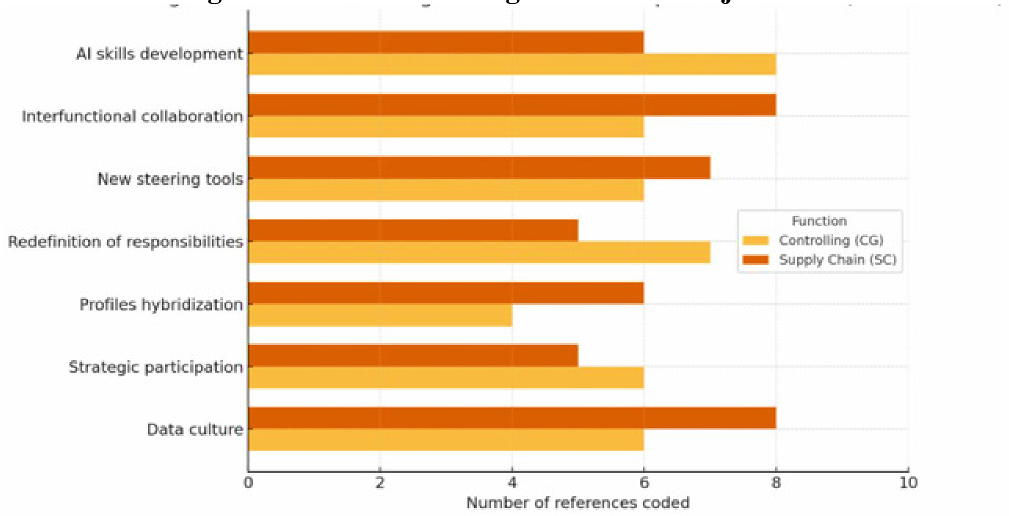
The interviews reveal that all sectors and all sizes of Moroccan companies report a marked transformation in professional practices. In large industrial structures, roles are becoming more strategic, with greater emphasis on predictive analysis, participation in investment decisions, and co-construction of AI strategies. Respondents from both MC and SC functions report a closer alignment of their missions, fueled by the shared use of AI tools.

In SMEs and mid-sized companies, the transformation is manifested by an increase in skills in visualization tools, the interpretation of dashboards, and the gradual integration of flow logic into budgetary thinking. Cross-functionality is becoming a functional norm, with increasing involvement in collaborative projects and inter-departmental committees.

This hybridization of skills is supported by training initiatives, the development of mixed career paths, and a more shared project culture. The boundaries between MC and SC are becoming increasingly permeable, particularly in environments where the constraints of responsiveness and agility are strong.

The recurring themes around this professional transformation were strongly represented in NVivo, as Figure 5 shows. Some players express the need to develop a more cross-functional culture, with a better understanding of the other function's technical or financial issues. Others emphasize the structuring effect of AI tools on their day-to-day role, with greater emphasis on predictive analysis, collaborative decision-making and real-time management.

Figure 5 : Thematic coding of transformed job roles



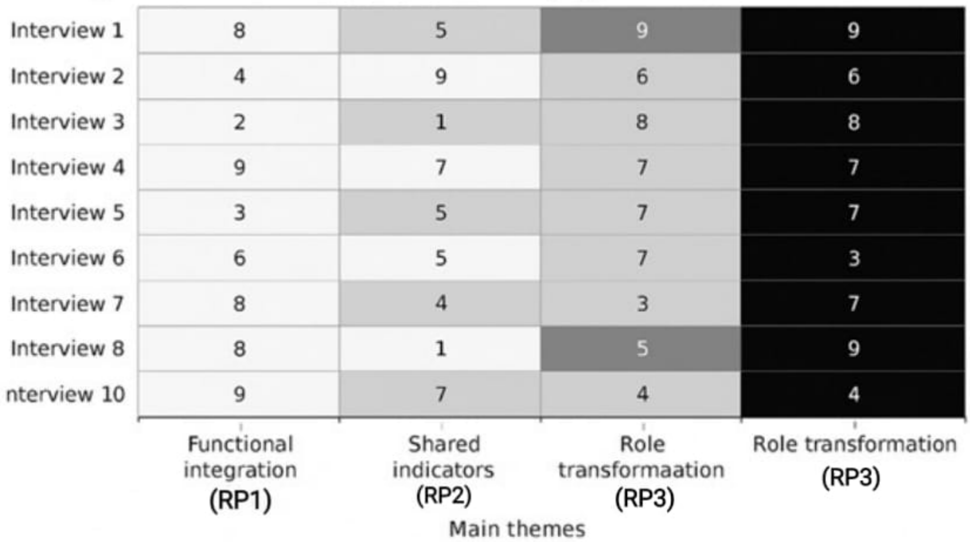
Source : NVivo

4.4. Cross-sectional interview coding

Figure 6 below presents a cross-visualization of the coding density of the three main themes in the ten interviews conducted. This table shows a relatively balanced coverage, with a strong recurrence of functional integration and shared indicators.

This table shows that all respondents mobilized at least two of the three key dimensions analyzed, confirming the cross-functional nature of the transformations observed at the interface between management control and the supply chain as a result of artificial intelligence.

Figure 6: Cross-Coding Matrix of Interview Themes by Research Propositions



Source: NVivo Analysis

4.4. Summaryof results by research proposition

This section synthesizes the main empirical findings from the thematic analysis of the ten interviews, in light of the three research propositions. Rather than confirming hypotheses in the statistical sense, the results highlight patterns and convergences that support the propositions formulated during the conceptual phase, as summarised in Table 2. The objective is not to validate universal laws, but to explore how the mechanisms described by respondents reflect the theoretical dimensions addressed.

Table 2: Validation of Research Propositions on the effects of AI in the dynamics between Management Control and Supply Chain

Research Proposition	Key Observations	Empirical Validation
RP1. AI promotes functional integration between MC and SC	Synchronization of planning processes, automation of data exchange, generation of shared alerts, alignment between operational and financial flows	Validated through convergence of narratives across sectors and firm sizes; saturation of themes in interviews; triangulation of perspectives (MC, SC, IT)
RP2. AI encourages the co-construction of performance indicators	Use of shared dashboards (e.g., Power BI), development of hybrid KPIs combining financial and operational data, creation of common repositories	Validation based on recurrence of shared tools mentioned by respondents, cross-functionality in KPI design, and consistent references to collaborative data practices
RP3. AI transforms professional roles and practices	Increased analytical skills, hybridization of roles, cross-functional collaboration, new project dynamics	Validated through thematic coding showing role evolution, frequent mentions of upskilling initiatives, and consistent discourse across interviewees about changing identities

Research Proposition 1 (RP1): Artificial intelligence fosters functional integration between management control (MC) and supply chain (SC). The analysis reveals consistent narratives indicating that AI supports the synchronization of decision-making processes across the two functions. Interviewees describe how AI tools facilitate joint planning, automate information flows, and reduce communication barriers. These patterns suggest that AI contributes to a more coordinated and less compartmentalized operational model, aligning with the concept of strategic cross-functional integration.

Research Proposition 2 (RP2): Artificial intelligence enables the co-construction of shared performance indicators between MC and SC. The empirical material highlights the emergence of hybrid KPIs, combining operational and financial dimensions, and jointly developed by cross-functional teams. Respondents point to the role of AI dashboards in enabling a shared understanding of performance through dynamic and visual tools. These elements reflect a shift from fragmented measurement systems to integrated governance logics, in line with the theories of performance alignment and collaborative control.

Research Proposition 3 (RP3): Artificial intelligence contributes to the transformation of professional roles and practices between MC and SC. Across all company types, participants emphasize a transformation in their professional practices driven by the use of AI. Thematic coding shows a recurrent focus on skill hybridization, collaborative routines, and the emergence of analytical competencies. The evolving roles suggest a transition towards more strategic and interconnected profiles, supporting the dynamic capability framework and the notion of organizational learning in digital environments.

Overall, the propositions formulated at the outset of the study are supported by recurrent empirical patterns found in the field data. AI appears not only as a technical tool but as a socio-technical enabler of integration, coordination, and transformation. These findings echo the methodological approach adopted, rooted in qualitative exploration and grounded interpretation, rather than statistical verification.

5. Discussion

The results of this study confirm several theoretical contributions while shedding contemporary light on the effects of AI on cross-functional dynamics. The structuring effect of AI on internal coordination ties in with the strategic alignment perspective developed by (Henderson and Venkatraman, 1993), while at the same time incorporating a contemporary update provided by recent works such as those by (Mithas et al., 2022) and (Pech et al., 2021), which emphasize the role of intelligent technologies in reducing organizational silos.

In this sense, AI appears to be a catalyst for fluid decision-making across functions, reinforcing the transparency and responsiveness of internal interactions. These observations are in line with (McAfee and Brynjolfsson, 2017), for whom AI plays a decisive role in improving real-time coordination through better availability of information. (Van der Aalst, 2016) goes further, showing that AI-induced process mining techniques enable continuous analysis of cross-functional processes, promoting more agile and adaptive governance.

The empirical findings show that AI concretely enables the synchronization of decisionsbetween supply chain and management control, notably through the automation of data exchanges and the generation of shared alerts. As one testimonial illustrates: “Coordination is more natural now. There's less unnecessary back-and-forth”. (Interview 3). This observation echoes those of (Choi et al., 2018) on AI as a lever for orchestrating decision-making flows.

Regarding performance measurement, our findings corroborate earlier works such as(Kaplan and Norton, 1996) but are also reinforced by the more recent work of (Mikalef et al., 2019) which demonstrate that AI solutions enable a hybrid reading of performance from multidimensional data. This approach enables dynamic management that simultaneously integrates financial, operational and strategic objectives. This is in line with the conclusions of (Raisch and Krakowski, 2021) AI's ability to combine automation and increased human capacity to improve overall governance. The use of shared, dynamic KPIs responds to a logic of integrated steering and strengthens the ability of functions to converge around common objectives. As one respondent put it, “AI now links flows to their budgetary impact.” (Interview 2).

Finally, the reconfiguration of professional roles observed in this study is in line with the analyses of (Mehta et al., 2025) and is updated by the results of (Dellermann et al., 2019), which show that AI is leading to an increase in analytical skills and a redefinition of the boundaries between functions. The players interviewed speak of an evolution towards hybrid, more strategic and interconnected profiles: “Training in data culture and AI logic.” (Interview 8). This evolution is in line with the dynamic of “T-shaped profiles” identified by (Colbert et al., 2016), where employees possess both in-depth functional expertise and cross-disciplinary data analysis skills. (Tarafdar et al., 2019) also emphasize this transformation, which they describe as a techno-organizational merger, redefining roles within the company.

These findings are in line with the dynamic capabilities theory of organizational transformation (Teece et al., 1997; Helfat and Peteraf, 2003), which underlines the importance of adaptation and learning in an evolving technological environment. Furthermore, the results allow us to invoke the notion of organizational ambidexterity (O'Reilly and Tushman, 2013), insofar as AI simultaneously supports the exploitation of existing resources and the exploration of new strategic opportunities. Taken together, these insights reinforce the idea that AI not only enhances functional efficiency but also transforms the very architecture of performance governance.All the results confirm that AI acts as a systemic lever, structuring tools, processes and roles in an integrated governance logic.

These dynamics must also be interpreted in light of the Moroccan context, where structural constraints, limited digital maturity, and functional compartmentalization often slow down transformation processes. The fact that AI fosters cross-functional convergence even in such settings highlights its potential as a driver of organizational change, especially in emerging economies.

These results pave the way for concrete managerial implications, presented in the next section.

5.1. Managerial implications

The results obtained call for in-depth reflection on the levers of managerial support in a context of increasing AI integration. Firstly, artificial intelligence cannot be seen as a simple technological solution. It implies a cultural transformation based on the decompartmentalization of functions, the fluid circulation of information and co-responsibility in the creation of value. Managers must therefore adopt a proactive posture of cross-functional coordination, encouraging structured dialogue and shared governance practices(Bhattacharya et al., 2024).

Secondly, skills development is becoming a central focus. Management control and supply chain functions need to converge around a common knowledge base: mastery of data analytics tools, understanding of algorithms, joint interpretation of indicators. This calls for cross-training programs, hybrid development paths and field experiments (Chen et al., 2024).

Thirdly, companies would benefit from institutionalizing intelligent steering systems, drawing on AI technologies to build shared, dynamic and scalable dashboards. These tools must become supports for collaborative decision-making, rather than instruments of unilateral control. They promote transparency, traceability and distributed responsibility.

Finally, the commitment of senior management is crucial. By promoting an integrated vision of performance, revising incentive systems and investing in common infrastructures, they ensure the strategic coherence of digital transformation.

These implications suggest that the success of AI-enhanced governance rests as much on organizational choices as on technological ones. AI thus becomes a vector for systemic change, a catalyst for enhanced cross-functional performance.

6. Conclusion

This research highlights the structuring role played by artificial intelligence in strengthening cross-functional dynamics between management control and the supply chain. Through a qualitative exploratory approach based on semi-structured interviews, analysis of Moroccan industrial companies from various sectors and sizes reveals that AI is not limited to a technical optimization tool, but acts as a vector of strategic alignment, facilitating the synchronization of decision-making processes, promoting the creation of shared repositories, and catalyzing the evolution of professional roles towards greater transversality and collaboration.

The results obtained confirm that this transformation is based on a dual dynamic: on the one hand, a technological infrastructure that enables the fluid, real-time circulation of information; on the other, a managerial determination to break down the barriers between functions and establish integrated management logics. The joint appropriation of analytical tools, intelligent dashboards and forecasting algorithms contributes to establishing a common language between departments, reinforcing the legitimacy of shared decisions and structuring global performance-oriented governance.

In addition, this study highlights the need to accompany the integration of AI with changes in professional skills and practices. Respondents mention a transformation of their missions towards more analytical, strategic and interactive roles, reflecting a growing hybridization between financial and operational logics. This hybridization, far from dissolving professional identities, seems to foster better mutual understanding and enhanced collective effectiveness.Taken together, these insights reinforce the idea that AI not only enhances functional efficiency but also transforms the very architecture of performance governance.

Ultimately, this research calls for artificial intelligence to be seen not just as a lever for efficiency, but as an opportunity to rethink modes of cross-functional cooperation in industrial organizations. It also highlights the value of an inductive methodological approach in capturing these complex transformations, making visible the lived realities and evolving practices of professionals. It invites researchers to continue investigating the conditions for successful integration, notably through the study of governance arrangements, resistance to change, and organizational learning trajectories. For practitioners, it provides the keys to designing more flexible, more connected management architectures, better aligned with the demands of a rapidly changing industrial environment.

6.1. Study limitations and future prospects

This study has a number of limitations that must be considered when interpreting the results. The first lies in its exploratory and qualitative nature, as well as the limited sample size (10 interviews), which restricts the ability to generalize the findings to all industrial organizations. Furthermore, the respondents were all drawn from companies that had already initiated AI integration projects, which may introduce an optimism bias in the feedback collected.

Although this research is based on qualitative data derived from actors' narratives, it offers an in-depth understanding of the transformation logics and cross-functional dynamics experienced in the field. However, these subjective perceptions do not allow for the objective measurement of AI’s numerical impact on performance. A complementary study combining qualitative and quantitative methods would thus enable more robust triangulation, allowing researchers to empirically validate the results and more precisely assess the measurable effects of AI on performance indicators.

While the findings are not statistically generalizable, they provide valuable theoretical insights into how AI fosters cross-functional integration between management control and supply chain functions. These insights could serve as a basis for future quantitative studies aiming to test the scalability and transferability of AI-driven coordination mechanisms across a wider range of sectors or geographical contexts.

In light of the findings, future research could explore how AI-enabled synchronization of decisions affects the quality and speed of cross-functional governance over time. In particular, it would be relevant to examine how these dynamics evolve in organizations at different levels of digital maturity, or in companies that are only beginning their AI transformation journeys.
It would also be beneficial to extend the study to other sectors (e.g., banking, retail, public services) to compare how industry-specific structures and functional cultures shape the integration of AI into managerial processes. Comparative studies between countries could also highlight the role of institutional, cultural, and technological factors in shaping AI adoption and coordination practices.

Finally, future lines of inquiry could investigate the impact of AI on power dynamics between functions, on the transformation of strategic skills, and on the organizational learning capacity induced by intelligent systems. The role of collaborative tools and the ethical dimension of AI in performance governance are also promising avenues for further academic exploration.

7. References

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