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Artificial Intelligence and Smart Dashboards: A Lever for Decision-Making Performance in Management Control – An Empirical Study

Intelligence artificielle et tableaux de bord intelligents : Un levier pour la performance décisionnelle du contrôle de gestion. Étude empirique

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Abstract
This research examines the integration of artificial intelligence (AI) into management dashboards and its effect on the decision-making performance of management control within SMEs of the Souss-Massa region, in a context where traditional steering tools struggle to cope with the growing complexity of organizational environments. Theoretically, the study situates the emergence of intelligent dashboards at the convergence of artificial intelligence and Business Intelligence. Empirically, a sequential mixed-methods design was mobilized, combining an exploratory qualitative phase (nineteen semi-structured interviews) and a confirmatory quantitative phase (a questionnaire administered to eighty respondents, processed using PLS-SEM). The results confirm that artificial intelligence significantly improves the quality of intelligent dashboards ($\beta = 0.846$), which in turn strengthens the decision-making performance of management control ($\beta = 0.397$); data quality also exerts a direct and significant effect on this performance ($\beta = 0.486$), with the model explaining respectively 71.5% and 60.9% of the variance of intelligent dashboards and of decision-making performance. On the other hand, no significant moderating effect of data quality is observed, and the mediation of dashboards between AI and performance remains partial and conditional. These results indicate that artificial intelligence does not act on performance automatically: its value depends on its articulation with reliable data, suitable steering tools and the digital skills of users.
Keywords : artificial intelligence; management control; intelligent dashboards; decision-making performance; data quality
Résumé
Cette recherche examine l'intégration de l'intelligence artificielle (IA) dans les tableaux de bord de gestion et son effet sur la performance décisionnelle du contrôle de gestion au sein des PME de la région Souss-Massa, dans un contexte où les outils de pilotage traditionnels peinent à répondre à la complexité croissante des environnements organisationnels. Sur le plan théorique, l'étude situe l'émergence des tableaux de bord intelligents à la convergence de l'intelligence artificielle et de la Business Intelligence. Sur le plan empirique, une démarche mixte séquentielle a été mobilisée, associant une phase qualitative exploratoire (dix-neuf entretiens semi-directifs) et une phase quantitative confirmatoire (questionnaire auprès de quatre-vingts répondants, traité par PLS-SEM). Les résultats confirment que l'intelligence artificielle améliore significativement la qualité des tableaux de bord intelligents ($\beta = 0{,}846$), laquelle renforce à son tour la performance décisionnelle du contrôle de gestion ($\beta = 0{,}397$) ; la qualité des données exerce par ailleurs un effet direct et significatif sur cette performance ($\beta = 0{,}486$), le modèle expliquant respectivement 71,5 % et 60,9 % de la variance des tableaux de bord intelligents et de la performance décisionnelle. En revanche, aucun effet modérateur significatif de la qualité des données n'est observé, et la médiation des tableaux de bord entre l'IA et la performance demeure partielle et conditionnelle. Ces résultats indiquent que l'intelligence artificielle n'agit pas de manière automatique sur la performance : sa valeur dépend de son articulation avec des données fiables, des outils de pilotage adaptés et les compétences numériques des utilisateurs
Mots clés : intelligence artificielle ; contrôle de gestion ; tableaux de bord intelligents ; performance décisionnelle ; qualité des données

Introduction

The contemporary economic environment is characterized by heightened competition, the growing complexity of business activities and rapid technological transformation, which oblige organizations to strengthen their steering systems in order to secure their decision-making performance. Within this framework, management control constitutes an essential function, guiding managerial decisions so as to optimize the use of resources and monitor organizational performance. Among the tools that structure this function, dashboards occupy a central place: they synthesize the organization's key indicators and facilitate the monitoring of objectives, the evaluation of results and the detection of variances between forecasts and actuals.

However, faced with the exponential growth of data and the complexity of organizational environments, the traditional tools of management control are showing their limits, both in terms of information processing and in terms of analysis and anticipation capacity. Advances in artificial intelligence offer, from this perspective, new opportunities to strengthen the effectiveness of steering systems: advanced data analytics, machine learning and decision-support systems make it possible to automate certain analytical tasks, improve the accuracy of analyses and produce predictive information. Artificial intelligence thereby contributes to transforming traditional dashboards into more dynamic, interactive and intelligent systems, capable of monitoring performance in real time, detecting trends and anomalies, and supporting strategic decision-making.

It is within this context that the present research is situated. It aims to analyze the extent to which the integration of artificial intelligence into management dashboards contributes to the emergence of a new generation of steering tools and to the improvement of the decision-making performance of management control, drawing on the case of small and medium-sized enterprises (SMEs) in the Moroccan region of Souss-Massa. To answer this question, the article mobilizes a sequential mixed-methods approach, combining an exploratory qualitative phase and a confirmatory quantitative phase based on structural equation modeling (PLS-SEM). After a literature review covering management control, artificial intelligence and dashboards, the article sets out the research problem and objectives, details the methodology adopted, presents the results of the two empirical phases, and then discusses their theoretical and managerial significance.

1. Literature Review

Management control rests on two complementary notions: control, which aims to direct actions toward specific objectives, and management, which consists of optimizing the use of available resources. As early as 1965, R. N. Anthony defined management control as the process by which managers ensure that resources are obtained and used effectively and efficiently to achieve the organization's objectives. This initial, resource-centered conception has since evolved through successive contributions broadening it to formal information-based routines (Simons, 1995), a decision-support process spanning action (Teller, 1999), the formal and informal mechanisms shaping members' behavior (Otley, 2003), and the central role of information in linking decisions, actions and results (Bouquin, 2010). More recently, Alazard and Sépari (2021) and the IFACI–AMCF (2022) have extended it to risk management, sustainability and corporate social responsibility. This evolution reflects one underlying movement: management control, initially confined to cost and budgetary monitoring, now asserts itself as a strategic function oriented toward overall performance and decision support.

This conceptual shift finds a direct echo in the evolution of management control tools, foremost among which are dashboards. Having appeared in the early twentieth century as operational instruments for monitoring production, dashboards progressively shifted toward budgetary control, then performance monitoring by responsibility center, and, since the 1990s, toward a strategic steering logic enabling variance analysis and anticipation. Kaplan and Norton (1992), through the Balanced Scorecard, define the dashboard as a strategic management system translating vision and strategy into coherent performance indicators, while Gervais (2005) frames it as an information and steering instrument guiding managerial decisions. Several design methods (OAVR, OKAI, the Skandia Navigator, the Balanced Scorecard) now structure their development, each linking, according to its own logic, strategic objectives to operational indicators.

This transformation of steering tools cannot, however, be fully understood without placing it within the broader context of the technological revolution driven by artificial intelligence, which today constitutes one of the major pillars of the digital transformation of organizations. Its theoretical foundations date back to Turing's (1950) question of whether machines can think and to the 1956 Dartmouth conference, where McCarthy defined AI as the science and engineering of making intelligent machines; Minsky (1968) later emphasized its functional dimension, while Russell and Norvig (2010) centered their definition on the notion of an intelligent agent capable of perceiving its environment and acting accordingly. This foundation gave way to successive technological waves, from early expert systems and machine learning to deep learning, and, since 2018, to generative AI and large language models (Feuerriegel et al., 2024). Recent applications of these generative tools to accounting and management research, for instance in textual analysis (de Kok, 2025) and in the pursuit of transparent, explainable decision-support systems (Rane et al., 2023), illustrate a further shift toward AI systems able to interact more autonomously with, and more transparently for, their users.

At the technological level, AI rests on several complementary families of tools, machine learning, deep learning, natural language processing, computer vision, expert systems, whose applications span sectors as varied as industry, healthcare, finance and scientific research. Applied to management control, AI is profoundly transforming the traditional practices described above. Whereas the management controller historically devoted a disproportionate share of their time, on the order of 80%, to producing data rather than analyzing it, the automation made possible by AI reverses this ratio by freeing up time for higher-value-added activities. AI-assisted management control thus differs from traditional management control through resolutely predictive rather than reactive analysis, data reliability strengthened by the automatic correction of anomalies, and a strategic vision extended to anticipation and simulation. The empirical work mobilized in the literature, notably that on the use of ERP systems (Dechow and Mouritsen, 2005) and on the exploitation of Big Data, confirms that these technologies foster real-time analysis, the extraction of relevant information and the production of instant reporting, while requiring management controllers to develop new competencies in data science and data analysis.

It is precisely at the meeting point of these two dynamics, the evolution of dashboards and the rise of artificial intelligence, that the emergence of intelligent dashboards is situated, which constitutes the central theoretical foundation of this research. This convergence operates in particular through Business Intelligence (BI), which combines business analytics, data mining, visualization and data-management infrastructures in order to help companies base their decisions on reliable data. Tools such as Microsoft Power BI, Tableau (Salesforce) and SAP (Systems, Applications and Products in Data) Business Objects have thus established themselves as the main supports for designing modern dashboards, by making it possible to collect, structure and visualize data from multiple sources (ERP, CRM, external databases). The integration of artificial intelligence into these platforms considerably enriches their capabilities: it makes it possible to go beyond merely descriptive analysis to develop predictive and prescriptive functionalities, automatic anomaly detection, trend anticipation, action recommendations. Turban et al. (2018) as well as Rikhardsson and Yigitbasioglu (2018) show that this combination of BI and AI strengthens the quality of decision-making information and significantly improves organizational performance, by fostering greater responsiveness to change and a reduction of uncertainty.

These technological contributions do not, however, translate mechanically into decision-making performance. On the contrary, the literature stresses that the value of technological systems depends heavily on their integration into organizational practices. Granlund and Malmi (2002) thus show that technological systems improve operational efficiency without automatically transforming decision-making quality, while Dechow and Mouritsen (2005) insist that technology generates value only when it is embedded in suitable organizational and analytical practices. Conversely, Scapens and Jazayeri (2003) as well as Chapman and Kihn (2009) show that technological tools can significantly strengthen the performance of management control when they are integrated into well-structured steering systems, while acknowledging that these effects remain conditioned by the organization's level of digital maturity and by users' competencies. It is precisely this tension between the technological potential of AI and the organizational conditions of its valorization that structures the research problem of the present study.

2. Research Problem and Objectives

The theoretical framework set out above highlights a central tension: on the one hand, artificial intelligence and Business Intelligence offer real opportunities to transform traditional dashboards into intelligent tools capable of analyzing data in real time and producing more relevant information for decision-makers; on the other hand, the literature reminds us that this technological transformation produces its effects only on the condition of being embedded in suitable organizational practices and supported by quality data. This tension is particularly salient in the fabric of small and medium-sized enterprises, where technological resources, digital skills and the maturity of information systems often remain heterogeneous.

It is from this observation that the central question of this research is formulated: to what extent does the integration of artificial intelligence into management dashboards contribute to the emergence of a new generation of steering tools, and what implications does this generate for the decision-making performance of management control in the SMEs of the Souss-Massa region? This central question breaks down into two complementary research questions: to what extent does the integration of artificial intelligence transform management dashboards into a new generation of steering tools? And to what extent does the quality of these intelligent dashboards influence the decision-making performance of management control? The general hypothesis underlying this research is that the integration of artificial intelligence technologies into management control can contribute to improving the quality of the information used in the decision-making process and to strengthening the effectiveness of performance steering within organizations, without this effect being necessarily direct or automatic.

To address this research problem, this study pursues a general objective consisting of analyzing the role played by artificial intelligence in the evolution of management control practices, in particular through the emergence of intelligent dashboards capable of processing data in real time and facilitating decision-making. This general objective breaks down into four specific objectives, which structure the entire empirical approach: first, to examine, on the basis of the perceptions and practices of management control professionals, the concrete modalities of integrating artificial intelligence into steering tools; second, to identify the relevant conceptual dimensions , beyond those derived from the literature review alone , likely to explain the relationship between artificial intelligence, intelligent dashboards and decision-making performance, and to derive from them a conceptual model adjusted to the context under study; third, to test empirically, using structural equation modeling, the direct and indirect relationships linking artificial intelligence, the quality of intelligent dashboards, data quality and the decision-making performance of management control; fourth, to discuss the organizational and human conditions , in particular the digital skills of management controllers , that condition the effective valorization of these technologies within the SMEs of the Souss-Massa region.

3. Research Methodology and Field of Investigation

This research adopts a post-positivist stance, following a hypothetico-deductive approach based on the formulation of hypotheses drawn from the literature and their subsequent confrontation with field reality. Unlike strict positivism, for which only observable and measurable reality can produce scientific knowledge, post-positivism recognizes that reality can be apprehended imperfectly and influenced by the context of observation, while maintaining the requirement of scientific rigor. This stance, close to what Miles and Huberman (1991) call "moderated positivism," makes it possible to articulate the explanation of generative mechanisms, in this case, the mechanisms by which artificial intelligence transforms management control, with the understanding of the perceptions of field actors.

This epistemological stance translates, at the methodological level, into the use of a mixed approach combining an exploratory qualitative phase and a confirmatory quantitative phase, regarded by Johnson and Onwuegbuzie (2004) as the "third movement" of scientific research, alongside strictly qualitative and quantitative approaches. This choice is justified by the complementarity of the two approaches: the qualitative phase allows an in-depth understanding of actors' practices and perceptions, while the quantitative phase makes it possible to test statistically the relationships between the variables of the model. According to the typology proposed by Venkatesh et al. (2013), this research follows a developmental logic, in which the qualitative study served to refine the conceptual model and to formulate the hypotheses subsequently submitted to quantitative validation. Concretely, the qualitative phase was conducted through nineteen semi-structured interviews with management control professionals, carried out remotely and preceded by an explanatory note guaranteeing the confidentiality of the exchanges. The quantitative phase then relied on the administration of a structured questionnaire, processed using the PLS-SEM method with the SmartPLS software. The articulation of these two approaches strengthened the validity of the results obtained and ensured greater coherence between the theoretical framework mobilized, the research hypotheses and the empirical conclusions.

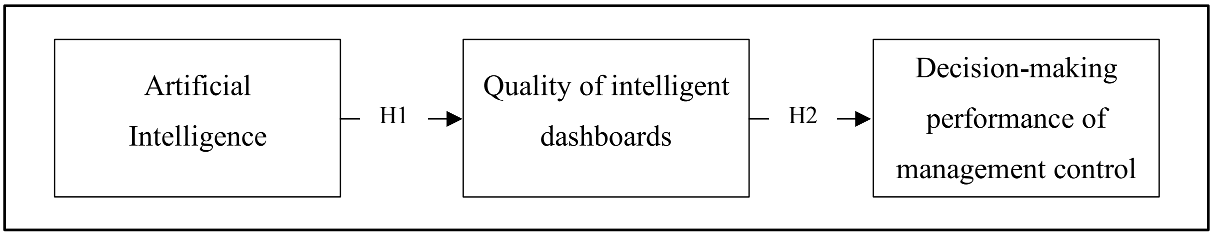
It is within this methodological framework that the choice of the research field is situated, the Souss-Massa region, a region that occupies a strategic place in the Moroccan economy thanks to its geographical position, its territorial diversity and its economic dynamism, notably in agriculture, fisheries and tourism, where the private sector plays an essential role in the creation of wealth and jobs. This regional context, marked by a diversified entrepreneurial fabric comprising industry, services and trade, offers a relevant setting for observing the practices of integrating artificial intelligence in SMEs facing variable constraints in terms of resources and digital skills. For the quantitative phase, a sample of eighty respondents was retained, composed mainly of management controllers (40%), finance managers (26.3%) and chief administrative and financial officers (23.7%), drawn mostly from medium-sized companies (50 to 250 employees, 53.8% of the sample) and distributed across the services (33.8%), trade (32.5%) and industry (30%) sectors.

4. Research Hypotheses and Initial Conceptual Model

On the basis of the literature review, an initial conceptual model was developed, articulated around two founding hypotheses. The first (H1) postulates that artificial intelligence contributes positively to improving the quality of intelligent dashboards, notably in terms of data reliability and the relevance of the information produced. The second (H2) proposes that the quality of intelligent dashboards positively influences the decision-making performance of management control. This model highlights the central role of the quality of intelligent dashboards as the mechanism linking the technological capabilities of artificial intelligence to the improvement of performance steering, as well as the role of error reduction and strengthened data reliability as underlying explanatory mechanisms.

This causal architecture is anchored in a combination of complementary theoretical lenses. Dynamic Capabilities Theory (Teece, Pisano, & Shuen, 1997) frames artificial intelligence as an organizational capability that must be continuously reconfigured to generate value, which is consistent with H1's emphasis on AI's contribution to the quality of the steering tool rather than to performance directly. The Resource-Based View (Barney, 1991) complements this reading by treating intelligent dashboards, and the data that feed them, as valuable, rare and imperfectly imitable resources whose strategic exploitation, rather than mere possession, drives decision-making performance (H2). Finally, the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) situates this technological capability within the organizational and environmental conditions of Moroccan SMEs, thereby explaining why the same AI-enabled tools may yield heterogeneous performance outcomes across firms.

Figure 1: Initial conceptual model and research hypotheses



Source: The authors

This initial model served as the foundation for the exploratory qualitative phase, whose purpose was to examine the actual practices of integrating business intelligence and artificial intelligence tools within the companies studied, prior to its empirical validation during the confirmatory quantitative phase.

5. Exploratory Qualitative Study: Results and Discussion

The qualitative phase constitutes the first empirical stage of the research. In accordance with the logic of qualitative research, oriented toward understanding the questions “what? how? why?” (McCusker and Gunaydin, 2015), it aims less at establishing statistical relationships than at understanding reality as experienced by management control professionals in the face of the growing integration of artificial intelligence. Nineteen semi-structured interviews were conducted for this purpose, structured around a guide organized into three complementary themes: the management control process and its current practices; artificial intelligence in management control and its effects on the role of the management controller and on the dashboards used; and the decision-making performance of management control, understood as the capacity of intelligent dashboards to facilitate and improve the quality of decision-making. This structure, consistent with the principles of the semi-structured interview (Wacheux, 1996), allowed respondents freedom of expression while ensuring the coherence of data collection.

The responses thus collected were subjected to a lexicographic analysis, combining the generation of a word cloud and the construction of thematic word trees (synapsies) around the main concepts mobilized by the respondents. The word cloud generated from the corpus highlights the centrality of terms such as "decision-making performance," "data," "dashboards," "management control" and "artificial intelligence," which confirms the relevance of the theoretical dimensions retained in the initial model. The strong presence of the term "data" underscores in particular the central role of information in control and decision-making processes, while the occurrences related to "quality" reflect a broadly positive perception of intelligent tools as levers for improving the speed and accuracy of managerial decisions.

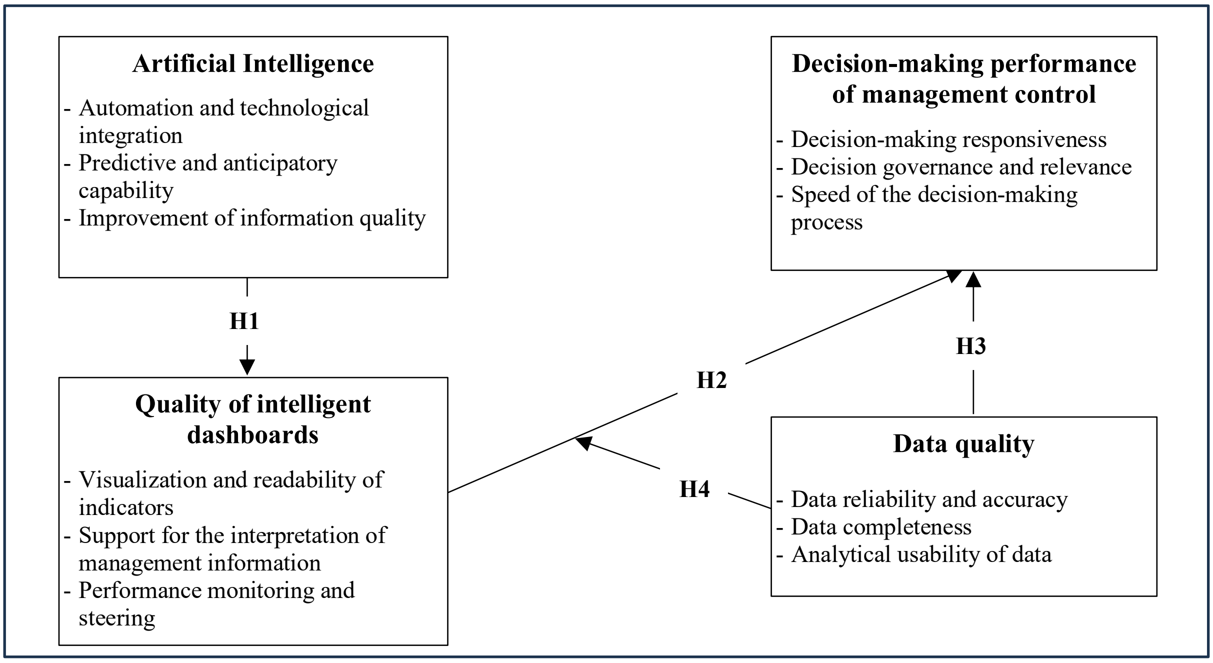
Figure 2: Word cloud generated by the lexicographic analysis of the interview corpus

Source: The authors

The analysis of the textual word trees constructed around the concepts of "decision-making performance," "management control," "artificial intelligence," "dashboards" and "data quality" converges toward a single observation: the respondents systematically associate artificial intelligence with better information reliability, simplified processes and a reduction of human errors thanks to the automation of processing. They also underscore the evolution of the management controller's role, which is no longer limited to a classic control function but becomes that of a strategic actor capable of interpreting the results produced by intelligent systems and of carrying out predictive analyses. This observation converges with the findings of the literature review regarding the transformation of the management controller into a genuine business partner. The interviews nevertheless also reveal certain recurrent limitations, notably related to the lack of technical skills and to the insufficient quality of some of the available data, which constitutes a first signal of the need to enrich the initial conceptual model. *[Authors' note, to be completed with the original corpus: this paragraph should be enriched with two to three representative verbatim excerpts from the nineteen interview transcripts, illustrating respectively (i) the perceived gain in information reliability attributed to AI, (ii) the reported shift in the management controller's role toward a more strategic, interpretive function, and (iii) the recurrent limitations linked to technical skills and data quality. Anchoring the lexicographic analysis in a small number of direct quotations would substantiate the thematic categories identified above and directly address the reviewer's request for a deeper qualitative analysis.]*

The exploitation of the interviews made it possible, first, to confirm qualitatively the two hypotheses of the initial model: the respondents attest that artificial intelligence improves the quality of intelligent dashboards and that the latter in turn exert a positive effect on the decision-making performance of management control. Second, the analysis of the discourse brought out a transversal concept absent from the initial model but systematically mentioned by the respondents: data quality. It appears as a sine qua non condition for the effectiveness of intelligent dashboards and for the relevance of the analyses produced by artificial intelligence, reliable, accessible and well-structured data improve decision-making, whereas insufficient data quality limits the effectiveness of intelligent systems and can negatively affect decision-making performance. This observation led to the formulation of a third hypothesis, H3, according to which better data quality directly and positively impacts the decision-making performance of management control, and a fourth, H4, which proposes that the quality of the data used in intelligent dashboards strengthens the decision-making performance of management control. The conceptual model was consequently readjusted to integrate four interdependent concepts: artificial intelligence, intelligent dashboards, data quality and the decision-making performance of management control. This enriched model, presented below, constitutes the analytical framework submitted to the empirical validation of the quantitative phase.

Figure 3: Hypothetical model readjusted at the end of the qualitative study



Source: The authors

6. Confirmatory Quantitative Study: Results and Discussion

6.1. Presentation of the study

This study aims to verify empirically, through structural equation modeling, the extent to which artificial intelligence (AI), data quality (DQ) and intelligent dashboards (ID) contribute, directly or indirectly, to improving the decision-making performance of management control (DMPMC) within companies of the Souss-Massa region. It constitutes the confirmatory component of the research, whose objective is to test the hypotheses initially formulated from the literature review and then refined and enriched at the end of the exploratory qualitative phase, notably through the integration of data quality as a construct in its own right in the model. This test requires examining not only the intensity of these relationships, but also their nature, direct, mediated or moderated, as specified by the hypotheses of the readjusted model.

To this end, the research mobilizes structural equation modeling under the PLS-SEM approach (Partial Least Squares Structural Equation Modeling), implemented using the SmartPLS software. This methodological choice is not incidental: the PLS-SEM method was preferred on account of its flexibility with respect to constraints related to sample size and data distribution , often non-Gaussian in management science research , as well as its capacity to analyze simultaneously complex relationships between several latent variables, including moderating and mediating effects, which corresponds precisely to the architecture of the conceptual model readjusted at the end of the qualitative study. The evaluation of the model was thus conducted in two successive and complementary stages: first, the evaluation of the measurement model (outer model), covering item reliability as well as the convergent and discriminant validity of the constructs; second, the evaluation of the structural model (inner model), covering the path coefficients, the coefficients of determination (R^2), the effect sizes (f^2) and the mediating effects estimated using the bootstrap procedure. Upstream of these statistical treatments, the corresponding data collection was itself carried out rigorously, using a structured questionnaire built according to the four-step methodological approach proposed by Evrard (1993): the identification of information needs, necessary to delineate precisely the constructs to be measured; the definition of the question format, oriented toward a five-point Likert scale ranging from “strongly disagree” to “strongly agree”; the structuring of the length and order of the questions, in order to ensure a coherent progression between the different thematic modules of the questionnaire; and finally the drafting and pre-testing of the instrument, the latter having made it possible to verify the clarity and relevance of the items before their dissemination in final form. It should be noted that some of these items were validated beforehand by the lessons drawn from the qualitative interviews, thereby ensuring methodological continuity between the two phases of the research.

The population targeted by this survey consists of companies located in the Souss-Massa region. Given the field, time and organizational constraints inherent in this type of research, a sample of seventy-three companies was retained as representative of the regional economic fabric, and the questionnaire administered to finance and management control professionals within these companies yielded, at the end of the collection phase, eighty usable responses, which constitute the empirical basis for all the statistical treatments presented in the remainder of this study. The following tables present the distribution of this sample by position held, company size and sector of activity.

This sample size was assessed against the requirements of the PLS-SEM method. Applying the 10-times rule (Hair et al., 2014), the minimum sample size is ten times the largest number of structural paths pointing at any single construct in the model; here, the decision-making performance of management control (DMPMC) receives the largest number of incoming paths (three, from ID, DQ and the DQ × ID interaction), yielding a minimum requirement of thirty respondents. With eighty usable responses, the sample comfortably exceeds this threshold, which supports the statistical adequacy of the quantitative phase, even though a larger sample would further strengthen the precision of the interaction-effect estimates.

Table 1: Distribution of respondents by position held

Position held	Number	Percentage
Management controller	32	40%
Finance manager	21	26.3%
Chief administrative and financial officer	19	23.7%
Other positions (chief accountant, general controller, firm manager, risk management officer, inventory manager, other)	8	10%
Total	80	100%

Source: The authors

Table 2: Distribution of respondents by company size

Company size	Number	Percentage
Fewer than 50 employees	18	22.5%
50 to 250 employees	43	53.8%
More than 250 employees	19	23.8%
Total	80	100%

Source: The authors

Table 3: Distribution of respondents by sector of activity

Sector of activity	Number	Percentage
Industry	24	30%
Services	27	33.8%
Trade	26	32.5%
Agriculture	1	1.2%
Agri-food	1	1.2%
Hospitality	1	1.2%
Total	80	100%

Source: The authors

6.2. Data analysis and results with SmartPLS

Measurement model: item reliability (factor loadings)

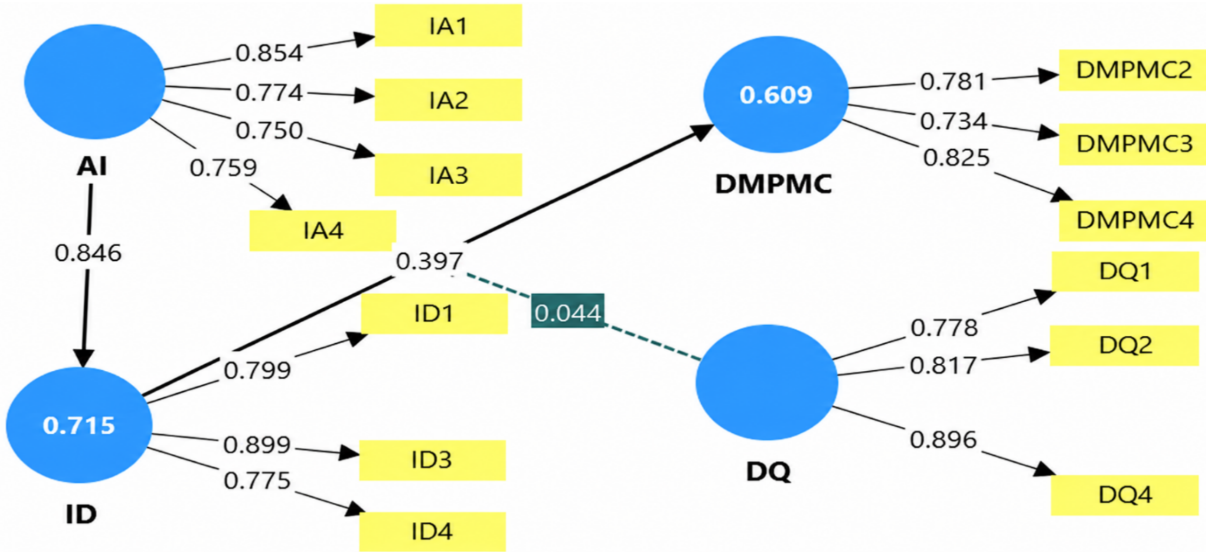
The initial evaluation of the factor loadings (recommended threshold ≥ 0.708) led to the removal of the items showing insufficient reliability, notably ID2 (0.648) and DQ3, in accordance with the recommendations of Hair et al. (2014). After purification, all the retained items exceed the recommended threshold, with the exception of DQ2 (0.817 after adjustment) and ID1 (0.799), which nonetheless remain acceptable. The table below presents the factor loadings retained after purification of the model.

Table 4: Item reliability after purification of the model

Item	AI	DMPMC	DQ	ID
AI1	0.854	—	—	—
AI2	0.774	—	—	—
AI3	0.750	—	—	—
AI4	0.759	—	—	—
DMPMC2	—	0.781	—	—
DMPMC3	—	0.734	—	—
DMPMC4	—	0.825	—	—
DQ1	—	—	0.778	—
DQ2	—	—	0.817	—
DQ4	—	—	0.896	—
ID1	—	—	—	0.799
ID3	—	—	—	0.899
ID4	—	—	—	0.775

Source: Results obtained from computations with SmartPLS

Figure 4: Research model after purification (factor loadings)



Source: Results obtained from computations with SmartPLS

Composite reliability (CR) and average variance extracted (AVE)

Composite reliability (rho_c) and AVE were used to assess convergent validity, in accordance with the recommendations of Chin (1998) and Fornell and Larcker (1981). This paper does not report Cronbach's alpha values; only the CR (rho_c) and the AVE appear in the SmartPLS outputs presented.

Table 5: Composite reliability (CR) and average variance extracted (AVE)

Construct	AVE	Composite reliability (rho_c)
Artificial Intelligence (AI)	0.624	0.862
Decision-Making Performance of MC (DMPMC)	0.617	0.829
Data Quality (DQ)	0.696	0.873
Intelligent Dashboard (ID)	0.676	0.862

Source: Results obtained from computations with SmartPLS

Discriminant validity: the Fornell-Larcker criterion

Discriminant validity was assessed using the Fornell-Larcker criterion (square root of the AVE compared with the inter-construct correlations) as well as through the analysis of cross-loadings. TheThis study does not present HTMT ratios. The results confirm that each construct shares more variance with its own indicators than with the other latent variables of the model.

Table 6: Discriminant validity of the variables

	AI	DMPMC	DQ	ID
AI	0.785			
DMPMC	0.745	0.781		
DQ	0.756	0.732	0.832	
ID	0.846	0.690	0.669	0.826

Source: Results obtained from computations with SmartPLS

Structural model: hypothesis testing (path coefficients, bootstrap)

The significance of the relationships was estimated using the bootstrap procedure in SmartPLS (threshold: $T > 1.96$; $p < 0.05$, following Hair et al., 2014).

Table 7: Path coefficients

Relationship	β (O)	Mean (M)	STDEV	T-stat.	p-value	Decision
AI → ID (H1)	0.846	0.856	0.037	22.622	0.000	Supported
DQ → DMPMC (H3)	0.486	0.494	0.152	3.201	0.001	Supported
DQ × ID → DMPMC (H4)	0.044	0.018	0.126	0.352	0.725	Rejected
ID → DMPMC (H2)	0.397	0.385	0.174	2.283	0.022	Supported

Source: Results obtained from computations with SmartPLS

Coefficient of determination (R^2) and predictive relevance

The R^2 reflects the predictive capacity of the structural model (significance threshold: $R^2 > 0.1$ according to the thresholds retained in this study). This research work does not report Q^2 (blindfolding) values.

Table 8: Coefficient of determination (R square) test

Endogenous variable	R^2	Adjusted R^2
ID	0.715	0.711
DMPMC	0.609	0.594

Source: Results obtained from computations with SmartPLS

Effect size (f^2)

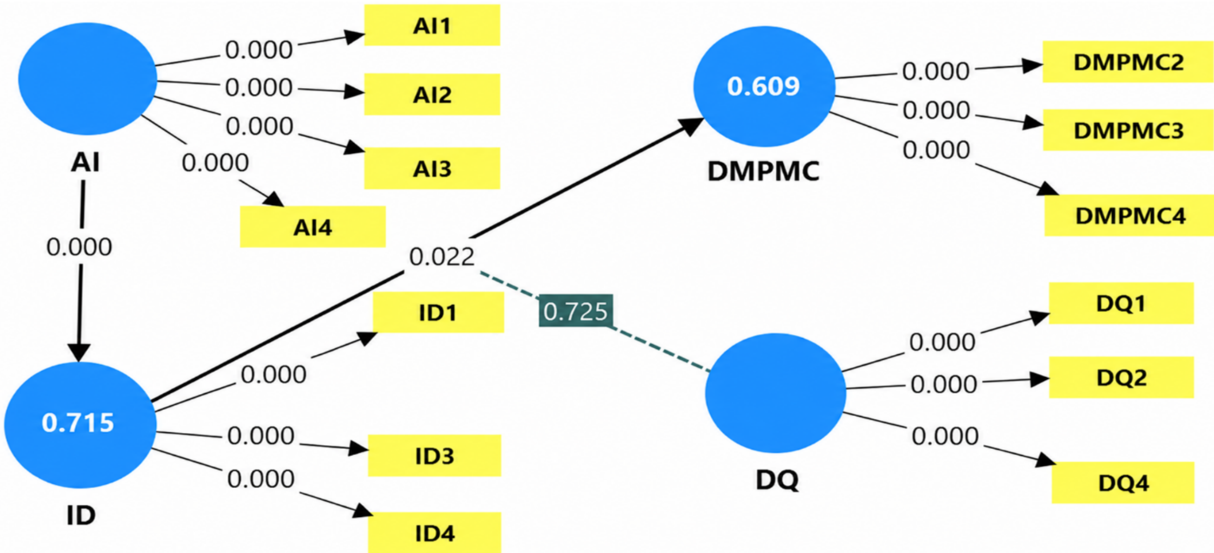
In accordance with Cohen's (1988) guidelines: $f^2 < 0.02$ = negligible effect; 0.02–0.15 = small effect; 0.15–0.35 = medium effect; ≥ 0.35 = large effect.

Table 9: Assessment of effect sizes

Relationship	f²	Magnitude of the effect
AI → ID	2.509	Very large effect
DQ → DMPMC	0.332	Large effect
ID → DMPMC	0.140	Small effect
DQ × ID → DMPMC	0.003	Negligible effect

Source: Results obtained from computations with SmartPLS

Figure 5: Research model after bootstrapping (T-statistics)



Source: Results obtained from computations with SmartPLS

Indirect effects and mediation analysis

The mediating effect of the ID in the AI → DMPMC relationship was tested under two configurations conditional on data quality (DQ “at one” and DQ “at zero”):

Table 10: Testing the hypotheses of the mediator variable

Indirect effect: AI → ID → DMPMC	β (O)	Mean (M)	STDEV	T-stat.	p-value
DQ “at one”	0.373	0.347	0.233	1.601	0.109 (non-significant)
DQ “at zero”	0.336	0.331	0.153	2.190	0.029 (significant)

Source: Results obtained from computations with SmartPLS

Furthermore, in the discussion of the results, this paper also tests artificial intelligence as a potential mediator of the ID → DMPMC relationship: the indirect effect obtained is positive but non-significant at the 5% level (β = 0.441; t = 1.655; p = 0.098), whereas the residual direct effect ID → DMPMC remains significant ($\beta = 0.397$; $t = 2.283$; $p = 0.022$), confirming the partial character of this mediation.

Main results and interpretation

The set of statistical treatments presented in the preceding section now makes it possible to draw up a synthetic assessment of the testing of the hypotheses of the readjusted model, before offering an overall interpretation. The table below summarizes, for each of the relationships tested, the direction of the decision reached as well as the main associated statistical indicators.

Table 11: Summary of the main results of the confirmatory quantitative study

Result	Detail
H1 supported	AI → ID ($\beta = 0.846$; $t = 22.622$; $p = 0.000$), very large effect ($f^2 = 2.509$)
H2 supported	ID → DMPMC ($\beta = 0.397$; $t = 2.283$; $p = 0.022$), small effect ($f^2 = 0.140$)
H3 supported	DQ → DMPMC ($\beta = 0.486$; $t = 3.201$; $p = 0.001$), large effect ($f^2 = 0.332$)
H4 rejected	DQ × ID → DMPMC ($\beta = 0.044$; $t = 0.352$; $p = 0.725$), negligible effect ($f^2 = 0.003$)
Mediation of the ID (AI → ID → DMPMC)	Partial and conditional - significant only in the “DQ at zero” configuration ($p = 0.029$)
Explanatory power of the model	$R^2 = 0.715$ (ID) and $R^2 = 0.609$ (DMPMC), both well above the significance threshold of 0.1

Source: The authors

The interpretation of these results highlights the structuring role of artificial intelligence upstream of the steering system: with an extremely strong effect ($f^2 = 2.509$) and a path coefficient of 0.846, AI constitutes the most powerful determinant of the development of intelligent dashboards. Its influence on decision-making performance nevertheless remains indirect, since it passes mainly through the ID, whose own effect on the DMPMC remains significant but small ($f^2 = 0.140$). Data quality appears as the second direct and strong lever of decision-making performance ($f^2 = 0.332$), while the non-significance of the DQ × ID interaction (H4 rejected) indicates that data quality acts independently rather than in synergy with intelligent dashboards. Finally, the partial and conditional character of the ID's mediation, significant only when data quality is low (“DQ at zero”), suggests that intelligent dashboards play a more decisive relay role when data quality is not sufficient, on its own, to guarantee decision-making performance.

This rejection of H4 deserves closer scrutiny in light of the literature. Rather than contradicting the theoretical intuition that data quality conditions the value of intelligent dashboards, the non-significant interaction is consistent with findings such as those of Dechow and Mouritsen (2005), who show that technology generates value only when embedded in suitable practices, without necessarily implying a statistically detectable multiplicative effect. Three complementary explanations can be advanced. First, data quality and intelligent-dashboard quality may operate as parallel, direct antecedents of performance rather than as interacting forces, echoing Granlund and Malmi's (2002) observation that technological and organizational conditions often act independently rather than in synergy. Second, interaction effects in PLS-SEM typically require larger samples than main effects to reach statistical significance, so the sample of eighty respondents, while adequate for the direct paths, may lack the power needed to detect a moderating effect of modest magnitude. Third, a ceiling-type mechanism cannot be excluded: in firms where data quality is already perceived as satisfactory, dashboards may find little additional room to be moderated by it, whereas the conditional mediation results (significant only when DQ is “at zero”) suggest that data quality's influence is better captured as a boundary condition for mediation than as a linear moderator of the ID → DMPMC path.

Ultimately, the quantitative study confirms three of the four hypotheses tested (H1, H2, H3) and rejects the hypothesis relating to the moderating effect of data quality (H4). The high explanatory power of the model ($R^2 = 0.715$ for the ID and $R^2 = 0.609$ for the DMPMC) attests to the relevance of the conceptual framework mobilized. Artificial intelligence, data quality and intelligent dashboards thus constitute significant but differentiated levers for improving the decision-making performance of management control, whose combined effect remains conditioned by the quality of the available data and by the effective integration of these tools into organizational practices.

Conclusion

This research set out to analyze the extent to which the integration of artificial intelligence into management dashboards contributes to the emergence of a new generation of steering tools and improves the decision-making performance of management control, through the case of SMEs in the Moroccan region of Souss-Massa. To answer this question, a sequential mixed-methods approach was mobilized, articulating a literature review covering the evolution of management control, the foundations of artificial intelligence and the transformation of dashboards; an exploratory qualitative phase based on nineteen semi-structured interviews; and then a confirmatory quantitative phase relying on a questionnaire processed using the PLS-SEM method.

The results obtained show that artificial intelligence significantly improves the quality of intelligent dashboards, which in turn exerts a positive influence on the decision-making performance of management control, while data quality constitutes a direct, distinct and equally significant determinant of this performance. These effects nevertheless remain conditional: the absence of a moderating effect of data quality and the partial character of the mediation exerted by intelligent dashboards between artificial intelligence and decision-making performance indicate that technology does not act automatically, but that its value depends on its integration into a coherent system combining reliable data, suitable steering tools and users' digital skills.

At the theoretical level, this research contributes to enriching the understanding of the mechanisms by which artificial intelligence transforms management control, by proposing a conceptual model articulating four interdependent dimensions and by highlighting the conditional character of the mediation effects observed. At the methodological level, it illustrates the value of a sequential mixed-methods approach, in which the qualitative phase makes it possible to enrich and readjust an initial model before its quantitative validation. At the managerial level, finally, it invites the executives and management controllers of SMEs not to regard the adoption of artificial intelligence tools as an end in itself, but to accompany it with a parallel investment in data quality and in the development of their teams' digital skills.

This research nevertheless has certain limitations, related in particular to the relatively small size of the quantitative sample, the self-reported nature of the data collected and the cross-sectional nature of the study, which call for caution in generalizing the results beyond the regional context studied. Several avenues for future research can therefore be envisaged: extending the study to other regional or sectoral contexts, and conducting longitudinal analyses to better grasp the dynamics of adoption of these technologies over time. The digital skills of management controllers, only touched upon here as a qualitative signal, constitute a particularly promising avenue: future research could examine them not merely as a control variable but as a construct in its own right, testing, for instance, whether they moderate the AI → intelligent-dashboard-quality relationship, mediate the translation of dashboard quality into effective decisions, or interact with organizational factors such as digital maturity, change-management support and top-management sponsorship. Longitudinal designs would further help establish whether these skills are a precondition for, or a consequence of, sustained AI adoption in management control. Ultimately, this research highlights that the decision-making performance of management control rests less on the technological sophistication of the tools than on the dynamic interaction between artificial intelligence, data quality and human factors, which constitutes the true lever of the digital transformation of management control.

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