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Artificial Intelligence as a Driver of Managerial Competency Transformation: An Empirical Study of Telecommunications Operators in Tunisia.

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Résumé

Objectif : Cet article examine comment l'intelligence artificielle (IA) transforme les compétences managériales dans le secteur tunisien des télécommunications, industrie fortement numérisée où les algorithmes soutiennent la segmentation de la clientèle, la maintenance prédictive et l'optimisation des réseaux. Les mécanismes par lesquels l'IA remodèle les compétences des managers demeurent peu explorés, en particulier dans les économies émergentes d'Afrique du Nord.

Approche méthodologique : L'étude adopte une démarche quantitative, positiviste et hypothético-déductive. Mobilisant les théories des capacités dynamiques et des systèmes sociotechniques, complétées par les modèles d'acceptation technologique et la perspective institutionnelle, elle teste un modèle reliant l'IA, la confiance dans l'IA et la culture organisationnelle (variable modératrice) à quatre familles de compétences : collaboratives, augmentées, centrées sur l'humain et émergentes. L'IA est modélisée comme un construit réflexif de second ordre à six dimensions. Les données, recueillies par questionnaire auto-administré (échelles de Likert à sept points), sont analysées par PLS-SEM (SmartPLS 4.0, 5 000 rééchantillonnages). Les hypothèses testent les effets directs des six dimensions de l'IA et les effets d'interaction de quatre dimensions culturelles (adoption, soutien organisationnel, intégration stratégique et formation).

Échantillon questionné : 72 cadres supérieurs et top managers de Tunisie Télécom, Ooredoo et Orange (24 par opérateur), interrogés sur une période de quatre mois.

Résultats : L'IA exerce un effet positif et significatif sur les compétences collaboratives ($\beta = 0,53$; $p < 0,001$) et augmentées ($\beta = 0,41$; $p < 0,001$). L'interaction homme-IA est le prédicteur le plus fort des compétences collaboratives ($\beta = 0,71$), et la confiance dans l'IA ($\beta = 0,38$) agit comme un mécanisme actif de développement des compétences. Les coefficients d'interaction, négatifs, suggèrent que la culture organisationnelle standardise l'influence de l'IA plutôt qu'elle ne l'amplifie.

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Originalité et implications : L'étude propose un modèle intégrateur IA–compétences–culture et une grille à quatre familles de compétences, et en tire des implications pour le recrutement, la formation continue, la construction de la confiance et la gouvernance de l'IA.

Limites : Taille de l'échantillon et caractère transversal.

Mots clés : intelligence artificielle ; compétences managériales ; transformation numérique ; PLS-SEM ; économies émergentes ; télécommunications ; Tunisie

Abstract

Purpose: This article examines how artificial intelligence (AI) transforms managerial competencies in the Tunisian telecommunications sector, a highly digitalized industry in which algorithms support customer segmentation, predictive maintenance and network optimization. The mechanisms through which AI reshapes managers' skills remain under-explored, particularly in North African emerging economies.

Design/methodology/approach: The study adopts a quantitative, positivist and hypothetico-deductive approach. Drawing on dynamic capabilities and sociotechnical systems theories, complemented by technology acceptance models and an institutional perspective, it tests a model linking AI, trust in AI and organizational culture (moderator) to four families of competencies: collaborative, augmented, human-centric and emerging. AI is modeled as a second-order reflective construct with six dimensions. Data were collected through a self-administered questionnaire (seven-point Likert scales) and analyzed with PLS-SEM (SmartPLS 4.0, 5,000 bootstrap resamples). The hypotheses test the direct effects of the six AI dimensions and the interaction effects of four cultural dimensions (adoption, organizational support, strategic integration and training).

Sample: 72 senior managers and top executives of Tunisie Télécom, Ooredoo and Orange (24 per operator), surveyed over four months.

Findings: AI has a positive and significant effect on collaborative ($\beta = 0.53$; $p < 0.001$) and augmented competencies ($\beta = 0.41$; $p < 0.001$). Human–AI interaction is the strongest predictor of

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collaborative competencies (β = 0.71), and trust in AI (β = 0.38) acts as an active mechanism of competency development. The negative interaction coefficients suggest that organizational culture standardizes the influence of AI rather than amplifying it.

Originality and implications: The study proposes an integrative AI–competencies–culture model and a four-family competency framework, and derives implications for recruitment, continuous training, trust building and AI governance.

Limitations: Sample size and cross-sectional design.

Keywords: artificial intelligence; managerial competencies; digital transformation; PLS-SEM; emerging economies; telecommunications; Tunisia

Introduction

Digital transformation is among the forces that most deeply reshape contemporary organizations: structures, decision-making processes and value-creation mechanisms are evolving simultaneously across most sectors (Vial, 2019). Among the technologies that underpin this transformation, artificial intelligence (AI) occupies a central place. When it moves from an analytical tool to a cognitive partner, it changes the way managers interpret information, learn and coordinate action.

This development raises the question of how managerial competencies are being transformed. Effective management has long been grounded in leadership, communication, emotional intelligence and team mobilization. In AI-enabled environments, these competencies must be complemented by new capabilities: understanding intelligent systems, interpreting advanced analytics, overseeing algorithmic decisions and integrating digital tools into complex organizations.

Yet the mechanisms through which AI contributes to this transformation remain insufficiently explored. Research has concentrated on technological capabilities or organizational performance (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020), and has paid less attention to the managerial competencies needed to take advantage of these systems.

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In Tunisia, these dynamics are particularly visible in the telecommunications sector, a highly digitalized industry in which algorithms support customer segmentation, predictive maintenance, network optimization and customer-experience management. To our knowledge, no empirical study has yet specifically examined the AI-induced transformation of managerial competencies in Tunisian telecommunications operators.

This article pursues two objectives. It identifies the dimensions of AI that influence the development of managerial competencies. It also examines the moderating role of an AI-friendly organizational culture in the relationship between AI use and competency development.

To address these objectives, we draw on four complementary frameworks: dynamic capabilities theory (Eisenhardt & Martin, 2000; Teece, 2018), sociotechnical systems theory (Trist & Emery, 1965), the TAM and UTAUT technology acceptance models (Davis, 1989; Venkatesh et al., 2003) and neo-institutional theory (Meyer & Rowan, 1977). These objectives translate into a research question: to what extent does AI transform managerial competencies in the Tunisian telecommunications sector, and how does organizational culture condition this relationship?

Our contribution is threefold. At the theoretical level, we propose an integrative AI–competencies–culture model, which extends dynamic capabilities theory (Eisenhardt & Martin, 2000) and sociotechnical systems theory (Trist & Emery, 1965). We then consider trust in AI not only as a condition for adoption but as an active mechanism of competency development, building on the work of Glikson and Woolley (2020). Finally, we propose a four-family competency framework (collaborative, augmented, human-centric, emerging), transferable to other sectors.

The article successively presents the theoretical framework and hypotheses, the methodology, the results, and then their discussion and the conclusion.

1 Theoretical Framework and Hypotheses

1.1 Theoretical Foundations

Two main theoretical frameworks, complemented by technology acceptance models and the institutional perspective, shed light on the relationship between AI and managerial competencies.

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Dynamic capabilities theory holds that organizational performance depends on the ability to sense opportunities, seize innovations and reconfigure resources in changing environments (Eisenhardt & Martin, 2000; Teece, 2018). Applied to AI, it suggests that the technology amplifies managerial capabilities when it is aligned with strategy and when it modifies decision routines. Sociotechnical systems theory asserts that optimal performance results from the joint optimization of the social and technical subsystems (Trist & Emery, 1965). From this perspective, AI creates value only when it co-evolves with managerial practices: it redistributes decision responsibilities and reconfigures coordination and trust mechanisms. Dynamic capabilities explain how competencies are reconfigured in the face of a new technology (Teece et al., 1997), while the sociotechnical approach emphasizes the articulation between technology and work organization (Trist & Bamforth, 1951).

Technology acceptance models complete this framework. The TAM (Davis, 1989) and the UTAUT (Venkatesh et al., 2003) show that adoption depends on perceived usefulness, ease of use, trust and cultural alignment, and not only on technical performance. TAM3 extends these determinants to organizational factors and training (Venkatesh & Bala, 2008), which justifies integrating organizational culture as a moderating variable.

1.2 AI as a Lever of Managerial Transformation

AI increasingly functions as a cognitive and decision-making partner: it supports scenario analysis, predictive diagnosis and decision optimization (Jarrahi, 2018; Raisch & Krakowski, 2021). It also transforms decision structures, shifting some analyses to systems and redistributing judgment among actors (Shrestha et al., 2019). Contrary to the initial concerns about the replacement of managers, several studies suggest that AI augments human judgment more than it replaces it (Jarrahi, 2018; Raisch & Krakowski, 2021). Managers must therefore develop analytical, ethical and oversight competencies to ensure coherent, unbiased AI-assisted decision-making (Makridakis, 2017).

1.3 Families of Managerial Competencies in an AI Context

We distinguish three families of competencies in AI contexts. Augmented competencies are directly strengthened by AI: data-driven analysis, predictive analytics and algorithm-assisted

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planning (Mikalef & Gupta, 2021). Human-centric competencies, such as leadership, interpersonal communication, ethical judgment and emotional intelligence, remain, in our view, relatively stable and hard for technology to substitute, with AI complementing human judgment rather than replacing it (Jarrahi, 2018). Emerging competencies are new capabilities required for human–AI collaboration: algorithmic literacy, AI governance and digital creativity. This typology extends the classic distinction between technical, human and conceptual skills (Katz, 1955) and the competency-based approach (Boyatzis, 1982), adding interaction with intelligent systems.

A fourth family, that of collaborative competencies, accounts for the ability to work in continuous interaction with AI systems (Wilson & Daugherty, 2018). We define it as the manager's ability to coordinate action between humans and intelligent systems: sharing and interpreting with teams the information produced by AI, allocating roles between human judgment and algorithmic processing, and collectively deciding on AI-assisted outcomes. Emerging competencies, measured in the questionnaire, are not subject to a structural test in this article (see Section 3.3 and the conclusion).

1.4 Trust in AI as a Mechanism of Competency Development

Trust is decisive for the adoption and effective use of AI (Glikson & Woolley, 2020). It rests on algorithmic transparency, the interpretability of recommendations and perceived ethical consistency. When managers trust AI outputs, they integrate them more readily into their decisions, which fosters managerial learning and redirects cognitive resources toward strategic thinking, coordination and innovation. Conversely, distrust leads to cognitive resistance and limits the potential for competency development. Users, moreover, give less credit to machine recommendations in certain contexts (Longoni & Cian, 2022). We hypothesize that trust is not only a condition for adoption but an active mechanism of competency development. This distinction remains little demonstrated empirically. Trust is approached here through perceived competence, benevolence and integrity (Mayer et al., 1995), transposed to automated systems (Jian et al., 2000; Lee & See, 2004).

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1.5 An AI-Friendly Organizational Culture as a Moderator

Organizational culture shapes AI adoption and competency development (Schein, 2017). An AI-friendly culture encourages experimentation, continuous learning, tolerance for error and collaboration between humans and algorithms. Organizations tend to standardize their practices in order to gain legitimacy (Meyer & Rowan, 1977), which suggests that culture may channel the influence of technology rather than merely amplify it. The normative and mimetic pressures of a given sector reinforce this homogenization (DiMaggio & Powell, 1983).

The moderating role of culture is distinct from its direct effect. Culture does not only shape competencies; it conditions the extent to which AI becomes a lever for competency development. This distinction is testable through interaction terms in a PLS-SEM model. The four dimensions of culture draw on the organizational factors of AI capability (Mikalef & Gupta, 2021; Berente et al., 2021) and on work on organizational culture (Schein, 2017; Cameron & Quinn, 2011); training refers to absorptive capacity (Cohen & Levinthal, 1990).

1.6 Research Hypotheses

On the basis of this framework, we formulate the following hypotheses:

H1: AI significantly and positively affects managerial competencies. This hypothesis breaks down into six sub-hypotheses: H1a, AI use and integration strengthen competencies; H1b, AI-based decision support strengthens analytical and oversight competencies; H1c, the perceived impact of AI on performance fosters adaptive capabilities; H1d, the strategic implementation of AI strengthens change-management competencies; H1e, human–AI interaction fosters hybrid competencies; H1f, trust in AI supports managerial learning and governance competencies.

H2: AI contributes to the augmentation of managerial competencies, particularly in analysis, planning and information management.

H3: An AI-friendly organizational culture moderates the relationship between AI and managerial competencies. This hypothesis breaks down into four sub-hypotheses: H3a, the adoption of AI in the organization accelerates individual competency development; H3b, organizational support

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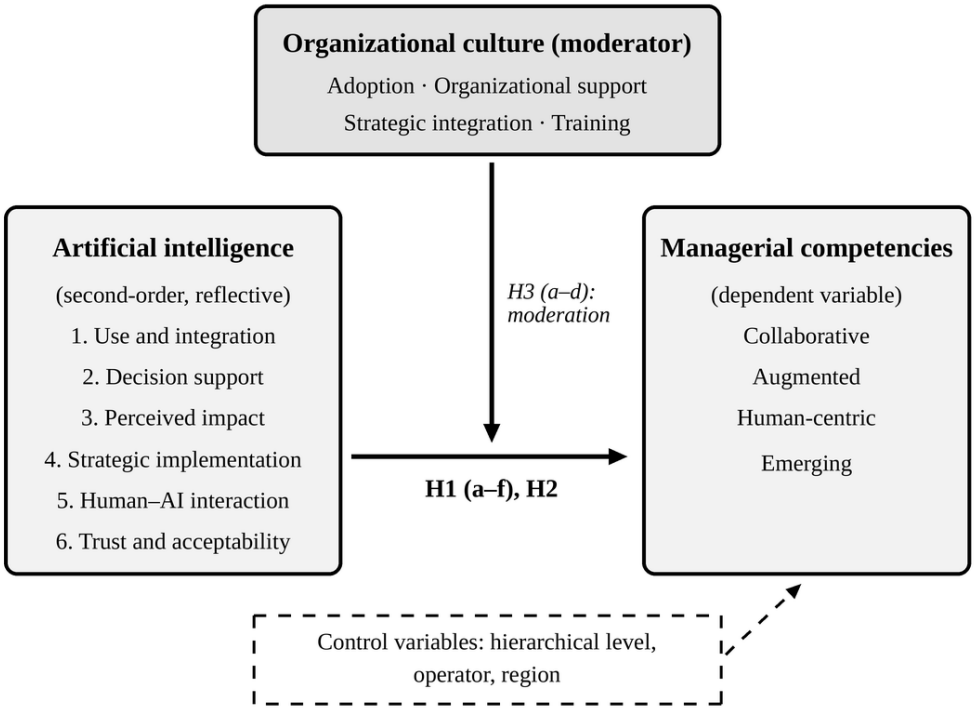
strengthens the appropriation of AI-related competencies; H3c, the strategic integration of AI amplifies its impact on competencies; H3d, continuous AI training enables managers to update their competencies.

Foundations of the hypotheses. H1 rests on the idea that AI acts as a cognitive partner (Jarrahi, 2018; Raisch & Krakowski, 2021) and on dynamic capabilities (Teece et al., 1997). Its sub-hypotheses reflect the six dimensions of AI: H1a extends work on technology integration (Venkatesh et al., 2003; Mikalef & Gupta, 2021); H1b draws on Shrestha et al. (2019) and Brynjolfsson and McElheran (2016); H1c on perceived usefulness (Davis, 1989) and the AI–performance link (Wamba-Taguimdje et al., 2020); H1d on strategic alignment (Vial, 2019; Berente et al., 2021); H1e on collaborative intelligence (Wilson & Daugherty, 2018); H1f on trust (Glikson & Woolley, 2020; Mayer et al., 1995). H2 is part of the argument of augmentation rather than substitution (Brynjolfsson & McAfee, 2017; Raisch & Krakowski, 2021). H3 articulates the cultural (Schein, 2017) and institutional (Meyer & Rowan, 1977; DiMaggio & Powell, 1983) perspectives, with H3d drawing on absorptive capacity (Cohen & Levinthal, 1990).

1.7 Conceptual Model

The conceptual model consists of three components. The independent variable is AI, operationalized as a second-order reflective construct with six dimensions: use, decision support, perceived impact, strategic implementation, human–AI interaction, and trust and acceptability. The dependent variable groups managerial competencies into four categories: collaborative, augmented, human-centric and emerging. The moderating variable is an AI-friendly organizational culture, composed of adoption, organizational support, strategic integration and training. The control variables are hierarchical level, operator and geographic region. The structural model is written as: $MC = \beta_0 + \beta_1 AI + \beta_2 CULT + \beta_3(AI \times CULT) + \varepsilon$, where β_3 captures the moderating effect. It is summarized in Figure 1. These variables derive from the literature cited in Sections 1.1 to 1.6; the control variables neutralize differences in access to AI, technological maturity and location.

Figure 1: Conceptual Model of the Transformation of Managerial Competencies by AI



Source: Authors' elaboration.

2 Methodology

2.1 Positioning and Study Setting

We adopt a quantitative, positivist approach based on hypothesis testing. The setting is the Tunisian telecommunications sector, chosen for its high digital maturity, its competitive intensity and its early adoption of AI: predictive analytics, customer relationship management (CRM), process optimization and performance management. These companies operate in a regulated and dynamic environment, which makes them particularly relevant for studying AI-induced managerial transformation.

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2.2 Sample and Data Collection

The data were collected through a structured, self-administered questionnaire, an approach widely validated for capturing managerial perceptions and practices in information systems research (Podsakoff et al., 2003). The survey targets the senior managers and top management of each of the three operators, who are directly involved in AI-related strategic and operational decisions.

The final sample comprises 72 respondents, senior managers and top management of the three main Tunisian telecommunications operators (Tunisie Télécom, Ooredoo and Orange), distributed across 24 governorates of Tunisia (Table 1). The sample size is modest, but it is compatible with the requirements of the PLS-SEM method, which is designed for exploratory models with complex constructs and moderate sample sizes (Hair et al., 2019). The ten-times rule (Barclay et al., 1995) is satisfied: the endogenous construct with the most predictors has five, which requires a minimum of fifty respondents. A sensitivity analysis carried out with G*Power (F tests, multiple linear regression, five predictors, $\alpha = 0.05$, power = 0.80) indicates that a sample of 72 respondents makes it possible to detect effects of size $f^2 \approx 0.19$, that is, medium-to-large effects. According to the inverse square root method (Kock & Hadaya, 2018), the minimum sample is approximately 39 observations for path coefficients close to 0.40, but approximately 120 for coefficients close to 0.23. The sample is therefore adequate for the medium-to-large effects that underpin the main conclusions, but insufficient for weak effects, notably that of perceived impact (H1c), which should be interpreted with caution. The parameters of this analysis follow Faul et al. (2009).

Table 1: Sample Profile

Characteristic	**Value**
Sample size	72 respondents
Operators	Tunisie Télécom, Ooredoo, Orange (3 operators)
Hierarchical level	Senior managers and top management of each operator
Geographic distribution	24 governorates
Distribution by operator	24 managers per operator
Data collection period	4 months

Source: Authors' survey.

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To encourage sincere responses and limit social desirability bias, the questionnaire was preceded by a presentation of its strictly academic purpose and a guarantee of anonymity (Podsakoff et al., 2003).

2.3 Measurement Instruments

All constructs are measured by multi-item reflective scales, adapted from the established literature in management and information systems. Items are rated on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree), which offers sufficient sensitivity while improving reliability (Hair et al., 2019).

The AI construct, the independent variable, is conceptualized as a second-order reflective construct comprising six dimensions: use and integration (4 items), decision support (4 items), perceived impact on performance (4 items), strategic implementation (4 items), human–AI interaction (3 items), and trust and acceptability (4 items), for a total of 23 items. This specification is justified by the fact that these dimensions share the same theoretical domain and co-vary as expected in a reflective specification (Hair et al., 2019).

The managerial competencies construct, the dependent variable, comprises four dimensions: collaborative (3 items), augmented (8 items), human-centric (3 items) and emerging (7 items), for a total of 21 items. The AI-friendly organizational culture, the moderating variable, is measured by four dimensions: adoption, organizational support, strategic integration and training. The control variables are hierarchical level, operator and region. In this article, the structural analysis covers collaborative and augmented competencies (direct effects, Table 5) and human-centric competencies, considered invariant (effects of culture, Table 6); emerging competencies, although measured, are not tested structurally and will be the subject of a dedicated analysis.

The items draw on reference works detailed in Appendix 1: AI capability and technology adoption for use, decision support, perceived impact and strategic implementation; collaborative intelligence for human–AI interaction (Wilson & Daugherty, 2018); trust in automation for trust and acceptability (Mayer et al., 1995; Jian et al., 2000); competency typologies for managerial

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competencies (Katz, 1955; Boyatzis, 1982); and Schein (2017) and Cameron and Quinn (2011) for culture.

2.4 Analytical Strategy: PLS-SEM

The analysis is conducted using partial least squares structural equation modeling (PLS-SEM), with SmartPLS 4.0 software. We prefer this method to covariance-based modeling (CB-SEM) for three reasons: the study is exploratory and aims at theory building; the model includes a second-order construct (AI); and the sample is of moderate size, a condition for which the PLS method is well established (Hair et al., 2019). The analysis follows a two-step approach: assessment of the measurement model (reliability and validity), then estimation of the structural model (direct and moderating effects). Significance is tested by bootstrapping with 5,000 resamples. The software is SmartPLS 4 (Ringle et al., 2022), the second-order construct follows Wetzels et al. (2009) and Sarstedt et al. (2019), and the moderating effects are tested through interaction terms (Henseler & Fassott, 2010).

2.5 Controlling for Common Method Bias

Since all variables are measured by the same questionnaire at the same time, common method bias is a potential concern (Podsakoff et al., 2003). Harman's single-factor test attributes 24.3% of the total variance to a single factor, below the critical threshold of 50%. As procedural remedies, items were presented in random order across constructs and respondent anonymity was guaranteed in order to reduce evaluation apprehension.

3 Results

3.1 Descriptive Statistics

Before the multivariate analyses, we examined the distribution of the items. According to the usual benchmarks in the social sciences (Kline, 2016), skewness should lie between −2 and +2 and kurtosis should be below 7 in absolute value. All retained items meet these thresholds (Table 2). The AI items show a slightly negative skewness, which reflects globally favorable perceptions of AI use, consistent with the respondents' professional exposure to AI tools.

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Table 2: Descriptive Statistics for a Selection of Measurement Items

Construct	Item	Skewness	Kurtosis
AI use	USA34	−0.21	−1.21
AI use	USA35	0.08	−1.14
Perceived impact	IMPCT38	−0.30	−1.30
Perceived impact	IMPCT39	−0.65	−0.51
Decision support	CONT42	−1.18	0.39
Decision support	CONT43	−0.42	2.88
Trust in AI	TRUST53	−0.44	0.62
Trust in AI	TRUST54	−0.51	0.38
Organizational culture	CULT60	−0.52	0.41
Managerial competencies	MC71	−0.38	0.54

Note: all items meet the thresholds |skewness| < 2 and |kurtosis| < 7 (Kline, 2016). Table reduced to illustrative items.

Source: Authors' calculations (SmartPLS 4.0).

3.2 Quality of the Measurement Model

Internal consistency reliability is assessed using Cronbach's alpha and composite reliability (CR), with thresholds of 0.70; convergent validity is assessed using the average variance extracted (AVE), with a threshold of 0.50 (Fornell & Larcker, 1981; Hair et al., 2019). Table 3 shows that all constructs satisfy these thresholds. The overall AI construct shows particularly high reliability ($\alpha = 0.969$; CR = 0.974; AVE = 0.723). The human–AI interaction dimension shows the lowest values ($\alpha = 0.70$; CR = 0.78; AVE = 0.56), but remains above all thresholds, which is acceptable for the exploratory measurement of human–AI interaction in an emerging context.

Table 3: Reliability and Convergent Validity of the Constructs

Construct / dimension	**Cronbach's α**	**CR**	**AVE**
Artificial intelligence (overall)	0.969	0.974	0.723
AI use	0.98	0.98	0.93
Perceived impact	0.97	0.97	0.89
Decision support	0.85	0.86	0.62
Strategic implementation	0.98	0.98	0.94
Human–AI interaction	0.70	0.78	0.56
Trust and acceptability	0.91	0.93	0.72
Organizational culture (overall)	0.97	0.97	0.80
Adoption	0.97	0.97	0.93
Organizational support	0.93	0.94	0.84
Strategic integration	0.93	0.94	0.85
Training	0.89	0.88	0.80
Competencies: collaborative	0.92	0.92	0.81
Competencies: augmented	0.88	0.88	0.55
Competencies: human-centric	0.92	0.92	0.85
Competencies: emerging	0.87	0.89	0.61

Source: Authors' calculations (SmartPLS 4.0).

Discriminant validity is assessed using the heterotrait–monotrait ratio (HTMT), a stricter criterion than the Fornell–Larcker criterion in PLS-SEM models (Hair et al., 2019; Henseler et al., 2015). All ratios remain below the thresholds of 0.85 to 0.90 (Table 4). The ratio between AI and organizational culture (0.84) approaches the threshold, which is explained by the conceptual overlap between AI adoption and an AI-friendly culture.

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Table 4: Discriminant Validity (HTMT Ratios)

Pair of constructs	HTMT	Threshold	Result
AI vs managerial competencies	0.72	< 0.85	Validated
AI vs organizational culture	0.84	< 0.90	Validated
Culture vs managerial competencies	0.68	< 0.85	Validated
AI dimensions (between constructs)	0.61–0.79	< 0.90	Validated

Source: Authors' calculations (SmartPLS 4.0).

3.3 Direct Effects of AI on Managerial Competencies

Table 5 presents the standardized path coefficients and their significance (bootstrapping, 5,000 resamples). AI, considered globally, exerts a direct, positive and highly significant effect on collaborative competencies ($\beta = 0.5306$; $p < 0.001$) and on augmented competencies ($\beta = 0.4064$; $p < 0.001$), which strongly supports H1 and H2.

At the dimension level, human–AI interaction is the strongest predictor of collaborative competencies ($\beta = 0.7120$; $p < 0.001$), which supports H1e. Next come decision support ($\beta = 0.4503$), strategic implementation ($\beta = 0.4394$) and AI use ($\beta = 0.4354$), which confirm H1b, H1d and H1a. Trust in AI also has a significant effect ($\beta = 0.3812$; $p < 0.001$), which confirms H1f. Perceived impact shows a more modest but significant effect ($\beta = 0.2274$; $p = 0.013$): H1c is only partially supported.

Table 5: Direct Effects of the AI Dimensions on Managerial Competencies

Predictor	Dependent variable	β	p	Decision
AI (overall)	Collaborative	0.5306	< 0.001	H1 supported
AI (overall)	Augmented	0.4064	< 0.001	H2 supported
AI use	Collaborative	0.4354	< 0.001	H1a supported
Perceived impact	Collaborative	0.2274	0.013	H1c partial
Decision support	Collaborative	0.4503	< 0.001	H1b supported

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Predictor	Dependent variable	β	p	Decision
Strategic implementation	Collaborative	0.4394	< 0.001	H1d supported
Human–AI interaction	Collaborative	0.7120	< 0.001	H1e supported
Trust in AI	Collaborative	0.3812	< 0.001	H1f supported

Source: Authors' calculations (SmartPLS 4.0).

3.4 Effects of an AI-Friendly Organizational Culture

Table 6 presents the effects of organizational culture for human-centric competencies, considered invariant. The overall effect of AI on these competencies remains positive and significant (β ranging from 0.5546 to 0.6764; $p < 0.001$). By contrast, some interaction terms between cultural dimensions and AI dimensions are significant. These terms do not, on their own, constitute a complete test of hypothesis H3: the overall interaction coefficient of the AI × culture relationship is not reported here, which limits the scope of our conclusions on moderation (see the limitations). In particular, training reduces the effect of perceived impact on invariant competencies ($\beta = -0.4424$; $p < 0.001$). The same type of result appears, more modestly, for adoption ($\beta = -0.1572$; $p = 0.045$), whereas the interaction between training and human–AI interaction is only marginally significant ($\beta = -0.1269$; $p = 0.058$).

These negative coefficients do not mean that culture weakens the impact of AI. They suggest a standardization mechanism: organizational culture channels the influence of AI and reduces the individual variability of its use and perception. Organizational support and strategic integration, by contrast, show positive direct effects on invariant competencies.

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Table 6: Direct and Moderating Effects of Organizational Culture on Invariant Competencies

Moderator	Tested term	β	p	Type of effect
Training	AI (overall) → invariant	0.5546	< 0.001	Amplifying
Training	Perceived impact × training	−0.4424	< 0.001	Standardizing
Training	Human–AI interaction × training	−0.1269	0.058	Marginal
Adoption	AI (overall) → invariant	0.6764*	< 0.001	Amplifying
Adoption	Perceived impact × adoption	−0.1572	0.045	Standardizing
Strategic integration	AI (overall) → invariant	0.6764*	< 0.001	Amplifying
Organizational support	AI (overall) → invariant	0.5912	< 0.001	Amplifying

Note: * Identical value for the two dimensions (adoption and strategic integration).

Source: Authors' calculations (SmartPLS 4.0).

3.5 Summary of the Hypotheses

Table 7 presents the decision for each of the hypotheses formulated.

Table 7: Summary of the Hypothesis Tests

Hypothesis	Statement	Decision
H1	AI significantly affects managerial competencies (β = 0.53)	Supported
H1a	AI use and integration strengthen competencies	Supported
H1b	AI-based decision support strengthens analytical competencies	Supported
H1c	The perceived impact of AI fosters adaptive capabilities	Partial

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Hypothesis	Statement	Decision
H1d	Strategic implementation strengthens change-management competencies	Supported
H1e	Human–AI interaction fosters hybrid competencies (β = 0.71)	Supported
H1f	Trust in AI supports learning and governance	Supported
H2	AI contributes to the augmentation of analytical and planning competencies	Supported
H3a	AI adoption accelerates individual competency development	Not confirmed (significant but negative interaction, β = −0.1572)
H3b	Organizational support strengthens competency appropriation	Not confirmed (direct effect only)
H3c	Strategic integration amplifies the impact of AI on competencies	Not confirmed (direct effect only)
H3d	Continuous training makes it possible to update competencies	Partial (significant but negative interaction, β = −0.4424)

Source: Study results.

4 Discussion and Implications

4.1 Interpretation of the Main Findings

The results support the central idea that AI is a significant lever for transforming managerial competencies in Tunisian telecommunications operators. This transformation is, however, neither automatic nor homogeneous. The most notable result is the dominant role of human–AI interaction (β = 0.71) in the development of collaborative competencies. It is therefore not an effect of technology taken in isolation, but of the way managers work with it: AI acts as a partner in

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managerial cognition rather than as a mere calculation tool, which is consistent with the human-augmentation perspective (Brynjolfsson & McAfee, 2017; Raisch & Krakowski, 2021).

The positive effect of AI on augmented competencies (β = 0.41) indicates that AI does not erode analytical and planning competencies: it strengthens them by enabling managers to process larger volumes of information with greater precision. Finally, the significant effect of trust in AI (β = 0.38) shows that trust is not only a condition for adoption but an active mechanism of competency development.

4.2 Theoretical Contributions

This research makes three contributions. First, it proposes an integrative AI–competencies–culture model that extends dynamic capabilities theory (Eisenhardt & Martin, 2000) and sociotechnical systems theory (Trist & Emery, 1965). It shows that the impact of AI on managerial competencies is conditioned by organizational culture, and that capability development results from the co-evolution of human, technological and institutional factors rather than from a mere technological investment.

Second, the negative interaction coefficients suggest that organizational culture exerts a standardizing effect on certain dimensions of AI. This result qualifies approaches that regard culture solely as a facilitator: it channels the use of AI and shifts competency development from subjective experience to institutionalized learning (Meyer & Rowan, 1977).

Third, the four-family competency framework (collaborative, augmented, human-centric, emerging) provides a reusable analytical framework for other sectors.

4.3 Managerial Implications and HR Practices

The results lead to concrete recommendations for human resources departments and those responsible for digital transformation. These recommendations follow from the estimated effects, but they have not been tested through an intervention; they should be regarded as courses of action to be evaluated.

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Recruitment and manager profiles. Since human–AI interaction is the main determinant of collaborative competencies (β = 0.71), managerial job descriptions should explicitly include the ability to work with AI systems and to interpret their recommendations.

Structured continuous training. The coefficients suggest that training acts as a standardization mechanism (β = −0.4424, interaction term). It should therefore be designed as an institutional, continuous program, and not as a one-off introduction to a piece of software.

Building trust. Trust in AI contributes to competency development (β = 0.38). To strengthen it, organizations can require explainable recommendations, set up feedback loops in which managers flag errors and relevant suggestions, and formalize a usage charter specifying which decisions AI may prepare and which fall exclusively under human judgment.

Strategic alignment and organizational support. The positive effects of organizational support and strategic integration suggest avoiding isolated technology initiatives.

Adapting to profiles. Augmented, human-centric and emerging competencies are not developed through the same mechanisms. Development plans should therefore be differentiated: analytical training for operational managers, work on governance and ethics for executive management, and support for hybrid leadership for team managers. The effect of hierarchical level was, however, not exploited in the analysis, and this differentiation remains a hypothesis to be tested.

4.4 Applicability: From the Model to Practice

Table 8 links each retained mechanism to a management action and a monitoring indicator. The proposed indicators are a decision-support aid for HR managers; they were not measured in the present study.

Table 8: Applicability of the Concepts Developed: Mechanisms, Actions and Indicators

Identified mechanism	**Management or training action**	**Proposed monitoring indicator**
Human–AI interaction (β = 0.71)	Assisted-decision simulations in training programs and recruitment interviews	Share of managerial decisions documented with an explicit justification of the algorithmic recommendation
Trust in AI (β = 0.38)	Recommendation validation committee; feedback loop on errors and relevant suggestions	Number of errors reported and handled; rate of recommendations accepted with justification
Augmented competencies	Data analysis and assisted planning modules	Proportion of managers who completed the module and use analytical tools in their performance reviews
Human-centric competencies	Hybrid leadership workshops for managers of teams with a strong AI presence	Engagement indicators and quality of coordination in the teams concerned
Emerging competencies	Algorithmic literacy and AI governance; participation in a periodic governance review	Managers' participation in AI governance reviews; number of usage rules updated
Organizational culture (training, support)	Continuous training program; appointment of internal focal points	Training coverage rate; number of active focal points per department

Source: Authors' elaboration.

4.5 Relevance for Emerging Economies

The Tunisian telecommunications sector is a relevant case of an intensively digital industry in North Africa, where organizations face comparable pressures: rapid AI adoption, a limited pool of digital talent and AI governance frameworks that are still under construction. We do not claim that these results transfer as they stand to other emerging economies. Only an empirical comparison will make it possible to assess their scope.

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Conclusion

This study aimed to understand how artificial intelligence transforms managerial competencies in the Tunisian telecommunications sector and how organizational culture conditions this process. Empirically, data from 72 senior managers and top managers of three operators show that AI exerts a positive and highly significant effect on collaborative competencies ($\beta = 0.53$; $p < 0.001$) and augmented competencies ($\beta = 0.41$; $p < 0.001$). The negative interaction coefficients suggest that organizational culture standardizes the influence of AI rather than amplifying it; the moderation hypotheses (H3) are, however, only partially supported, which calls for further tests.

At the theoretical level, the article integrates dynamic capabilities and sociotechnical systems theories, technology acceptance models and the institutional perspective into a single AI–competencies–culture model. It also presents trust as an active mechanism of competency development, and proposes a four-family competency framework transferable to other sectors.

At the methodological level, the study relies on a quantitative and positivist approach, a self-administered questionnaire with seven-point reflective scales, and PLS-SEM modeling in SmartPLS 4.0 with a second-order AI construct and 5,000 resamples. For practitioners, the results suggest integrating human–AI interaction into managers' routines and recruitment, structuring continuous training, building trust through explainable systems and aligning AI projects with strategy.

These conclusions should be read in light of several limitations. The sample of 72 respondents, limited to three operators, restricts statistical power and generalization. The cross-sectional design precludes any causal inference, the data rely on self-reported perceptions, and the overall AI × culture interaction coefficient is not reported. Emerging competencies, measured but not tested structurally, remain to be analyzed. Leadership style, organizational structure and HR policies were not examined as additional moderators.

Longitudinal studies, larger probability samples, cross-sector comparisons and comparisons between countries of the MENA region, as well as qualitative interviews, would make it possible to distinguish the mechanisms specific to the Tunisian context from those that are more general,

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and to shed light on the concrete processes through which AI transforms everyday managerial practice.

References

Barclay, D., Higgins, C., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies*, *2*(2), 285–309.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*, *45*(3), 1433–1450.

Boyatzis, R. E. (1982). *The competent manager: A model for effective performance*. Wiley.

Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.

Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review*, *106*(5), 133–139.

Cameron, K. S., & Quinn, R. E. (2011). *Diagnosing and changing organizational culture: Based on the competing values framework* (3rd ed.). Jossey-Bass.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108–116.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*(2), 147–160.

African Scientific Journal
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Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10–11), 1105–1121.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Henseler, J., & Fassott, G. (2010). Testing moderating effects in PLS path models: An illustration of available procedures. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares* (pp. 713–735). Springer.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586.

Jian, J.-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics*, *4*(1), 53–71.

Katz, R. L. (1955). Skills of an effective administrator. *Harvard Business Review*, *33*(1), 33–42.

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

African Scientific Journal
ISSN : 2658-9311
Vol : 03, Num 38 Octobre 2026

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, *28*(1), 227–261.

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: How organizations can win over skeptical managers. *Strategy & Leadership*, *45*(1), 37–43.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, *46*(1), 50–80.

Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing*, *86*(1), 91–108.

Makridakis, S. (2017). The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734.

Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. *American Journal of Sociology*, *83*(2), 340–363.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), Article 103434.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210.

Ringle, C. M., Wende, S., & Becker, J.-M. (2022). *SmartPLS 4* [Computer software]. SmartPLS GmbH.

African Scientific Journal
ISSN : 2658-9311
Vol : 03, Num 38 Octobre 2026

Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, *27*(3), 197–211.

Schein, E. H. (2017). *Organizational culture and leadership* (5th ed.). Jossey-Bass.

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, *61*(4), 66–83.

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning*, *51*(1), 40–49.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations*, *4*(1), 3–38.

Trist, E. L., & Emery, F. E. (1965). The causal texture of organizational environments. *Human Relations*, *18*(1), 21–32.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, *28*(2), 118–144.

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924.

African Scientific Journal
ISSN : 2658-9311
Vol : 03, Num 38 Octobre 2026

Wetzels, M., Odekerken-Schröder, G., & van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS Quarterly*, *33*(1), 177–195.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, *96*(4), 114–123.

Appendix 1: Constructs, Dimensions, Number of Items and Reference Sources

Construct	Dimension	Items	Reference sources
AI (second order)	Use and integration	4	Mikalef & Gupta (2021); Venkatesh et al. (2003)
	Decision support	4	Shrestha et al. (2019); Brynjolfsson & McElheran (2016); Jarrahi (2018)
	Perceived impact	4	Davis (1989); Wamba-Taguimdje et al. (2020)
	Strategic implementation	4	Berente et al. (2021); Mikalef & Gupta (2021)
	Human–AI interaction	3	Wilson & Daugherty (2018); Jarrahi (2018)
	Trust and acceptability	4	Mayer et al. (1995); Jian et al. (2000); Lee & See (2004); Glikson & Woolley (2020)
Managerial competencies	Collaborative	3	Wilson & Daugherty (2018); Kolbjørnsrud et al. (2017)
	Augmented	8	Mikalef & Gupta (2021); Davenport & Ronanki (2018); Makridakis (2017)
	Human-centric	3	Katz (1955); Boyatzis (1982); Jarrahi (2018)
	Emerging	7	Berente et al. (2021); Makridakis (2017)
AI-friendly culture	Adoption, support, integration, training		Schein (2017); Cameron & Quinn (2011); Cohen & Levinthal (1990); Venkatesh & Bala (2008)

Source: Authors' elaboration.