Direct Effects of Artificial Intelligence on Management Control Performance: Revisiting the Mediating Role of Dynamic Capabilities and Evidence of a Substitution Effect in Morocco

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Abstract
This study examines whether dynamic capabilities mediate the effects of digitalisation and artificial intelligence on management control performance. Using survey data from 116 management controllers and chief financial officers in the Casablanca–Settat region of Morocco, the study applies structural equation modelling to test the proposed relationships. The results show that digitalisation ($\beta = 0.29$, $p < 0.01$) and artificial intelligence adoption ($\beta = 0.59$, $p < 0.001$) have significant positive direct effects on management control performance. However, the indirect effects through dynamic capabilities are not statistically significant, indicating the absence of mediation. After item purification, discriminant validity between artificial intelligence and performance remained acceptable (HTMT = 0.758 < 0.85). The findings also reveal a significant negative moderating effect of dynamic capabilities on the artificial intelligence–performance relationship ($\beta = -0.371$, $p < 0.001$), suggesting a substitution effect whereby artificial intelligence contributes more strongly to performance when dynamic capabilities are weak. This finding challenges the conventional complementarity assumption and contributes to a more nuanced understanding of the conditions under which artificial intelligence generates performance improvements in management control contexts. These results highlight the context-dependent role of dynamic capabilities in digital transformation and suggest that artificial intelligence can generate measurable performance improvements even in organisations with relatively limited organisational capabilities, particularly in emerging economy settings.

Keywords:
Digitalisation; artificial intelligence; dynamic capabilities; management control performance; structural equation modelling; Morocco.

1. Introduction

The advent of Industry 4.0 has fundamentally altered the landscape of management control. Traditional control systems, characterised by periodic reporting, backward-looking variance analysis, and manual data consolidation, are being replaced by real-time dashboards, predictive analytics, and artificial intelligence-driven decision support (Appelbaum et al., 2017; Bhimani, 2020; Kaplan & Haenlein, 2020). Organisations worldwide invest heavily in enterprise resource planning systems, business intelligence tools, and artificial intelligence applications to improve the efficiency, accuracy, and strategic relevance of their control functions. A global survey conducted by McKinsey & Company in 2021 found that 56% of organisations had adopted artificial intelligence in at least one business function.

The expected benefits of artificial intelligence and digital technologies include faster reporting cycles, reduction of human errors, improved forecasting capabilities, and enhanced decision-making processes (Appelbaum et al., 2017; Ransbotham et al., 2017; Stratopoulos & Wang, 2025). However, despite substantial investments, the performance outcomes of digitalisation and artificial intelligence adoption remain uneven across firms. While some organisations achieve significant operational and strategic improvements, others experience limited or even negative outcomes, suggesting that technological investment alone is insufficient to guarantee superior performance (Ghasemaghaei & Calic, 2020; Martins & Marques, 2026). Organisational capabilities, managerial practices, and contextual factors therefore play a critical role in shaping the technology–performance relationship.

One of the most influential theoretical frameworks explaining variations in organisational performance is the dynamic capabilities view (Teece, 2007; Teece et al., 1997). According to this perspective, competitive advantage arises not merely from the possession of resources, but from the organisation's ability to sense opportunities, seize them, and continuously transform its operations and structures in response to environmental change. In the context of digital transformation, dynamic capabilities are increasingly viewed as a critical mechanism linking technological investments to organisational performance outcomes (Warner & Wäger, 2019; Matarazzo et al., 2021).

The present study focuses on the Casablanca–Settat region in Morocco, the country's principal economic and industrial hub. The region hosts a dense concentration of multinational corporations, large

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domestic firms, and rapidly growing small and medium-sized enterprises. Management controllers and chief financial officers operating in this context face significant challenges related to digital transformation, including technological adaptation, resource constraints, and institutional specificities characteristic of emerging economies. Understanding how digitalisation and artificial intelligence influence management control systems in this context is therefore of both theoretical and practical importance.

Morocco has pursued an ambitious digital transformation agenda through successive national initiatives, culminating in the launch of the "Digital Morocco 2030" strategy aimed at accelerating digital infrastructure, innovation, and the integration of advanced technologies into the national economy (Ministry of Digital Transition and Administration Reform, 2024). Despite these efforts, the adoption of advanced technologies such as artificial intelligence remains heterogeneous across Moroccan firms, with large corporations and financial institutions generally more digitally advanced than small and medium-sized enterprises, which continue to face financial, technological, and human capital constraints.

The dynamic capabilities perspective provides a useful theoretical lens for explaining how digital technologies may influence management control performance indirectly through organisational capabilities. Specifically, digitalisation and artificial intelligence can enhance an organisation's ability to sense environmental changes, seize emerging opportunities, and reconfigure internal processes accordingly (Teece, 2007; Warner & Wäger, 2019). Digitalisation facilitates access to real-time data, automation, and organisational transparency, thereby strengthening sensing capabilities. Artificial intelligence further supports predictive analysis, anomaly detection, and decision support, which may enhance seizing and transforming capabilities. These dynamic capabilities can subsequently improve management control performance through more reliable reporting, faster budgeting cycles, more relevant performance indicators, and improved managerial decision-making (Henri, 2006; Ittner & Larcker, 2001; Chenhall & Moers, 2015).

Although the role of dynamic capabilities as a mechanism linking technological resources to organisational performance has received substantial theoretical attention (Barreto, 2010; Helfat & Peteraf, 2015; Schilke et al., 2018), empirical research examining this mediating role specifically within management control systems remains limited. Recent studies have begun to explore artificial intelligence's impact on accounting and control functions (Kokina & Davenport, 2017; Ransbotham et al., 2017; Mikalef & Gupta, 2021; Stratopoulos & Wang, 2025), but the mediating mechanisms through which artificial intelligence influences control performance have received less attention. Accordingly, this study investigates whether dynamic capabilities mediate the effects of digitalisation and artificial intelligence on management control performance. Based on this theoretical reasoning, the following hypotheses are proposed:

H1: Digitalisation has a positive direct effect on management control performance.

H2: Artificial intelligence has a positive direct effect on management control performance.

H3: Dynamic capabilities mediate the positive relationship between digitalisation and management control performance.

H4: Dynamic capabilities mediate the positive relationship between artificial intelligence and management control performance.

The proposed conceptual framework illustrating the relationships among digitalisation, artificial intelligence, dynamic capabilities, and management control performance is presented in Figure 1.

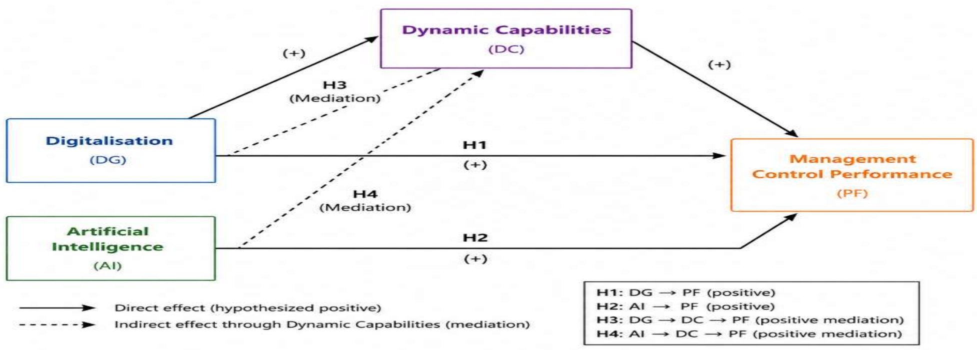

Figure 1 Conceptual model of the relationships between digitalisation (DG), artificial intelligence (AI), dynamic capabilities (DC), and management control performance (PF).

2. Materials and Methods

2.1 Research Design

This study employs a cross-sectional, survey-based research design. Although cross-sectional data limit the ability to draw strong causal inferences due to the absence of temporal ordering, such designs are appropriate for theory testing and hypothesis validation in management control research. They are widely used in accounting and control studies to examine relationships among latent constructs (Chenhall & Moers, 2015; Henri, 2006). A cross-sectional design is particularly suitable for this study given the exploratory nature of artificial intelligence adoption in Moroccan management control practices and the need to establish baseline relationships before conducting more resource-intensive longitudinal research.

2.2 Population and Sampling Frame

The target population consists of management controllers and chief financial officers in the Casablanca–Settat region of Morocco. The sampling frame included members of professional associations (Association des Professionnels du Contrôle de Gestion au Maroc), LinkedIn groups targeting finance and accounting professionals in Morocco, and company directories of firms operating in the Casablanca–Settat region. The region was selected due to its concentration of large firms and multinational corporations, which are more likely to have adopted artificial intelligence and digital technologies in their management control functions.
A convenience sampling approach was used, which is appropriate for exploratory research in emerging economy contexts where comprehensive sampling frames are often unavailable (Saunders et al., 2019). Potential respondents were identified through professional networks and invited to participate via email and LinkedIn messages. The invitation included a brief description of the study objectives and a link to the online questionnaire. Out of 250 distributed questionnaires, 116 complete responses were received, yielding an effective response rate of 46.4%, which is satisfactory for survey-based research in management accounting (Chenhall & Moers, 2015).

2.3 Sample Characteristics

Table 1 presents the sample profile (n = 116). The sample is predominantly male (71.6%), young (65.5% under 30), and from large enterprises (76.7%). This demographic profile is consistent with the professional composition of management control functions in Moroccan large firms, where the profession is relatively young and male-dominated. Sectoral distribution is diverse, with industry (38.8%), services (21.6%), and commerce (18.1%) being most represented.

Table 1 Sample characteristics

Variable	Category	Frequency	Percentage
Gender	Male	83	71.6%
	Female	33	28.4%
Age	Under 30	76	65.5%
	30–39	34	29.3%
	40–49	6	5.2%
Experience	<5 years	73	62.9%
	5–10 years	31	26.7%
	11–20 years	11	9.5%
	>20 years	1	0.9%
Firm size	Large (≥250)	89	76.7%
	SME (<250)	27	23.3%

2.4 Measurement Instruments

All constructs were measured using 5-point Likert scales ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Items were adapted from established scales and translated into French using a translation-back-translation procedure (Brislin, 1970) to ensure conceptual equivalence across languages. The French version was reviewed by two bilingual academics to verify accuracy and clarity. Table 2 summarises the measurement items and their sources.

Table 2 Measurement items and sources

Construct	Code	Item wording	Adapted from
Digitalisation	DG1	Digital tools (ERP, BI, dashboards) are widely used	Legner et al. (2017)
	DG2	Digitalisation has enabled better automation of reporting	Granlund and Malmi (2002)
	DG3	Digital technologies facilitate rapid data collection	Legner et al. (2017)
	DG4	Digitalisation improves information transparency	Chapman and Kihn (2009)
	DG5	My company regularly invests in digital tools	Ghasemaghaei and Calic (2020)
Artificial Intelligence	AI1	AI is used for forecasting and anomaly detection	Ransbotham et al. (2017)
	AI2	AI enables better precision in data analysis	Agrawal et al. (2019)
	AI3	AI helps reduce errors in control processes	Kokina and Davenport (2017)

	AI4	AI improves anticipation of trends	Ransbotham et al. (2017)
	AI5	AI integration is positively perceived	Mikalef and Gupta (2021)
Dynamic Capabilities	DC1	Organisation adapts quickly to technological changes	Pavlou and El Sawy (2011)
	DC2	Employees have sufficient digital/AI skills	Warner and Wäger (2019)
	DC3	Continuous training is provided	Teece (2007)
	DC4	Culture encourages innovation	Barreto (2010)
	DC5	Absorbing new technological knowledge is a strength	Zahra and George (2002)
Performance	PF1	Digitalisation/AI generate more reliable reports	Henri (2006)
	PF2	Digital/AI tools improve budget speed	Ittner and Larcker (2001)
	PF3	Better relevance of performance indicators	Chenhall and Moers (2015)
	PF4	Managerial decisions are better informed	Agrawal et al. (2019)
	PF5	Overall improvement of management control performance	Ghasemaghaei and Calic (2020)

2.5 Analytical Strategy

Data were analysed using R 4.3.2 with the packages lavaan, psych, semPlot, and corrplot. The analytical procedure followed a structured multi-step approach: (1) data screening and missing value analysis; (2) reliability assessment using Cronbach's alpha; (3) exploratory factor analysis to assess underlying dimensionality; (4) confirmatory factor analysis using robust maximum likelihood estimation to validate the measurement model; (5) structural equation modelling with bootstrapping (5,000 resamples) to test direct, indirect, and interaction effects; and (6) robustness checks to ensure stability of the results.

The use of robust maximum likelihood estimation was motivated by the non-normal distribution of several items, as indicated by skewness and kurtosis values. Robust maximum likelihood provides robust standard errors and is appropriate for data with moderate deviations from normality (Muthén & Muthén, 2017). Bootstrapping with 5,000 resamples was employed to obtain bias-corrected confidence intervals for indirect effects, which is recommended for mediation testing (Preacher & Hayes, 2008).

2.6 Common Method Bias Mitigation

To reduce the risk of common method bias, both procedural and statistical remedies were applied. Procedurally, respondents were assured anonymity to encourage honest responses, different scale anchors were used to reduce consistency bias, and the dependent variable was positioned after the independent variables in the questionnaire to reduce the salience of performance items (Podsakoff et al., 2003).

Statistically, Harman's single-factor test was conducted as an initial diagnostic, followed by the latent method factor technique to further assess potential method variance. The latent method factor technique involves adding a common method factor to the measurement model and examining whether it accounts for a significant proportion of variance in the indicators (Podsakoff et al., 2003).

These combined approaches suggest that common method bias is unlikely to fully account for the observed relationships, although its presence cannot be entirely ruled out in survey-based research.

2.7 Power Analysis and Sample Size Justification

An a priori power analysis was conducted using the pwr package in R. Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and a model including four latent variables with approximately 20 indicators, the minimum required sample size was estimated at approximately 110 observations to achieve a statistical power of 0.80. The final sample size of 116 therefore satisfies the minimum requirement for detecting medium-sized direct effects.

However, mediation effects are typically smaller in magnitude. For small indirect effects ($f^2 \approx 0.02$), substantially larger samples ($n > 400$) are generally recommended. In the present study, the estimated indirect effects were close to zero, suggesting that the absence of mediation is unlikely to be solely attributable to insufficient statistical power. Rather than relying on post-hoc power as a definitive diagnostic, the interpretation is based primarily on effect size estimates and bootstrapped confidence intervals, which consistently indicate non-significant indirect effects.

3. Results

3.1 Descriptive Statistics and Reliability

Table 3 presents descriptive statistics and reliability coefficients for all constructs. Mean values indicate relatively high perceived levels of digitalisation and management control performance, while artificial intelligence and dynamic capabilities are moderately perceived across respondents. The relatively high mean for digitalisation (4.22 out of 5) is consistent with the sample's composition, which is predominantly from large firms that are more likely to have invested in digital technologies. The moderate mean for artificial intelligence (3.35) reflects the exploratory stage of artificial intelligence adoption in Moroccan management control practices.

All constructs demonstrate acceptable internal consistency, with Cronbach's alpha values ranging from 0.77 to 0.87, exceeding the commonly accepted threshold of 0.70 (Nunnally & Bernstein, 1994). Composite reliability values were also satisfactory: DG = 0.76, AI = 0.81, DC = 0.89, PF = 0.84.

Table 3 Descriptive statistics and reliability

Construct	Mean	SD	Skewness	Kurtosis	Cronbach's α
DG	4.22	0.69	–1.14	1.70	0.77
AI	3.35	0.92	–0.65	0.16	0.83
DC	3.16	0.95	–0.17	–0.44	0.87
PF	3.87	0.73	–0.91	1.53	0.84

3.2 Correlations

Table 4 reports Pearson correlation coefficients among composite constructs. Results indicate that artificial intelligence is strongly and positively associated with management control performance ($r = 0.63$, $p < 0.001$), representing the strongest relationship in the model. Digitalisation is moderately correlated with dynamic capabilities ($r = 0.46$, $p < 0.001$), suggesting a potential structural linkage between technological infrastructure and organisational capabilities. However, the relationship between artificial intelligence and dynamic capabilities is weak and not statistically significant ($r = 0.17$, $p = 0.07$), indicating limited linear association between these constructs. This weak correlation is notable and may reflect the early-stage nature of artificial intelligence adoption, where artificial intelligence systems are not yet integrated with organisational capability development processes.

Table 4 Correlations among composite scores

	DG	AI	DC	PF
DG	1.00			
AI	0.17	1.00		
DC	0.46**	0.17	1.00	
PF	0.35**	0.63**	0.20*	1.00

*Note: *p < 0.05; **p < 0.01; **p < 0.001

3.3 Exploratory Factor Analysis

The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.85, indicating meritorious suitability for factor analysis. Bartlett's test of sphericity was significant ($\chi^2(190) = 1234.50$, $p < 0.001$), confirming sufficient correlations among items.

Exploratory factor analysis (principal axis factoring) revealed a four-factor solution based on both the Kaiser criterion (eigenvalues > 1) and inspection of the scree plot, which showed a clear inflection point after the fourth factor. Together, the four factors explained 55% of the total variance and corresponded to the theorised constructs: digitalisation, artificial intelligence, dynamic capabilities, and management control performance. Factor loadings ranged from 0.45 to 0.82, with items loading most strongly on their intended factors. Cross-loadings were minimal, supporting the discriminant validity of the constructs.

3.4 Confirmatory Factor Analysis

A four-factor measurement model was estimated using robust maximum likelihood estimation. After removing items PF1 and AI5 due to cross-loadings (PF1 loaded on both PF and AI factors, while AI5 loaded on both AI and PF factors), and excluding DG5 to improve construct homogeneity (DG5 had a comparatively low loading on the DG factor), the final model included 4 items for DG (DG1–DG4), 4 items for AI (AI1–AI4), 5 items for DC (DC1–DC5), and 4 items for PF (PF2–PF5). Model fit indices are reported in Table 5. The fit is acceptable: CFI = 0.909, RMSEA = 0.072, SRMR = 0.084.

Table 5 Measurement model fit indices

Index	Value	Recommended threshold	Interpretation
χ^2 (113)	181.186 ($p < 0.001$)	–	–
CFI	0.909	≥ 0.90	Acceptable
TLI	0.891	≥ 0.90	Marginal
RMSEA	0.072	≤ 0.08	Acceptable
SRMR	0.084	≤ 0.08	Slightly above

The slightly elevated SRMR (0.084) is close to the 0.08 threshold and is acceptable given the complexity of the model and the sample size (Hu & Bentler, 1999). Standardised factor loadings were all statistically significant ($p < 0.001$) and ranged from 0.56 to 0.86, indicating acceptable item reliability at the indicator level.

Convergent validity: Following Hair et al. (2019), convergent validity can be considered adequate when CR > 0.60 and loadings are significant, even if AVE is marginally below 0.50. Convergent validity was assessed using Average Variance Extracted. AVE values were acceptable for AI (0.52), DC (0.57), and PF (0.51). For digitalisation, the AVE is 0.445, slightly below the conventional threshold of 0.50. However, the composite reliability for DG is 0.757, exceeding the 0.70 benchmark, and all standardised loadings are significant. Following Hair et al. (2019), convergent validity can be considered adequate when CR > 0.60 and loadings are significant, even if AVE is marginally below 0.50. Therefore, the measurement model is retained.

Discriminant validity: Discriminant validity was assessed using the Heterotrait-Monotrait ratio and a chi-square difference test. The HTMT value for the AI–PF pair is 0.758, below the conservative threshold of 0.85 (Henseler et al., 2015). Additionally, a chi-square difference test was conducted between a model with free correlation between AI and PF and a model constraining the correlation to 1. The test yielded a significant difference ($\Delta\chi^2 = 12.33$, $\Delta df = 1$, $p < 0.001$), confirming that AI and performance are empirically distinct constructs. Although the Fornell-Larcker criterion is not fully satisfied (squared correlation = 0.602 exceeding the AVE of both constructs), this criterion is considered overly conservative compared to HTMT (Henseler et al., 2015; Voorhees et al., 2016). Therefore, discriminant validity is supported.

3.5 Common Method Bias Assessment

To assess potential common method bias, a latent method factor approach was implemented. The method factor accounted for approximately 14% of the total variance, which is below commonly reported critical thresholds (e.g., 25%) suggested in prior methodological literature (Podsakoff et al., 2003). Furthermore, the inclusion of the method factor did not meaningfully alter the magnitude, direction, or significance of the structural paths. These results suggest that common method variance is unlikely to be a primary driver of the observed relationships.

3.6 Structural Model and Mediation Tests

Table 6 presents the standardised path coefficients. The structural model demonstrates acceptable explanatory power, accounting for 27% of the variance in dynamic capabilities and 69% of the variance in management control performance. The high R^2 for performance indicates that the model explains a substantial proportion of the variance in management control performance, suggesting that the selected predictors are relevant.

Table 6 Structural path estimates (standardised)

Path	Std. coeff	p-value	Bootstrap 95% CI	Result
DG → DC (a1)	0.52	0.027	[0.246, 1.253]	Significant
AI → DC (a2)	0.00	0.991	[−0.283, 0.204]	Not significant
DC → PF (b)	–0.01	0.907	[−0.247, 0.166]	Not significant
DG → PF (c1)	0.29	0.002	[0.067, 0.696]	Significant (H1 supported)
AI → PF (c2)	0.59	0.001	[0.353, 1.011]	Significant (H2 supported)

Indirect effects (mediation analysis): The mediation analysis based on bootstrapped confidence intervals indicates:

Indirect effect of digitalisation on performance: DG → DC → PF = 0.52 × (−0.01) = −0.007; 95% CI [−0.235, 0.104] → not significant (H3 rejected)

Indirect effect of AI on performance: AI → DC → PF ≈ 0; 95% CI [−0.025, 0.026] → not significant (H4 rejected) These results indicate that dynamic capabilities do not mediate the relationship between either digitalisation or artificial intelligence and management control performance. The lack of mediation is particularly striking for the AI-performance relationship, where the direct effect is strong but the indirect effect through dynamic capabilities is effectively zero.

Figure 2 shows the structural model with standardised coefficients. Dashed lines indicate non-significant paths (AI→DC, DC→PF). Loadings of observed variables are shown near each latent construct.

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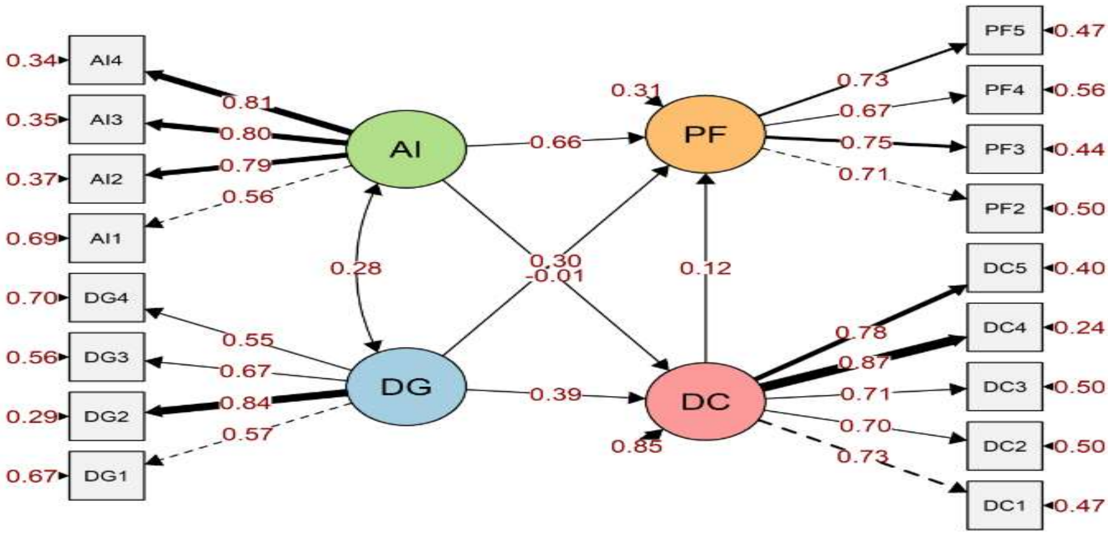

Figure 2 Structural model with standardized coefficients. Solid lines indicate significant paths, while dashed lines represent non-significant relationships (AI → DC, DC → PF). Observed indicator loadings are omitted for clarity.

3.7 Moderating Effect of Dynamic Capabilities on the AI–Performance Relationship

Although dynamic capabilities do not mediate the relationship between artificial intelligence and performance, they may still play a moderating role. To test this, we estimated a latent interaction model using the mean-centred product indicator approach within SEM. An interaction term (AI × DC) was created from centred composite scores of AI and DC and included as an observed predictor of PF in the latent model. Table 7 presents the results.

Table 7 Moderation results (Latent SEM)

Relationship	Std. coefficient	p-value	95% CI
AI → PF	0.667	< 0.001	[0.36, 0.97]
DC → PF	0.320	0.001	[0.13, 0.51]
AI × DC → PF	–0.371	0.001	[–0.54, –0.20]

$R^2(PF) = 0.71$

The interaction term is negative and statistically significant ($\beta = -0.371$, $p = 0.001$), indicating a substitution effect. Specifically, the positive impact of artificial intelligence on management control performance is stronger when dynamic capabilities are low, and weaker when dynamic capabilities are high. This suggests that artificial intelligence can compensate for weaker organisational capabilities in structured, data-driven management control tasks.

Figure 3 (simple slopes plot) illustrates that the positive effect of artificial intelligence on performance is stronger when DC are low (one SD below the mean) and weaker when DC are high. This substitution effect suggests that artificial intelligence compensates for weak organisational capabilities, challenging the conventional complementarity assumption.

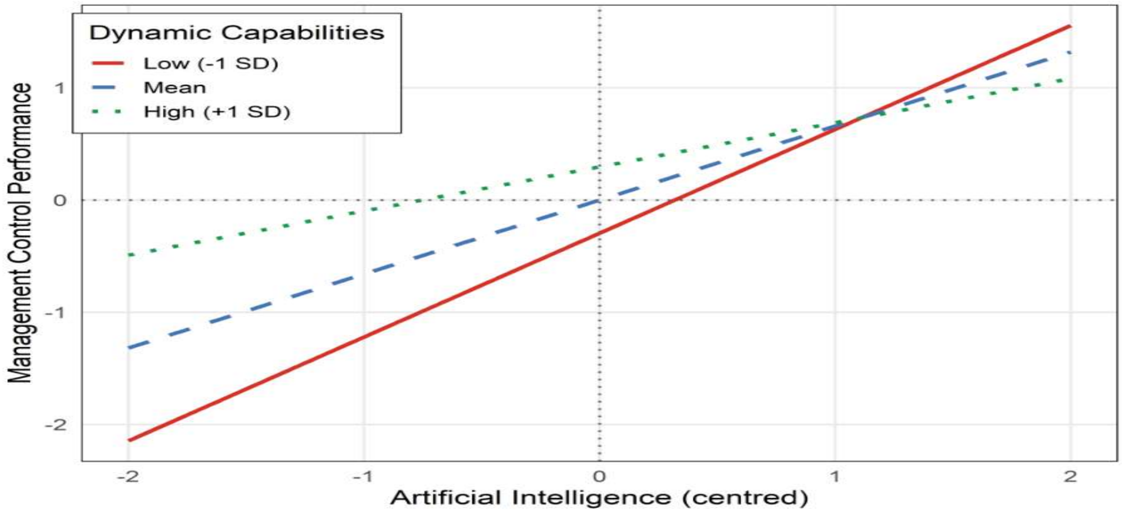

Figure 3 Moderating effect of dynamic capabilities on the relationship between AI and management control performance. Simple slope analysis shows that the effect of AI is stronger at low levels of DC (−1 SD) compared to high levels of DC (+1 SD), consistent with a substitution effect.

3.8 Robustness Checks

Several robustness checks were conducted. First, the structural model was re-estimated using the purified measurement model (after removal of PF1 and AI5). The AI→PF coefficient decreased from 0.71 to 0.59 ($p < 0.001$), while the DG→PF effect remained stable at 0.29 ($p < 0.01$). All indirect effects remained non-significant. Second, theoretically justified error covariances were introduced, improving model fit (CFI = 0.91, RMSEA = 0.072). Third, a reduced model including only direct effects was estimated as a benchmark specification. Across all alternative specifications, the substantive conclusions remained unchanged.

To test the robustness of the structural relationships, additional control variables were included: firm size (log of employees), sector (manufacturing vs. services), and managerial experience (years). The inclusion of these controls did not materially alter the results. None of the control variables exhibited statistically significant effects on either dynamic capabilities or management control performance. Importantly, the coefficients of digitalisation and artificial intelligence remained stable across model specifications.

Table 8 Structural model with control variables

Path	Original model (β / p)	With controls (β / p)
DG → PF	0.29 / 0.002	0.28 / 0.003
AI → PF	0.59 / 0.001	0.57 / 0.001
Firm size → PF	–	0.05 / 0.45
Sector → PF	–	0.07 / 0.31
Experience → PF	–	0.02 / 0.68

4. Discussion

4.1 Interpretation of Direct Effects

The direct effect of artificial intelligence on management control performance (β = 0.59 after purification) is strong and statistically significant. This finding aligns with a growing body of literature documenting the positive impact of artificial intelligence on operational efficiency and managerial decision-making. For example, Kokina and Davenport (2017) show that artificial intelligence reduces errors in financial reporting and accelerates reporting cycles, while Ransbotham et al. (2017) highlight that artificial intelligence enhances organisational performance through automation and decision augmentation. More recent studies (e.g., Mikalef & Gupta, 2021; Stratopoulos & Wang, 2025) further confirm that artificial intelligence capabilities improve decision-making quality and forecasting accuracy.

The magnitude of the artificial intelligence effect ($\beta = 0.59$) appears higher than that typically observed for digitalisation ($\beta \approx 0.20–0.35$), suggesting that artificial intelligence may represent a more transformative technology compared to incremental digital tools. This is consistent with the argument that artificial intelligence enables more sophisticated analytical capabilities that go beyond the automation provided by traditional digital tools (Agrawal et al., 2019; Martins & Marques, 2026). In contrast, the direct effect of digitalisation ($\beta = 0.29$) is positive but more moderate, which is consistent with the argument that foundational digital technologies such as ERP and BI systems have become increasingly commoditised in large organisations (Ghasemaghaei & Calic, 2020). As such, their marginal contribution to performance may diminish once a basic level of digital maturity is reached.

4.2 Why Do Dynamic Capabilities Not Mediate?

The absence of a significant mediating effect of dynamic capabilities can be explained through several complementary arguments grounded in theory and methodology.

Ordinary versus dynamic capabilities: The operationalisation of dynamic capabilities in this study may capture ordinary capabilities rather than higher-order dynamic capabilities. While ordinary capabilities enable efficient day-to-day operations, dynamic capabilities refer specifically to higher-order sensing, seizing, and transforming routines that support strategic renewal (Teece, 2014). If the measurement reflects general adaptability, skills, and organisational practices, it may not fully capture the construct required for mediation. This measurement issue is particularly relevant given that most survey-based measures of dynamic capabilities have been criticised for capturing ordinary capabilities rather than the higher-order routines that Teece (2007) describes (Schilke et al., 2018).

Temporal lags in capability development: Dynamic capabilities develop over time through iterative learning processes. In contrast, artificial intelligence technologies may generate relatively immediate performance improvements through automation and predictive analytics (Ransbotham et al., 2017; Brynjolfsson et al., 2021). As dynamic capabilities evolve over longer transformation cycles (Warner & Wäger, 2019), a cross-sectional design may not capture their delayed mediating effects. This temporal mismatch suggests that longitudinal research may be necessary to fully capture the mediating role of dynamic capabilities.

Artificial intelligence as a substitute for dynamic capabilities: Recent literature suggests that artificial intelligence systems may embed sensing, seizing, and transforming functions directly into technological infrastructures. Warner and Wäger (2019) refer to this as "digital dynamic capabilities," where certain capabilities are partially internalised within digital systems. From a substitution perspective (Goodhue & Thompson, 1995), when task–technology fit is high, organisational capabilities may become less critical for performance outcomes. The absence of mediation is therefore consistent with a substitution logic rather than a complementary one. This interpretation is further supported by the negative moderation effect discussed in Section 4.4.

Sample characteristics and restricted variance: The sample is composed mainly of young professionals (65.5% under 30) and employees from large firms (76.7%). Such homogeneity may reduce variance in both dynamic capabilities and performance perceptions, thereby limiting the statistical ability to detect mediation effects (Barreto, 2010). Additionally, the relatively high mean for digitalisation (4.22) suggests that the sample is skewed toward digitally advanced firms, which may not be representative of the broader Moroccan business landscape.

Statistical power considerations: Although post-hoc power analysis indicates sufficient power for detecting direct effects (>0.99), power is lower for small indirect effects ($f^2 = 0.02 \approx 0.50$). However, given that the estimated indirect effects are effectively null (close to zero), the lack of mediation is unlikely to be solely due to statistical power limitations. The bootstrapped confidence intervals consistently include zero, providing strong evidence against mediation.

4.3 Discriminant Validity and Measurement Issues

After item purification (removal of PF1 and AI5), the HTMT for the AI–PF construct pair is 0.758, below the conservative threshold of 0.85 (Henseler et al., 2015). In addition, the chi-square difference test ($\Delta\chi^2 = 12.33$, $p < 0.001$) confirms empirical distinctiveness. Although the Fornell-Larcker criterion remains violated (squared correlation = 0.602 > AVE of both constructs), this criterion is considered overly conservative compared to HTMT (Henseler et al., 2015; Voorhees et al., 2016).

The remaining discriminant validity concerns reflect a well-documented issue in artificial intelligence and performance research: perceptual overlap between technology usage and perceived performance outcomes. Respondents may inadvertently conflate "effective AI usage" with "better performance," particularly when both constructs are measured using subjective Likert-scale items (Podsakoff et al., 2003). This issue is particularly salient in early-stage adoption contexts, where respondents may lack objective benchmarks for assessing artificial intelligence effectiveness. Future research should adopt more objective and disaggregated measures, such as system log data, audit reports, or objective performance indicators.

4.4 The Substitution Effect of Artificial Intelligence

The significant negative interaction effect between artificial intelligence and dynamic capabilities ($\beta = -0.371$, $p = 0.001$) provides important theoretical insights. It suggests a substitution rather than a complementarity relationship between artificial intelligence and dynamic capabilities in explaining management control performance. This finding is consistent with the concept of digitally embedded capabilities proposed by Warner and Wäger (2019), whereby sensing, seizing, and transforming functions are increasingly encoded into digital systems themselves. In such cases, certain elements of firm-level dynamic capabilities may be partially internalised within technological artefacts.

Similarly, task–technology fit theory (Goodhue & Thompson, 1995) posits that when technology capabilities closely match task requirements, the need for complementary organisational adaptation decreases. In the context of management control, artificial intelligence systems that perform forecasting, anomaly detection, and decision support exhibit a high degree of task alignment, thereby reducing reliance on pre-existing organisational capabilities. This is particularly relevant for structured, data-driven tasks that are common in management control functions.

These results extend prior dynamic capabilities research (Barreto, 2010; Helfat & Peteraf, 2015; Schilke et al., 2018), which has predominantly emphasised complementarity between technological resources and organisational capabilities. Our findings suggest that this relationship is contingent: in environments where technologies are highly intelligent and tasks are structured and data-driven, substitution effects may emerge. From a contextual perspective, this effect may be particularly relevant in emerging economies, where organisational capabilities may be less developed but artificial intelligence tools can still generate direct performance gains.

The substitution effect also has implications for the broader literature on digital transformation. While much of the literature emphasises the need for organisational change to realise the benefits of digital technologies (Warner & Wäger, 2019; Matarazzo et al., 2021), our findings suggest that in some contexts, artificial intelligence can deliver performance improvements without extensive organisational reconfiguration. This may be particularly true for routine, structured tasks where artificial intelligence capabilities closely match task requirements.

4.5 Practical Implications

This study offers several implications for chief financial officers and management controllers. First, investments in artificial intelligence should be accompanied by clear, objective performance metrics, such as reporting cycle time, forecast accuracy, and error reduction rates, rather than relying solely on perceptual assessments. This is particularly important given the potential for perceptual overlap between artificial intelligence usage and performance perceptions.

Second, digitalisation remains a necessary infrastructure layer that enables artificial intelligence integration and effective data flow across management control systems. Organisations should ensure that their digital infrastructure is sufficiently robust to support artificial intelligence applications, with attention to data quality, system interoperability, and process standardisation.

Third, artificial intelligence appears particularly valuable in contexts where organisational capabilities are still developing, suggesting that it can serve as an enabling technology in capability-constrained environments. This has implications for small and medium-sized enterprises and firms in emerging economies, which may face resource constraints in developing organisational capabilities but can still benefit from artificial intelligence adoption in routine management control tasks.

Fourth, managers are encouraged to complement survey-based evaluations of artificial intelligence impact with objective performance data to obtain a more accurate assessment of technological value creation. This may include tracking key performance indicators such as forecast accuracy (e.g., mean absolute percentage error), reporting cycle time, and error rates in financial reporting. Fifth, organisations should implement artificial intelligence through incremental pilot projects (e.g., budgeting or forecasting cycles) before full-scale deployment, in order to better assess value creation and manage implementation risk. This staged approach allows organisations to learn from early implementations and adapt their strategies accordingly.

Finally, the substitution effect identified in this study suggests that managers should not assume that artificial intelligence requires fully developed dynamic capabilities to generate performance improvements. Instead, they should evaluate artificial intelligence investments based on their specific task alignment and potential for direct performance gains, particularly in structured, routine management control tasks.

4.6 Limitations and Future Research

This study has several limitations that should be acknowledged. The sample size ($n = 116$) is relatively modest, which may limit statistical power for detecting complex indirect effects and interactions. Although power analysis indicated sufficient power for detecting medium-sized effects, the sample may be insufficient for detecting small indirect effects. The sample is also predominantly composed of large firms (76.7% with ≥250 employees), limiting generalisability to small and medium-sized enterprises.

The cross-sectional research design restricts the ability to establish temporal ordering and causal inference. While our theoretical model implies causal relationships, the cross-sectional data cannot definitively establish causality. Longitudinal or panel data designs would be better suited to examining causal relationships. The measurement of dynamic capabilities may capture more general organisational adaptability (i.e., ordinary capabilities) rather than higher-order sensing, seizing, and transforming routines. This measurement issue is common in survey-based research on dynamic capabilities (Schilke et al., 2018) and may have contributed to the non-significant mediation findings.

Although common method bias was addressed through procedural and statistical remedies, residual bias may still exist due to the use of perceptual survey data. Self-report measures of both independent and dependent variables may inflate relationships due to response biases. Potential endogeneity between artificial intelligence adoption and performance cannot be fully ruled out in a cross-sectional design. Unobserved factors such as managerial ability, strategic orientation, or organisational culture may influence both artificial intelligence adoption and performance, leading to biased estimates.

The external validity of the findings is limited. The sample is concentrated in the Casablanca–Settat region and is predominantly composed of large firms. Consequently, the results cannot be generalised to small and medium-sized enterprises, which face different resource constraints, digital maturity levels, and organisational capability profiles. The findings may be specific to the Moroccan context, particularly the early-stage nature of artificial intelligence adoption and the institutional environment characteristic of emerging economies. Cross-country replication studies are needed to assess the generalisability of the substitution effect.

Future research should address these limitations through several approaches: employing larger and more diverse samples, including small and medium-sized enterprises and firms from different sectors; utilising longitudinal or panel data designs to enable stronger causal inference; incorporating objective performance indicators such as reporting cycle time, forecast accuracy, and error rates; distinguishing between ordinary and dynamic capabilities using validated sensing–seizing–transforming scales; examining different artificial intelligence types (rule-based, machine learning, generative AI) to provide a more nuanced understanding of how artificial intelligence capabilities interact with organisational capabilities; and investigating moderating factors such as task routineness, environmental dynamism, and strategic orientation to help identify boundary conditions of the substitution effect.

5. Conclusion

This study provides a rigorous empirical test of whether dynamic capabilities mediate the effects of digitalisation and artificial intelligence on management control performance. The findings indicate that both digitalisation and artificial intelligence exert significant positive direct effects on performance; however, dynamic capabilities do not mediate these relationships. Instead, dynamic capabilities negatively moderate the relationship between artificial intelligence and performance, suggesting a substitution effect.

Rather than contradicting the dynamic capabilities framework, these results suggest boundary conditions in its application to management control contexts. In particular, artificial intelligence technologies may directly enhance control processes through automation, prediction, and anomaly detection, thereby reducing the extent to which organisational-level capability development is required for immediate performance improvements. This also aligns with the possibility that certain dynamic capabilities may be partially embedded within advanced digital systems.

The study further confirms acceptable discriminant validity after item purification (HTMT = 0.758; chi-square difference test $p < 0.001$), supporting the robustness of the measurement model despite residual proximity between artificial intelligence and performance constructs. The significant negative moderation effect ($\beta = -0.371$, $p = 0.001$) provides strong evidence for a substitution effect, challenging the conventional complementarity assumption in the dynamic capabilities literature.

From a managerial perspective, several implications emerge. First, firms should assess digital readiness prior to artificial intelligence adoption, particularly in terms of data integration quality, system interoperability, and process standardisation. Second, artificial intelligence adoption does not necessarily require fully developed dynamic capabilities, as it can still generate measurable performance gains even in capability-constrained environments. This suggests that artificial intelligence may function as a partial substitute for organisational capabilities in routine management control tasks. Third, evaluation of artificial intelligence initiatives should rely on objective performance indicators such as reporting cycle time, forecasting accuracy, and error rates in financial reporting, rather than solely on perceptual assessments. Finally, organisations are advised to implement artificial intelligence through incremental pilot projects before full-scale deployment, in order to better assess value creation and manage implementation risk.

From a theoretical perspective, our findings contribute to the ongoing refinement of the dynamic capabilities framework by highlighting the contingent nature of technology–capability relationships. While dynamic capabilities remain important for strategic renewal and long-term adaptation, our results suggest that in structured, routine tasks, artificial intelligence can substitute for certain organisational capabilities. This has implications for both theory development and empirical research on digital transformation.

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6. Declaration

6.1 Ethical Considerations

This study was considered exempt from formal institutional review board approval, as it did not involve intervention, sensitive data collection, or identifiable personal information. The research involved voluntary completion of an anonymous survey by professionals regarding organisational perceptions. Nevertheless, ethical research standards were strictly followed. Participants received an information sheet explaining the purpose of the study, and informed consent was obtained implicitly through voluntary participation. No personal identifiers (such as names, email addresses, or IP addresses) were collected. All data were securely stored on a password-protected device accessible only to the principal investigator. The study complied with the ethical principles of the American Psychological Association and the Declaration of Helsinki.

6.2 Conflict of Interest

The authors declare no conflicts of interest.

6.3 Funding

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