

**THE TRANSFORMATION OF MANAGEMENT CONTROL IN THE AGE OF
BUSINESS INTELLIGENCE AND ARTIFICIAL INTELLIGENCE: AN EMPIRICAL
STUDY IN MOROCCO.**

Souleymane MARIKO

Master's Student

National School of Business and Management-Settat

Hassan First University - Settat, Morocco

Morocco

Amal EL MALLOULI

Associate Professor

National School of Business and Management-ENCG Settat

Hassan First University - Settat, Morocco

Finance, Accounting and Management Studies Laboratory - Information and Decision

Support System

Morocco

Dounia EL BOUZAIID CHIKHI

Associate Professor

Moroccan School of Engineering Sciences

Honoris United Universities

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Abstract

Purpose: This study examines the extent to which the progressive integration of Business Intelligence (BI) and Artificial Intelligence (AI) tools is associated with the value-creation mechanisms of the management controller within organisations.

Methodology: Grounded in a theoretical framework drawing on Anthony (1965), Lambert and Sponem (2009), Moll and Yigitbasioglu (2019), Davenport and Harris (2007), and Bhimani and Willcocks (2014), the study adopts a hypothetico-deductive approach and a quantitative methodology, with a cross-sectional design and a non-probability convenience sample. A structured questionnaire was administered to 80 professionals in management control, internal audit, and financial management, primarily based in Morocco and France. The primary field of study is Company X, a large multinational group operating in Morocco.

Findings: The statistical analysis provides support for all four research hypotheses ($p < 0.001$). Analytical BI Maturity is significantly and positively associated with the value creation of the management controller's role, in particular as reflected in the quality of managerial information (H1: $r = 0.610$; $\alpha = 0.917$); Operational AI Integration is also positively associated with value creation, in particular as reflected in the controller's evolution towards a business-partner role (H2: $r = 0.621$; $\alpha = 0.847$); and Cognitive AI Capabilities are likewise positively associated with value creation, in particular as reflected in the strengthening of forward-looking performance-management capabilities (H3: $r = 0.571$; $\alpha = 0.791$). In addition, Digital Organizational Maturity – encompassing digital competencies, top-management support, and data quality – is itself positively and significantly related to value creation (H4: $r = 0.754$; $\alpha = 0.871$). These findings suggest that value creation in management control is associated with both the maturity of BI/AI tools and the organisational maturity required for their effective integration and use. As the design is cross-sectional and correlational, these results indicate statistical associations rather than causal effects.

Originality/Value: This research provides original empirical evidence by quantifying, in an under-explored predominantly Moroccan context, the strength of the association between Digital Organizational Maturity and value creation through BI/AI tools.

Research Limitations/Implications: the study is based on small, non-probability sample ($N=80$) which limits generalizability of findings. The cross-sectional design and bivariate correlations preclude causal inference and assessment of each explanatory variable's unique contribution. Future research could use larger samples, longitudinal designs, cross-country comparisons, multivariate analyses, while investigating the potential moderating role of organizational digital maturity.

Practical Implications: The findings suggest that BI/AI investment alone may not be sufficient for value creation, and the results are consistent with the view that parallel investment in digital competencies, managerial sponsorship, and data governance is also relevant. Prioritised operational recommendations are proposed as prospective suggestions by the authors for Company X and, more broadly, for organisations undergoing digital transformation of their management-control function, to be interpreted with caution given the sample size and the correlational design.

Keywords: Business Intelligence; Artificial Intelligence; Management Control; Value Creation; Business Partner.

Introduction

For decades, the role of the management controller within organisations has been the subject of recurring debate in both academic and professional circles. As early as 1965, Anthony defined management control as the process by which managers obtain assurance that resources are acquired and used efficiently and effectively to achieve organisational objectives, a foundational definition that placed the manager, rather than the controller, at the centre of the control system, thereby raising early questions about the actual value added by the management-control function.

For a long time, the function remained confined to technical tasks such as budgetary follow-up, variance analysis, and periodic reporting, operating within an essentially retrospective and verification-oriented logic. From the 1990s onward, however, professional and academic literature progressively promoted a renewed ideal: that of the management controller as a “business partner,” acting as a genuine co-pilot in strategic decision-making and a close advisor to operational managers. Nevertheless, as demonstrated by Lambert and Sponem (2009), this model often remains largely theoretical, with organisational reality revealing a function whose authority remains limited and distant from this idealised role.

It is against this backdrop that the rise of digital technologies has profoundly transformed the conditions under which management control is exercised. The emergence of Business Intelligence (BI) and Artificial Intelligence (AI) tools has revolutionised data collection, processing, and visualisation. Solutions such as Power BI, Tableau, and SAP Analytics Cloud now offer real-time performance monitoring, while machine-learning algorithms introduce predictive and automation capabilities. These developments reduce low-value-added tasks and open the way for a repositioning of the controller towards more analytical and strategic missions.

In Morocco, this digital transformation forms part of a broader dynamic of economic modernisation. Companies, particularly in the industrial, energy, and services sectors, are increasingly investing in advanced information systems, supported by national initiatives such as the “Morocco Digital 2030” strategy. Within this context, Company X – a large multinational group operating in Morocco and actively engaged in the digitalisation of its support functions – constitutes a particularly relevant field of study, offering a favourable setting for observing the ongoing transformation of management control.

Despite the abundance of research devoted to the roles of the management controller, few studies have examined the relationship between BI and AI tools and the value-creation mechanisms of this function, particularly within organisational contexts undergoing digital transformation. This question is nonetheless of major importance: while these technologies can improve information quality and automate certain tasks, they may either foster the emergence of a more strategic management controller or reinforce limitations already identified in the literature. This gap – the scarcity of empirical evidence on how BI/AI tools are jointly related to value-creation mechanisms, as opposed to merely digitalising existing tasks – constitutes the point of departure for this research.

In this perspective, the present study aims to make a dual contribution. On the one hand, a theoretical contribution, by enriching reflection on the digitalisation of management control and its value-creation mechanisms. On the other hand, a managerial contribution, by proposing concrete analytical insights to help organisations optimise their BI and AI tools in support of performance management.

The central research question can thus be formulated as follows:

« To what extent is the progressive integration of Business Intelligence and Artificial Intelligence tools associated with the value-creation mechanisms of the management controller within organisations? »

This question builds on prior work concerning the evolving role of the management controller and the positioning of the management-control function within the organisation (Lambert and Sponem, 2009), while extending it toward a still under-explored dimension: the relationship between BI and AI tools and the value-creation mechanisms of this function.

To answer this central question rigorously, several research sub-questions were formulated:

- **What are the mechanisms through which management control contributes to organisational value creation?**
- **What contributions do Business Intelligence and Artificial Intelligence make to the evolution of management-control practices?**
- **How are these tools integrated into organisations' concrete practices?**
- **To what extent are they associated with the value-creation mechanisms of the management controller?**

The originality of this research lies in its empirical testing of an integrated model combining four dimensions – Analytical BI Maturity, Operational AI Integration, Cognitive AI Capabilities, and Digital Organizational Maturity – within a predominantly Moroccan setting that remains largely absent from the existing literature, which is dominated by studies conducted in developed markets.

Finally, this paper is structured as follows. Section 1 reviews the literature on management control and its value-creation mechanisms, before presenting the theoretical foundations of BI and AI adoption. Section 2 presents the study's research variables, develops the research hypotheses, and introduces the conceptual framework. Section 3 details the methodology, including the research context, quantitative approach, and data collection and analysis procedures. Section 4 presents the empirical results for each hypothesis. Section 5 discusses these findings in light of the literature and proposes managerial recommendations. The Conclusion summarises the study's contributions, its limitations, and avenues for future research.

1. Literature Review

1.1. Underpinning Theory

Management control, as an academic discipline and a structured managerial practice, traces its origins to Frederick Winslow Taylor's pioneering work on scientific management at the end of the nineteenth century. It was, however, Robert Anthony's (1965) foundational contribution that gave the discipline genuine conceptual autonomy. Anthony defined management control as the process by which managers influence other members of the organisation to implement its strategies, a definition centred on influence and strategic alignment that marked a decisive break from the purely accounting-based approaches that had dominated until then.

Contemporary definitions reflect the growing complexity and richness of a function in constant transformation. Simons (1995) proposed a broader vision through the concept of “levers of control,” distinguishing four complementary devices: belief systems, which communicate the organisation's core values; boundary systems, which delimit the range of acceptable behaviours; diagnostic control systems, which track results against objectives; and interactive control systems, which foster learning and the emergence of new strategies. This approach highlights the behavioural and organisational dimension of control, beyond its purely technical aspects. Malmi and Brown (2008) similarly conceive management control systems as a package of

interrelated controls rather than as isolated devices, while French-language reference works (Bouquin, 2011; Löning et al., 2013) offer complementary treatments of the discipline, the latter emphasising the passage from management tools to organisational practices.

The work of Lambert and Sponem (2009) constitutes a major contribution to understanding the diversity of configurations the management-control function can take within organisations. Based on an in-depth empirical study of French companies of varying sizes, these authors identify four distinct models according to the controller's positioning within the organisation, the degree of integration into decision-making processes, and the nature of interactions with other organisational actors – most notably the aspirational, yet frequently unrealised, model of the controller as “business partner.”

This study's conceptual model draws on three complementary theoretical streams. Contingency theory (Lawrence and Lorsch, 1967) posits that the effectiveness of control systems depends on the fit between these systems and the characteristics of their organisational context. The Resource-Based View (Barney, 1991) suggests that BI and AI tools can constitute strategic resources generating sustainable competitive advantage, provided they are embedded in specific organisational routines. Actor-network theory (Latour, 1987) further allows the integration of digital tools to be understood as a complex social phenomenon involving multiple interactions between human and technological actors. Among these streams, the Resource-Based View is treated in this study as the central theoretical anchor, since it underpins both the treatment of BI/AI capabilities as technological resources (H1 to H3) and that of digital competencies, top-management support, and data quality as complementary organisational resources (H4); contingency theory and actor-network theory are mobilised as complementary interpretive lenses rather than as sources of separate testable hypotheses.

Beyond these theoretical foundations, the literature identifies five interdependent mechanisms through which the management controller contributes to organisational value creation: informational value (the production of relevant, reliable, and available information), strategic partnership (advisory input and co-construction of decisions), operational efficiency (cost control and process optimisation), performance management (the design of multidimensional measurement systems), and compliance and governance (regulatory adherence and risk mitigation). Table 1 summarises these mechanisms and their theoretical grounding. Value creation is also approached in purely financial terms, notably through Economic Value Added and related value-based management metrics (Stewart, 1991);

Table 1. Value-Creation Mechanisms of the Management Controller

Mechanism	Description	Key authors
Informational value	Production of relevant, reliable and available information	Moll & Yigitbasioglu (2019); Järvenpää (2007)
Strategic partnership	Advisory input, decision support and co-construction of strategy	Lambert & Sponem (2009); Burns & Baldvinsdottir (2005)
Operational efficiency	Cost control and optimisation of processes and resources	Anthony (1965); Kaplan & Cooper (1998)
Performance management	Design and use of multidimensional performance-measurement systems	Kaplan & Norton (1992); Simons (1995)
Compliance & governance	Regulatory adherence, financial-reporting reliability, risk management	IFAC (2009); Merchant & Van der Stede (2007)

Source: authors, adapted from Lambert and Sponem (2009), Anthony (1965), Kaplan and Norton (1992), and Moll and Yigitbasioglu (2019).

The rise of digital technologies has since reframed this system of mechanisms. Business Intelligence, a term popularised by Gartner analyst Howard Dresner in 1989, refers to the set of processes, technologies, and tools used to collect, integrate, analyse, and present data from multiple sources to support decision-making (Watson and Wixom, 2007). Gartner's (2021) five-level analytics-maturity model – descriptive, diagnostic, predictive, prescriptive, and augmented – provides a useful lens for situating an organisation's progress in appropriating these tools. Artificial Intelligence, defined by Russell and Norvig (2010) as the study of intelligent agents capable of perceiving, reasoning, and acting to optimise outcomes, extends this trajectory through machine learning, natural-language processing, and robotic process automation, enabling a shift from retrospective to predictive and prescriptive analytics (Davenport and Harris, 2007; Bhimani and Willcocks, 2014).

Taken together, BI equips the controller with improved information quality, richer analytical capability, and reduced time spent on routine tasks, while AI extends these gains toward predictive risk management, cognitive-process automation, and the personalisation of managerial information (Bhimani and Willcocks, 2014; Moll and Yigitbasioglu, 2019). Their effective integration nonetheless raises three recurring challenges documented in the literature:

data quality and governance, the adaptation of controllers' skill sets, and change-management resistance from both controllers and operational managers (Davenport and Harris, 2007; Bhimani and Willcocks, 2014).

More recent research extends these questions. A review of business intelligence and analytics in management accounting found that little research had examined the link between the two and proposed a framework for studying it (Rikhardsson and Yigitbasioglu, 2018), while the literature on digitalisation in management accounting and control discusses its potential implications for control practices and for the role of the controller (Möller et al., 2020). Research on AI-based accounting points to changes in the tasks, skills, and roles of accounting professionals, some tasks being performed by AI-based technologies while other roles require humans to make informed use of, and to some extent collaborate with, such technologies (Leitner-Hanetseder et al., 2021). More broadly, work on human–AI collaboration argues that automation and augmentation cannot be neatly separated and that organisations must manage the tension between them (Raisch and Krakowski, 2021). Generative AI has also attracted growing attention, with multidisciplinary perspectives identifying productivity opportunities as well as open questions about the skills, resources, and capabilities needed to handle it and about its ethical and legal implications (Dwivedi et al., 2023). Finally, the governance of AI and of data is increasingly treated as an organisational concern: organisational AI governance has been positioned in relation to corporate, IT, and data governance (Mäntymäki et al., 2022), and data governance has been conceptualised as the exercise of authority and control over the management of data, with the aim of increasing its value and minimising data-related cost and risk (Abraham et al., 2019). These strands are consistent with the importance attributed in this study to digital competencies, top-management support, and data quality as organisational conditions, although the present survey does not directly measure generative-AI use or AI-governance practices.

2. Research Variables, Hypotheses and Conceptual Framework

2.1. Research Variables

2.1.1. Independent Variables

The independent variable in this study is the level of integration of Business Intelligence (BI) and Artificial Intelligence (AI) tools within the organisation. Rather than treating this integration as a single undifferentiated construct, it is conceptualised along three

complementary dimensions, each capturing a distinct facet of how BI/AI technologies are embedded in the practices of the management-control function. These three dimensions are jointly captured, at the empirical level, through the composite BI/AI-integration score described in the Methodology section, while each is more specifically mobilised in the theoretical development of one of the hypotheses below. Digital Organizational Maturity is treated as a fourth, distinct independent variable of the tested model, and not as a moderator or a mediator.

2.1.1.1. Analytical BI Maturity

Analytical BI Maturity denotes the degree of maturity reached by the organisation in its deployment of Business Intelligence tools oriented toward the reliability, timeliness, and availability of managerial information (Watson and Wixom, 2007; Gartner, 2021). It captures the extent to which the organisation has moved from manual, fragmented reporting toward automated, consolidated, and consistently available dashboards.

2.1.1.2. Operational AI Integration

Operational AI Integration refers to the degree to which artificial-intelligence technologies – automation, anomaly detection, and process-optimisation tools – have been embedded in the organisation's day-to-day operational and decision-support processes. It is distinguished from Analytical BI Maturity by its focus on task execution and automation rather than on information production per se (Davenport and Harris, 2007; Bhimani and Willcocks, 2014).

2.1.1.3. Cognitive AI Capabilities

Cognitive AI Capabilities is distinguished from Operational AI Integration by its orientation toward higher-value-added, judgment-intensive activities: it captures the organisation's capacity to leverage AI not merely to execute tasks, but to enrich the analytical and advisory contribution of the management-control function (Davenport and Harris, 2007; Bhimani and Willcocks, 2014).

2.1.1.4. Digital Organizational Maturity

Digital Organizational Maturity refers to the set of organisational conditions that enable an organisation to translate its BI/AI capabilities into effective managerial use. It comprises three complementary components: the digital competencies of management-control teams (their ability to master and exploit BI/AI tools in day-to-day practice), the support provided by top management for digital initiatives (visible sponsorship, resource allocation, and strategic

prioritisation of BI/AI projects), and the quality of the data mobilised by these tools (reliability, completeness, consistency, and availability over time). Unlike the three preceding dimensions, which describe technological capabilities themselves, Digital Organizational Maturity captures the organisational resources that condition the effective appropriation of these capabilities. This conceptualisation draws on Barney's (1991) Resource-Based View, which suggests that a technological resource is more likely to generate durable value when associated with complementary organisational resources, as well as on Järvenpää's (2007) work on the central role of human capital in the appropriation of analytical tools. In the model tested here, it is therefore specified as an independent variable related directly to Value Creation;

2.1.2. Dependent Variable – Value Creation

The dependent variable, Value Creation, denotes the contribution of the management-control function to organisational performance in a context in which BI and AI tools are increasingly embedded in its practices. Consistent with the mechanisms identified in the literature review (Table 1), value creation is not restricted here to its financial dimension; it also encompasses informational, decisional, and organisational dimensions – improvements in the quality and usability of managerial information, the evolution of the controller toward a more advisory and strategic positioning, the strengthening of forward-looking, anticipatory steering of performance, and, more broadly, gains in operational efficiency, resource optimisation, and responsiveness (Lambert and Sponem, 2009; Kaplan and Norton, 1992; Moll and Yigitbasioglu, 2019). In the present study, this dependent variable is examined through four hypotheses (H1 to H4), each testing a direct association of Value Creation with, respectively, Analytical BI Maturity (H1), Operational AI Integration (H2), Cognitive AI Capabilities (H3), and Digital Organizational Maturity (H4). Each hypothesis is associated with a specific facet of Value Creation: information quality (H1), business-partner positioning (H2), forward-looking performance management (H3), whereas H4 relates Digital Organizational Maturity, an explanatory construct rather than a facet of the outcome, to Value Creation as a whole. To limit conceptual overlap between the explanatory constructs and the outcome, the facets of Value Creation measured in this study are restricted to perceived outcomes of the management-control function (information quality, business-partner positioning, and forward-looking steering); the broader aspects mentioned above (operational efficiency, resource optimisation, and responsiveness) are not measured as separate dimensions. These facets remain conceptually

close to the consequences attributed to the explanatory variables; The items, their sources, and the construction of the composite scores are described in Section 3.

2.2. Hypotheses Development

2.2.1. *Analytical BI Maturity and Value Creation*

Analytical BI Maturity denotes the degree to which the organisation has developed and embedded analytically oriented Business Intelligence tools – from basic reporting to more advanced diagnostic and predictive capabilities – within its management-control practices (Watson and Wixom, 2007; Gartner, 2021). Within the organisation, this maturity conditions the controller's ability to collect, consolidate, and exploit data drawn from heterogeneous operational and financial systems, and to convert it into dashboards and reports that are both reliable and timely.

As BI maturity increases, the informational function of management control is expected to be strengthened: data consolidation becomes more automated, reporting errors are reduced, and information becomes more consistently available to decision-makers (Moll and Yigitbasioglu, 2019). This improvement in the technical quality of information constitutes the first mechanism through which Analytical BI Maturity may be related to value creation, since it provides controllers and managers with a more solid informational base from which to identify performance gaps, emerging trends, and areas requiring corrective action.

This mechanism connects directly to the core mission of management control as defined by Anthony (1965): assisting managers in the efficient and effective use of organisational resources. A controller working with mature analytical BI tools is better positioned to fulfil this mission, since the reliability and timeliness of the information produced directly conditions the quality of the diagnoses and recommendations that follow. In turn, higher-quality information supports faster and more accurate managerial decision-making and facilitates a more rigorous piloting of organisational performance (Kaplan and Norton, 1992).

Taken together, these arguments suggest a coherent theoretical rationale: greater analytical BI maturity would improve the availability and reliability of managerial information; this improvement would strengthen the controller's diagnostic and decision-support capacity; and this strengthened capacity would translate into better-informed decisions, more efficient use of resources, and, ultimately, value creation within the organisation. On this basis, the following hypothesis is proposed:

H1: Analytical BI Maturity is positively and significantly associated with Value Creation, as reflected in the quality and availability of the managerial information produced by the management controller.

2.2.2. Operational AI Integration and Value Creation

Operational AI Integration reflects the extent to which artificial-intelligence technologies – automation, anomaly detection, forecasting algorithms, and process-optimisation tools – have been embedded in the organisation's operational and decision-support processes (Davenport and Harris, 2007; Bhimani and Willcocks, 2014). Within management control, this integration typically manifests through the automation of recurring tasks such as data reconciliation, variance detection, and routine reporting.

By absorbing a growing share of these low-value-added tasks, operational AI integration is expected to free time and cognitive resources that controllers can redirect toward higher-value-added activities (Lambert and Sponem, 2009). This reallocation constitutes the central mechanism through which Operational AI Integration may be associated with value creation: the controller's role is progressively repositioned away from routine verification and toward advisory support to operational and strategic decision-making.

This repositioning is closely tied to the aspirational model of the controller as “business partner” described by Lambert and Sponem (2009): a genuine co-pilot engaged in strategic decision-making and a close advisor to operational managers, rather than a purely retrospective verifier. The extent to which AI absorbs operational tasks is therefore a direct enabling condition for this evolution: as AI-driven automation improves the efficiency and reliability of operational processes, the controller is expected to gain both the availability and the credibility needed to engage more closely with managers and contribute to decisions, a proposition further supported by Bhimani and Willcocks (2014).

This theoretical chain of effects – automation of operational tasks, freed capacity, closer engagement with decision-makers, and stronger business-partner positioning – constitutes a plausible route through which Operational AI Integration may be associated with value creation within the management-control function. On this basis, the following hypothesis is proposed:

H2: Operational AI Integration is positively and significantly associated with Value Creation, as reflected in the management controller's evolution toward a business-partner positioning.

2.2.3. Cognitive AI Capabilities and Value Creation

Cognitive AI Capabilities capture the organisation's ability to mobilise advanced AI functionalities – the interpretation of complex data, the generation of recommendations, trend detection, and the elaboration of prospective scenarios – in support of decisional activities of a strategic nature (Davenport and Harris, 2007; Bhimani and Willcocks, 2014). Where Operational AI Integration concerns the execution of tasks, Cognitive AI Capabilities concern the organisation's capacity to extract insight and foresight from data.

Within management control, these capabilities allow the function to move beyond a purely retrospective posture – centred on variance analysis and periodic reporting – toward an anticipatory, scenario-based approach to performance steering. Predictive algorithms make it possible to anticipate risks and performance drifts before they materialise, while more advanced, prescriptive uses of AI support the simulation of alternative scenarios and courses of action (Davenport and Harris, 2007; Gartner, 2021).

This shift from retrospective to prospective steering constitutes the core mechanism through which Cognitive AI Capabilities may be associated with value creation. By equipping the controller with tools capable of anticipating outcomes rather than merely recording past results, the organisation strengthens its capacity for proactive risk management and its ability to intervene before performance deviations become significant, directly enriching the strategic contribution of the management-control function, in line with the strategic dimension of control emphasised by Simons (1995).

The overall theoretical reasoning can thus be summarised as follows: more advanced cognitive AI capabilities would improve the organisation's ability to interpret complex data and generate forward-looking insight; this ability would strengthen the controller's anticipatory steering role; and this strengthened role would support better-informed strategic decisions and improved organisational performance, which is consistent with an association with value creation. On this basis, the following hypothesis is proposed:

H3: Cognitive AI Capabilities are positively and significantly associated with Value Creation, as reflected in the management controller's forward-looking performance-steering capabilities.

2.2.4. Digital Organizational Maturity and Value Creation

Digital competencies, top-management support, and data quality are conceptualised as the three components of Digital Organizational Maturity. This proposition is grounded in Barney's

(1991) Resource-Based View, which suggests that a technological resource is more likely to generate sustainable value when associated with complementary organisational resources, and in Järvenpää's (2007) work on the role of human capital in the appropriation of analytical tools. In line with H1 to H3, H4 is tested here as a direct positive association between Digital Organizational Maturity and Value Creation, and not as a statistically modelled interaction effect. Digital Organizational Maturity is therefore specified, in the tested model, as an independent explanatory variable, and neither as a moderator nor as a mediator. Given the correlational design of this study (see Methodology), a formal test of moderation – via regression with interaction terms – is identified below as an avenue for future research, rather than treated as a finding of the present study. Accordingly:

H4: Digital Organizational Maturity, encompassing the management controller's digital competencies, top-management support, and the quality of available data, is positively and significantly associated with Value Creation.

Table 2. Summary of Research Hypotheses

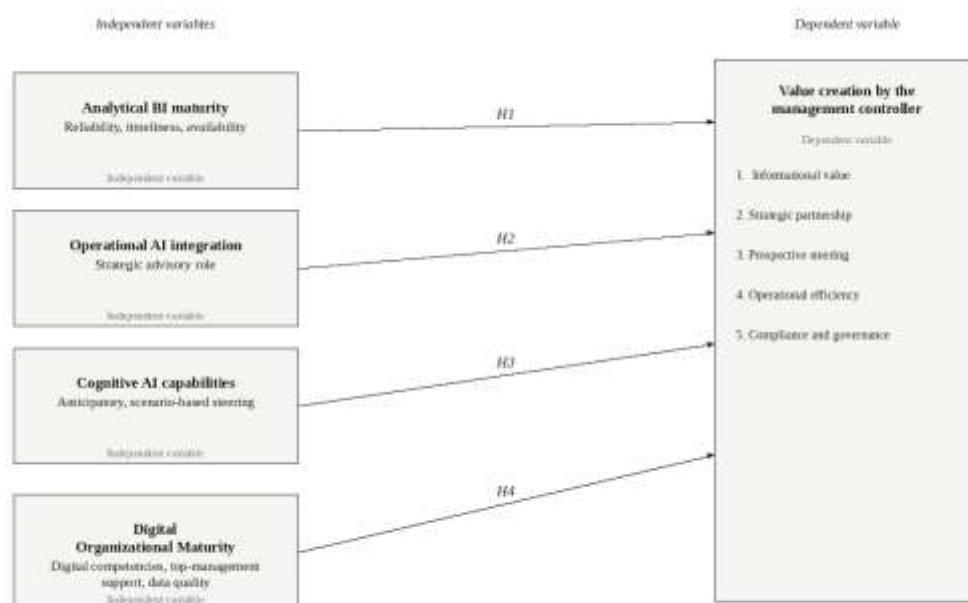
H	Statement	Theoretical grounding	Associated mechanism
H1	Analytical BI Maturity is positively associated with the quality and availability of managerial information	Moll & Yigitbasioglu (2019); Watson & Wixom (2007)	Informational value
H2	Operational AI Integration is positively associated with evolution toward a business-partner role	Lambert & Sponem (2009); Bhimani & Willcocks (2014)	Strategic partnership
H3	Cognitive AI Capabilities are positively associated with forward-looking, predictive steering capabilities	Davenport & Harris (2007); Bhimani & Willcocks (2014)	Performance management
H4	Digital Organizational Maturity is positively associated with Value Creation	Järvenpää (2007); Barney (1991)	Organizational enabling conditions

Source: authors, based on the literature reviewed above.

2.3. Conceptual Framework

The conceptual framework articulates three sets of constructs structured around the study's central research question. The first set comprises the three independent dimensions of BI/AI integration, Analytical BI Maturity, Operational AI Integration, and Cognitive AI Capabilities, which retain, in the figure below, the original labels of the underlying dissertation model. The second set comprises the three dependent facets of value creation directly tested in this study: information quality (H1), business-partner positioning (H2), and forward-looking performance management (H3), each linked respectively to Analytical BI Maturity, Operational AI Integration, and Cognitive AI Capabilities. The third set comprises Digital Organizational Maturity – encompassing digital competencies, top-management support, and data quality – which is hypothesised (H4) to be directly and positively associated with value creation, reflecting organisational enabling conditions rather than a moderating mechanism. Conceptually, each of the four dimensions – Analytical BI Maturity, Operational AI Integration, Cognitive AI Capabilities, and Digital Organizational Maturity – is hypothesised to be directly and positively associated with value creation.

Figure 1: Conceptual framework



Source: authors, adapted from the underlying dissertation.

3. Methodology

This research adopts a positivist epistemological stance, aiming to test empirically the relationships between observable variables through a hypothetico-deductive approach: hypotheses derived from the literature are confronted with empirical data. A quantitative methodology was privileged, relying on primary data collected through a structured questionnaire administered to management-control, internal-audit, and financial-management professionals. The study is cross-sectional: all data were collected at a single point in time.

The questionnaire comprised 33 closed items and 2 open-ended questions, organised into six thematic sections: respondent profile, BI/AI integration level (independent variable), information quality (H1), business-partner positioning and forward-looking steering (H2 and H3), digital organizational maturity (H4), and perceived obstacles and open commentary. All closed items were measured on a five-point Likert scale (1 = “strongly disagree” to 5 = “strongly agree”), ensuring standardisation and comparability of responses.

The target population comprised professionals in management control, finance, internal audit, and operational management within Francophone organisations. Company X served as the primary field of study, complemented by a broader sample of professionals from other organisations to allow for comparative perspective. A non-probability convenience and network sampling method was used, reflecting the absence of an exhaustive sampling frame and the objective of obtaining, within a constrained timeframe, sufficient diversity of professional profiles. The questionnaire was distributed through two complementary channels: Company X's internal professional network, and external finance and management-control professionals reached via LinkedIn.

At the close of data collection, 80 complete and usable questionnaires were retained for statistical analysis ($N = 80$), following a systematic consistency check of responses. The sample brings together management controllers, financial managers, internal auditors, and operational managers from organisations of varying sizes, located predominantly in Morocco and active across several sectors – a functional, sectoral, and geographic diversity that enriches the sample, although no subgroup (country or sector) analysis was conducted and the findings should be interpreted within the limits of the sample composition. The respondents were predominantly based in Morocco, and the results cannot be generalised to all Moroccan organisations. Given its size and its non-probabilistic nature, the sample is considered exploratory and makes no claim to statistical representativeness.

Data were processed using Microsoft Excel and Python (NumPy and SciPy libraries), combining descriptive and inferential analysis. Descriptive statistics (frequencies, means, standard deviations) characterised the sample and the distribution of responses across dimensions. Composite scores were then constructed for each dimension, and relationships between each independent variable and the dependent variable were tested using Pearson's correlation coefficient (r), with statistical significance assessed at the conventional two-tailed threshold of $\alpha = 0.05$.

The content validity of the questionnaire rests on the theoretical grounding of its items, developed from the management-control, BI, and AI literature reviewed above. The reliability of each measurement scale was assessed using Cronbach's alpha (α); values obtained ranged from 0.791 to 0.917, all exceeding the conventional 0.70 threshold and indicating good to excellent internal consistency across all constructs. Several precautions were taken to limit potential biases: response anonymity and a confidential academic framing to mitigate social-desirability effects, standardised item wording to limit interpretation bias, and the use of a five-point Likert scale to balance nuance with statistical tractability. These precautions aim at reducing certain biases but do not demonstrate the absence of common method bias (see limitations).

Operationalisation of the variables: Each construct was measured through closed Likert items belonging to the corresponding questionnaire section: the BI/AI integration level (Analytical BI Maturity, Operational AI Integration, and Cognitive AI Capabilities), information quality, business-partner positioning and forward-looking steering (the facets of Value Creation), and digital organizational maturity (digital competencies, top-management support, and data quality). The items were developed from the management-control, BI, and AI literature reviewed above. For each construct, a composite score was constructed and is reported on the same five-point scale as the individual items (Table 5, column M); The item-level evidence reported in Section 4.2 includes several items that describe perceived outcomes (for example, reduction of manual-processing errors or credibility with managers), which illustrates the conceptual proximity between some measured items and Value Creation discussed in Section 2.

Table 3. Summary of Methodological Choices

Dimension	Choice	Justification
Paradigm	Positivist	Objective, measurable reality; statistical validation of hypothesised relationships
Approach	Hypothetico-deductive	Theory → hypotheses → data collection → empirical validation
Method	Quantitative	Precise measurement of relationships between variables; replicability
Design	Cross-sectional, correlational	Single data-collection point; associations rather than causal effects
Instrument	Structured questionnaire (33 closed + 2 open items)	Standardisation; operationalisation of the four hypotheses
Sample	N = 80 (Company X network + LinkedIn)	Functional, sectoral and geographic diversity; exploratory sample, suited to bivariate analysis.
Analysis tools	Python (NumPy, SciPy) + Microsoft Excel	Pearson correlations, Cronbach's alpha, descriptive statistics
Reliability	Cronbach's alpha: 0.791–0.917	Good to excellent internal consistency across all four constructs
Bias controls	Anonymity, confidentiality, standardised wording	Aimed at reducing social-desirability bias; homogeneous response conditions; common method bias not excluded

Source: authors.

Table 4. Operationalisation of the Variables

Constructs	Role in the tested model	Questionnaire section	Item-level evidence	A
Analytical BI Maturity	Independent variable (H1)	BI/AI integration level; information quality (H1)	Reduction of manual-processing errors (M = 3.84); improved data consolidation (M = 3.90); facilitating actual decision-making (M = 3.52)	0.917
Operational AI Integration	Independent variable (H2)	BI/AI integration level; business-partner positioning (H2)	Enhanced credibility with managers (M = 3.52); reallocating time toward high-value-added tasks (M = 3.13) and toward advisory missions (M = 3.25)	0.847
Cognitive AI Capabilities	Independent variable (H3)	BI/AI integration level; forward-looking steering (H3)	Risk anticipation via predictive analytics (M = 3.44); scenario simulation (M = 3.25)	0.791
Digital Organizational Maturity	Independent variable (H4);	Digital organizational maturity (H4)	Top-management support (M = 3.15); data quality (M = 3.16); digital competencies (M=3.32)	0.871

Source: authors

4. Results

4.1. Sample Profile

Of the 80 valid respondents, management controllers formed the largest functional group (53.8%), followed by financial managers/CFOs (15.0%), internal auditors (10.0%), operational managers (10.0%), financial analysts/accountants (7.5%), and other internal-control functions (3.6%). This predominance of management controllers strengthens the relevance of the sample to the study's object, while the presence of complementary profiles – financial managers, auditors, and operational managers who use the information the controller produces – enriches

the analysis with multiple hierarchical perspectives. The sample is further diversified by sector, seniority, organisational size, and country of practice, with respondents based predominantly in Morocco (56.3%) and, to a lesser extent, in France (21.3%) and other countries (22.4%).

4.2. Hypothesis Testing

All four hypotheses were tested using Pearson's correlation coefficient between each independent-variable composite score and the Value Creation composite score, with internal consistency assessed via Cronbach's alpha. All four hypotheses are supported at $p < 0.001$. These results indicate statistical associations and do not establish causal effects.

Table 5. Summary of Hypothesis-Testing Results (N = 80)

H	Constructs	r	A	M (/5)	p	Decision
H1	Analytical BI Maturity	0.61 0	0.91 7	3.67	< 0.001	Supported
H2	Operational AI Integration	0.62 1	0.84 7	3.28	< 0.001	Supported
H3	Cognitive AI Capabilities	0.57 1	0.79 1	3.34	< 0.001	Supported
H4	Digital Organizational Maturity	0.75 4	0.87 1	3.24	< 0.001	Supported

Source: statistical analysis (Pearson, Cronbach's alpha). Note: all correlations significant at $p < 0.001$ (two-tailed, $N = 80$).

H1: Analytical BI Maturity. Hypothesis H1 is supported by a strong, highly significant correlation ($r = 0.610$; $p < 0.001$) and excellent internal consistency ($\alpha = 0.917$). Item-level analysis shows that respondents most strongly endorse the reduction of manual-processing errors ($M = 3.84$) and improved data consolidation ($M = 3.90$), which may suggest that the perceived benefits of BI/AI tools are more tangible at the operational level, although these cross-sectional data do not establish a temporal sequence. The item on facilitating actual decision-making scored comparatively lower ($M = 3.52$), suggesting that while technical information quality is perceived to improve, its translation into effective decision support may require additional enabling conditions.

H2: Operational AI Integration. Hypothesis H2 is supported ($r = 0.621$; $p < 0.001$; $\alpha = 0.847$), but the more modest composite score ($M = 3.28$) and the concentration of responses on “neutral” and “somewhat agree” categories point to a transition that appears to be underway but incomplete. The item on enhanced credibility with managers scored highest ($M = 3.52$), suggesting that the most tangible benefit associated with BI/AI tools so far is improved informational legitimacy rather than a deep change in the controller's mission. Items on reallocating time toward high-value-added tasks ($M = 3.13$) and toward advisory missions ($M = 3.25$) remain the least developed.

H3: Cognitive AI Capabilities. Hypothesis H3 is supported ($r = 0.571$; $p < 0.001$; $\alpha = 0.791$), the most modest of the three technology-related correlations, consistent with an intermediate level of analytics maturity. A decreasing gradient across items – from risk anticipation via predictive analytics ($M = 3.44$) to scenario simulation ($M = 3.25$) – is consistent with the progression toward advanced analytics described by Gartner's (2021) maturity model: organisations are increasingly using predictive analytics but have not yet systematically developed prescriptive, multi-scenario simulation capabilities.

H4: Digital Organizational Maturity. Hypothesis H4 records the strongest correlation in the entire model ($r = 0.754$; $p < 0.001$; $\alpha = 0.871$) – a result that does not by itself imply that this variable is causally the most important one. Item-level analysis reveals a paradox: top-management support is simultaneously the least-developed factor ($M = 3.15$; 30.4% agreement) and a component of the construct that records the strongest association with Value Creation, echoing Bhimani and Willcocks' (2014) argument that managerial sponsorship is a sine qua non of successful digital transformation. Data quality is the second most deficient factor ($M = 3.16$), consistent with Davenport and Harris (2007) on the primacy of data governance. Digital competencies, the third component of Digital Organizational Maturity, scored comparatively higher and is addressed separately below as a possible managerial lever. Despite this comparatively low absolute composite score ($M = 3.24$) and the lowest proportion of agreement (41.5%) across the four hypotheses, H4 exhibits the strongest correlation among the four hypotheses tested, suggesting that a comparatively low absolute level of these contextual factors does not preclude a strong association with the outcome variable. This finding resonates with Barney's (1991) Resource-Based View, which posits that organisational resources – even when only moderately developed – can become a decisive source of value when they enable the effective deployment of other capabilities within the firm.

Open-ended responses are broadly consistent with these quantitative findings. Respondents most frequently cited insufficient data quality, limited internal competencies, implementation costs, and organisational resistance to change as the principal barriers to BI/AI adoption. A majority of respondents anticipate that the controller's role will increasingly shift toward strategic partnership, advisory input, and decision support, while several emphasised that human interpretation of analytical outputs will remain indispensable despite growing automation.

5. Discussion of Key Findings

5.1. Interpretation in Light of the Hypotheses and Prior Literature

The pattern of results reveals a distinct profile across the four hypotheses. Improved information quality, associated with Analytical BI Maturity (H1: $r = 0.610$; $M = 3.67$), is the value-creation mechanism most favourably perceived by respondents, with the highest mean score among the three technology-related dimensions – although its correlation coefficient ($r = 0.610$) is marginally lower than that of Operational AI Integration (H2: $r = 0.621$). This pattern can be read as consistent with an interpretation in which BI tools first stabilise and make information more reliable before supporting more strategic uses – a sequencing consistent with the logic of technological maturation, whereby reliability precedes valorisation; it remains a theoretical interpretation, as the cross-sectional data do not allow a temporal sequence to be established. This finding is consistent with Moll and Yigitbasioglu's (2019) and Watson and Wixom's (2007) propositions on the informational contribution of BI, and echoes Lambert and Sponem's (2009) view of informational value as the most fundamental value-creation mechanism of the controller.

The evolution toward business-partner positioning associated with Operational AI Integration (H2) and the strengthening of forward-looking steering capabilities associated with Cognitive AI Capabilities (H3) are both statistically supported, yet their more modest composite scores signal a transition that is real but unfinished. This pattern is consistent with the “implementation gap” identified by Lambert and Sponem (2009) between the normative ideal of the business partner and organisational reality, and with Bhimani and Willcocks' (2014) argument that automating routine tasks is a necessary but not sufficient condition for role transformation. Earlier research on ERP systems points in a similar direction: Granlund and Malmi (2002)

report a moderate impact of ERP systems on management accounting, and Scapens and Jazayeri (2003) examine the relationship between ERP systems and management accounting change.

The strongest association among the variables tested is the one recorded for H4 ($r = 0.754$), which suggests that the value associated with BI/AI tools may not be attributable to the technology alone but is also strongly related to complementary organisational resources – digital competencies, top-management support, and data governance. In other words, Digital Organizational Maturity is itself directly and positively associated with value creation, and records the strongest relationship in the model. This finding resonates with the Resource-Based View (Barney, 1991) applied to digital transformation, which posits that organisational resources can become a decisive source of sustainable value when they enable the effective deployment of other organisational capabilities. Given the correlational design of this study, this result should be interpreted as indicating that Digital Organizational Maturity is, on its own, more strongly associated with value creation than the technological dimensions taken individually – rather than as evidence that organisational maturity statistically moderates the effect of BI/AI tools, or that BI/AI maturity and organisational maturity jointly determine value creation through some combined effect. Testing such an interaction directly is left to future research using larger samples (see Limitations and Future Research). The result should not be read as a causal ranking of the variables, nor as evidence that Digital Organizational Maturity is causally the most important determinant of value creation. The importance of professional judgement in interpreting analytical outputs also echoes the debate on whether the digitalisation of management accounting makes it wiser (Quattrone, 2016).

5.2. Managerial Recommendations

A distinction is drawn here between two levels. The implications directly supported by the results are limited to the following: the maturity of BI/AI tools and the level of digital organizational maturity are positively associated with perceived value creation, with the strongest association observed for Digital Organizational Maturity, and, among the components of Digital Organizational Maturity, respondents' ratings are lowest for top-management support and data quality. The recommendations below, by contrast, are prospective proposals by the authors; given the sample size ($N = 80$), the non-probability sampling, and the essentially correlational analysis, they go beyond what the data can demonstrate and should be read as suggestions for practice rather than as conclusions derived causally from the results.

The following recommendations, formulated as prospective proposals, are addressed to practitioners and finance functions engaged in digital-transformation projects.

First, the digital transformation of management control should be governed as a cross-functional organisational project, mobilising finance, human resources, and IT jointly around a coherent roadmap, rather than as a purely technical IT deployment, given the strong association observed for H4.

Second, investment in the digital competencies of management controllers appears to offer a lever for value creation, although the present data do not allow its relative effectiveness to be established: intensive training in BI platforms, financial data analysis, and generative-AI tools could be expected to support the dimensions examined in H1, H2, and H3 by enabling controllers to fully exploit available information, develop forward-looking analyses, and reinforce their business-partner positioning.

Third, data governance deserves priority attention. Top-management support and data quality emerged as the two least-developed dimensions of Digital Organizational Maturity; addressing them jointly, through visible managerial sponsorship of BI/AI initiatives alongside a formal Data Quality Management programme (reference-data standardisation, deduplication, master-data management), may be a relevant condition for realising the value perceived by respondents.

For Company X specifically, the authors propose a three-tier programme informed by the study's findings, with its effectiveness to be assessed through future implementation: (i) short term (0–6 months) – deploy a certifying digital-skills pathway for controllers and establish a formal data-governance framework; (ii) medium term (6–18 months) – optimise the integration between core enterprise systems and BI platforms to automate reporting, develop predictive-forecasting models for key indicators, and formally redefine controllers' job descriptions to include strategic-advisory responsibilities; (iii) longer term (18–36 months) – cultivate an organisation-wide digital culture through cross-functional workshops and pilot robotic-process-automation initiatives for closing and reconciliation processes.

Conclusion

Summary of the Study

This study set out to examine the extent to which the progressive integration of BI and AI tools is associated with the value-creation mechanisms of the management controller. Drawing on a theoretical framework combining contingency theory (Lawrence and Lorsch, 1967), the Resource-Based View (Barney, 1991), and the literature on the digitalisation of accounting and management control (Moll and Yigitbasioglu, 2019; Bhimani and Willcocks, 2014), a quantitative survey of 80 professionals – primarily based in Morocco and France, with Company X as the principal field of study – was conducted and analysed through descriptive and inferential statistics (Cronbach's alpha and bivariate Pearson correlations).

All four hypotheses were supported at $p < 0.001$, with reliability coefficients ranging from 0.791 to 0.917. Analytical BI Maturity is significantly and positively associated with value creation in the management controller's role, in particular as reflected in the quality of managerial information (H1: $r = 0.610$); Operational AI Integration is positively associated with value creation in particular as reflected in the controller's evolution toward a business-partner role (H2: $r = 0.621$); and Cognitive AI Capabilities are positively associated with value creation in particular as reflected in the strengthening of forward-looking, predictive steering capabilities (H3: $r = 0.571$). In addition, Digital Organizational Maturity – encompassing digital competencies, top-management support, and data quality – is itself positively and significantly associated with value creation, recording the strongest correlation among the variables tested (H4: $r = 0.754$). These findings are correlational and cannot be interpreted as evidence of causal effects.

Theoretical and Managerial Implications

Theoretically, this research extends the digitalisation-of-management-control literature by providing exploratory quantitative evidence consistent with Moll and Yigitbasioglu's (2019) propositions within an under-explored predominantly Moroccan, Francophone setting, and by providing correlational evidence consistent with the applicability of the Resource-Based View (Barney, 1991) to the digital transformation of management control – suggesting that a technological resource is more likely to generate durable value when associated with complementary organisational resources. Managerially, the results inform a prospective action programme – digital-skills development, data governance, systems integration, and cultural

change – that organisations undergoing similar transformations can adapt to their own context, as suggestions rather than as conclusions derived causally from the results.

Limitations and Future Research

This study has some limitations that should be considered when interpreting its findings. First, the sample is small ($N = 80$) and was obtained through non-probability convenience and network sampling; the study should therefore be regarded as exploratory, and its results cannot be generalised statistically. Furthermore, the sample is geographically heterogeneous: respondents were predominantly based in Morocco and, to a lesser extent, in France and other countries, so that the findings should be interpreted within the limits of the sample composition and cannot be generalised to all Moroccan organisations. Moreover, the design is cross-sectional and the analysis relies on Pearson correlations, which establish statistical associations but neither causal effects nor temporal sequences. Moreover, the analysis relies on bivariate correlations to examine the associations between the four independent variables and the outcome variable, while measurement reliability was assessed using Cronbach's alpha. Future research could extend these findings through factor and multivariate analysis to clarify each variable's unique contribution and complement the measurement assessment. Finally, since all variables were measured among the same respondents, at the same time, with the same questionnaire and mainly the same five-point Likert scale, common method bias may have inflated the observed correlations; the precautions taken (anonymity, confidentiality, standardised wording) reduce certain biases but do not demonstrate its absence.

Future research should therefore use longitudinal designs and larger, geographically more diverse samples, including comparisons between countries, estimate multiple regression or structural models including confidence intervals, and multicollinearity diagnostics, and test the potential moderating role of Digital Organizational Maturity, which was not tested here.

Concluding Remarks

The central conclusion of this research is, within the limits of an exploratory and correlational study, that the digital transformation of management control appears not to be fundamentally a technological phenomenon but a human and organisational one, in which technology may act as a catalyst whose perceived benefit is closely associated with organisational factors. BI/AI tools are strongly associated with the emergence of a more strategic, analytical, and forward-looking management controller, without on their own fully accounting for it. Investing in

technology without investing simultaneously in competencies, training, data governance, and change culture may risk confining the transformation to a superficial modernisation of interfaces, without a deeper renewal of practice. For Company X, as for organisations engaged in comparable trajectories, the challenge is therefore not to choose between the human and the machine, but to build a strategic alliance between the two – developing controllers capable not only of mastering analytical tools, but of interpreting their outputs with professional judgement, translating them into relevant strategic recommendations, and communicating them with the clarity and conviction of a trusted advisor.

BIBLIOGRAPHY

1. Abraham, R., Schneider, J. and vom Brocke, J. (2019), "Data governance: A conceptual framework, structured review, and research agenda", *International Journal of Information Management*, Vol. 49, pp. 424–438, doi: 10.1016/j.ijinfomgt.2019.07.008.
2. Agoudal, A., Kaizar, C., Gaga, D., Hilmi, Y., & Benarbi, H. (2025). PPP et contrôle de gestion: une alliance paradoxale entre contrôle public et logique privée. *International Journal of Research in Economics and Finance*, 2(8), 85-108.
3. Amer, M., Hilmi, Y., & El Kezazy, H. (2024, April). Big Data and Artificial Intelligence at the Heart of Management Control: Towards an Era of Renewed Strategic Steering. In *The International Workshop on Big Data and Business Intelligence* (pp. 303-316). Cham: Springer Nature Switzerland.
4. Amer, M., & Hilmi, Y. (2024). ERP and the Metamorphosis of Management Control: An Innovative Bibliometric Exploration. *Salud, Ciencia y Tecnología-Serie de Conferencias*, 3.
5. Anthony, R.N. (1965), *Planning and Control Systems: A Framework for Analysis*, Harvard Business School Press, Boston.
6. Barney, J.B. (1991), "Firm resources and sustained competitive advantage", *Journal of Management*, Vol. 17 No. 1, pp. 99–120.
7. Bhimani, A. and Willcocks, L. (2014), "Digitisation, 'Big Data' and the transformation of accounting information", *Accounting and Business Research*, Vol. 44 No. 4, pp. 469–490.
8. Bouquin, H. (2011), *Le contrôle de gestion*, 9th ed., Presses Universitaires de France, Paris.
9. Burns, J. and Baldvinsdottir, G. (2005), "An institutional perspective of accountants' new roles – the interplay of contradictions and praxis", *European Accounting Review*, Vol. 14 No. 4, pp. 725–757.
10. Carlos, K. M., Yassine, H., Driss, H., & Zahra, H. (2024). The Use of New Technologies in Management Control Systems and their Impact on Managerial Innovation. *Pakistan Journal of Life and Social Sciences (PJLSS)*, 22(2).
11. Davenport, T.H. and Harris, J.G. (2007), *Competing on Analytics: The New Science of Winning*, Harvard Business School Press, Boston.

12. Dounia, G. A. G. A., KAIZAR, C., AGOUDAL, A., BENARBI, H., & HILMI, Y. (2025). Transformation digitale et mutation du métier de contrôleur de gestion: revue de littérature et perspectives. *Revue Française d'Economie et de Gestion*, 6(3).
13. Dounia, G., Chaimae, K., Yassine, H., & Houda, B. (2025). ARTIFICIAL INTELLIGENCE AND BIG DATA IN MANAGEMENT CONTROL OF MOROCCAN COMPANIES: CASE OF THE RABAT-SALE-KENITRA REGION. *Proceedings on Engineering*, 7(2), 925-938.
14. Dwivedi, Y.K., Kshetri, N., Hughes, L. et al. (2023), ““So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy”, *International Journal of Information Management*, Vol. 71, article 102642, doi: 10.1016/j.ijinfomgt.2023.102642.
15. E. K. Hamza, A. Mounia, H. Yassine and I. Z. Haj Hocine, "Literature Review on Cost Management and Profitability in E-Supply Chain: Current Trends and Future Perspectives," 2024 IEEE 15th International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA), Sousse, Tunisia, 2024, pp. 1-6, doi: 10.1109/LOGISTIQUA61063.2024.10571529.
16. El Kezazy, H., & Hilmi, Y. (2023). The use of new technologies in management control systems and their impact on managerial innovation. *Ouvrage collectif: Innovation Managériale et Changement Organisationnel*.
17. el Kezazy, H., Hilmi, Y., Ezzahra, E. F., & Hocine, I. Z. H. (2024). Conceptual Model of The Role of Territorial Management Controller and Good Governance. *Revista de Gestão Social e Ambiental*, 18(7), e05457-e05457.
18. El Kezazy, H., & Hilmi, Y. (2023). Improving Good Governance Through Management Control in Local Authorities. *International Review of Management And Computer*, 7(3).
19. EL KEZAZY, H., & HILMI, Y. (2023). L'Intégration des Systèmes d'Information dans le Contrôle de Gestion Logistique: Une Revue de Littérature. *Agence Francophone*.
20. EL KEZAZY, H., & HILMI, Y. (2022). Towards More Agile Management: Literature Review of Information Systems as the Pillar of Management Control. *Revue Internationale du Chercheur*, 3(4).

21. EL KEZAZY, H., & HILMI, Y. (2024). Le contrôle de gestion territorial: levier de la bonne gouvernance. Essai sur le cas des collectivités territoriales au Maroc. *Alternatives Managériales Economiques*, 6(4), 287-305.
22. ESSAHLI, F. E., & HILMI, Y. (2026). Digitalisation et transformation du contrôle de gestion: vers un rôle de business partner. *Agence Francophone*, 689-706.
23. Gartner (2021), *Augmented Analytics Is the Future of Data and Analytics*, Gartner Research, Stamford.
24. Granlund, M. and Malmi, T. (2002), "Moderate impact of ERPS on management accounting: a lag or permanent outcome?", *Management Accounting Research*, Vol. 13 No. 3, pp. 299–321.
25. HILMI, Y. (2024). L'intégration des systèmes de contrôle de gestion via les plateformes numériques. *Revue Economie & Kapital*, (25).
26. Hilmi, Y. (2024). Cloud computing-based banking and management control. *International Journal Of Automation And Digital Transformation*, 3, 1-92.
27. HILMI, Y. (2024). Contrôle de gestion dans les banques islamiques: Une revue de littérature. *Recherches et Applications en Finance Islamique (RAFI)*, 8(1), 23-40.
28. HILMI, Y., & HELMI, D. (2024). Impact du big data sur le métier de contrôleur de gestion: Analyse bibliométrique et lexicométrique de la littérature. *Journal of Academic Finance*, 15(1), 74-91.
29. HILMI, Y., & KAIZAR, C. (2023). Le contrôle de gestion à l'ère des nouvelles technologies et de la transformation digitale. *Revue Française d'Economie et de Gestion*, 4(4).
30. HILMI Y. (2024). Le contrôle de gestion au niveau des clubs sportives : Approche théorique. *PODIUM OF SPORT SCIENCES*
31. IFAC – International Federation of Accountants (2009), *International Good Practice Guidance: Evaluating and Improving Governance in Organizations*, IFAC, New York.
32. Järvenpää, M. (2007), "Making business partners: a case study on how management accounting culture was changed", *European Accounting Review*, Vol. 16 No. 1, pp. 99–142.
33. KAIZAR, C., Dounia, G. A. G. A., & HILMI, Y. (2026). Intelligence artificielle et contrôle de gestion: leviers d'accountability et de gouvernance efficace. *Agence Francophone*, 576-607.

34. Kaplan, R.S. and Cooper, R. (1998), *Cost and Effect: Using Integrated Cost Systems to Drive Profitability and Performance*, Harvard Business School Press, Boston.
35. Kaplan, R.S. and Norton, D.P. (1992), “The balanced scorecard: measures that drive performance”, *Harvard Business Review*, Vol. 70 No. 1, pp. 71–79.
36. Kezazy, H. E., & Hilmi, Y. (2025). Promoting the Energy Transition Throughout Dealing with the Climate Change Issue. In *Digital Technology for an Innovative Energy Transition: Perspectives and Opportunities* (pp. 77-93). Cham: Springer Nature Switzerland.
37. Lambert, C. and Sponem, S. (2009), “La fonction contrôle de gestion : proposition d'une typologie”, *Comptabilité – Contrôle – Audit*, Vol. 15 No. 2, pp. 113–144.
38. Latour, B. (1987), *Science in Action: How to Follow Scientists and Engineers Through Society*, Harvard University Press, Cambridge.
39. Lawrence, P.R. and Lorsch, J.W. (1967), *Organization and Environment: Managing Differentiation and Integration*, Harvard Business School Press, Boston.
40. Leitner-Hanetseder, S., Lehner, O.M., Eisl, C. and Forstenlechner, C. (2021), “A profession in transition: actors, tasks and roles in AI-based accounting”, *Journal of Applied Accounting Research*, Vol. 22 No. 3, pp. 539–556, doi: 10.1108/JAAR-10-2020-0201.
41. Löning, H., Malleret, V., Méric, J. and Pesqueux, Y. (2013), *Contrôle de gestion : Des outils de gestion aux pratiques organisationnelles*, 4th ed., Dunod, Paris.
42. Malmi, T. and Brown, D.A. (2008), “Management control systems as a package – opportunities, challenges and research directions”, *Management Accounting Research*, Vol. 19 No. 4, pp. 287–300.
43. Mäntymäki, M., Minkinen, M., Birkstedt, T. and Viljanen, M. (2022), “Defining organizational AI governance”, *AI and Ethics*, Vol. 2 No. 4, pp. 603–609, doi: 10.1007/s43681-022-00143-x.
44. Merchant, K.A. and Van der Stede, W.A. (2007), *Management Control Systems: Performance Measurement, Evaluation and Incentives*, 2nd ed., Pearson Education, Harlow.
45. Moll, J. and Yigitbasioglu, O. (2019), “The role of internet-related technologies in reshaping the work of accountants: new directions for accounting research”, *The British Accounting Review*, Vol. 51 No. 6, article 100833.

46. Möller, K., Schäffer, U. and Verbeeten, F. (2020), “Digitalization in management accounting and control: an editorial”, *Journal of Management Control*, Vol. 31 No. 1–2, doi: 10.1007/s00187-020-00300-5.
47. Mounia, A. M. E. R., & HILMI, Y. (2025). Impact des systèmes ERP sur les rôles du contrôleur de gestion dans les établissements publics: étude qualitative exploratoire. *Revue Française d'Economie et de Gestion*, 6(9).
48. Mounia, A. M. E. R. Evolution des outils de contrôle de gestion suite au rapprochement université-entreprise: cas d'un établissement public. In *Actes du Colloque International Coopération Université-Entreprise: d'une recherche «sur» l'entreprise à une recherche «avec» l'entreprise*. (p. 64).
49. Quattrone, P. (2016), “Management accounting goes digital: will the move make it wiser?”, *Management Accounting Research*, Vol. 31, pp. 118–122.
50. Raisch, S. and Krakowski, S. (2021), “Artificial intelligence and management: the automation–augmentation paradox”, *Academy of Management Review*, Vol. 46 No. 1, pp. 192–210, doi: 10.5465/amr.2018.0072.
51. Rikhardsson, P. and Yigitbasioglu, O. (2018), “Business intelligence & analytics in management accounting research: status and future focus”, *International Journal of Accounting Information Systems*, Vol. 29, pp. 37–58, doi: 10.1016/j.accinf.2018.03.001.
52. Russell, S.J. and Norvig, P. (2010), *Artificial Intelligence: A Modern Approach*, 3rd ed., Prentice Hall, Upper Saddle River.
53. Scapens, R.W. and Jazayeri, M. (2003), “ERP systems and management accounting change: opportunities or impacts? A research note”, *European Accounting Review*, Vol. 12 No. 1, pp. 201–233.
54. Simons, R. (1995), *Levers of Control: How Managers Use Innovative Control Systems to Drive Strategic Renewal*, Harvard Business School Press, Boston.
55. Stewart, G.B. (1991), *The Quest for Value: A Guide for Senior Managers*, HarperBusiness, New York.
56. Yassine, H., Houmame, A. A., Amine, A., & Driss, H. (2024). Governance Optimization through Territorial Management Control in Local Authorities. *Pakistan Journal of Criminology*, 16(04), 93-110.
57. Watson, H.J. and Wixom, B.H. (2007), “The current state of business intelligence”, *Computer*, Vol. 40 No. 9, pp. 96–99.