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Human-centered AI Capability and employee outcomes in an emerging economy: mediating role of empowerment and moderating role of digital culture

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Abstract

Artificial intelligence (AI) is increasingly embedded in organizational life, yet whether and how this technology benefits employees remains poorly understood, particularly in emerging economies where digital transformation is proceeding rapidly but unevenly. Drawing on the Resource-Based View and Psychological Empowerment Theory, this study examines how organizational AI capability relates to employee performance and engagement and asks whether psychological empowerment channels this relationship and whether digital organizational culture strengthens or weakens it. Data were collected through a cross-sectional survey of 387 employees across 42 organizations in Egypt spanning the banking, telecommunications, healthcare, manufacturing, and retail sectors, and were analyzed using covariance-based structural equation modeling with bootstrapped mediation tests and multi-group comparisons. AI capability was positively associated with both employee performance and engagement, and employee empowerment partially mediated these relationships, indicating that AI's benefits for employees flow substantially through employees' sense of autonomy, competence, and impact rather than through technology alone. Digital organizational culture moderated this pathway: the AI capability-to-empowerment relationship was roughly twice as strong in organizations with a well-developed digital culture as in those without one. These findings extend the Resource-Based View to the individual level, position empowerment as a key psychological mechanism linking organizational AI resources to human outcomes and demonstrate that AI's human benefits are culturally and organizationally contingent rather than automatic. The results contribute emerging-economy evidence to a literature dominated by developed-country studies and offer practical guidance for organizations seeking to deploy AI in ways that empower, rather than sideline, their workforce.

1. Introduction

The global acceleration of artificial intelligence (AI) has fundamentally reconfigured how organizations create, deliver, and capture value (Mikalef & Gupta, 2021; Davenport & Ronanki, 2018). Firms across industries are channeling unprecedented investments into AI capabilities—spanning data infrastructure, algorithmic tools, and human–machine collaboration models—with the expectation of enhanced productivity, superior decision-making, and sustained competitive advantage (Watts & Munir, 2026; Chowdhury et al., 2024). Yet a striking paradox persists at the heart of this transformation: while AI adoption rates are surging, most organizations report an inability to translate technological deployment into meaningful workforce outcomes (Khan et al., 2025). This paradox is not merely a technical implementation challenge; it is, at its core, a human challenge—one that demands scholarly attention to the psychological and cultural mechanisms through which organizational AI resources are converted into individual performance, engagement, and empowerment (Sposato & Dittmar, 2026; Alzeiby et al., 2025).

1.1 Problem Statement

Despite the proliferation of AI research over the past decade, a critical and consequential problem remains unresolved in the management literature: we know remarkably little about how and under what conditions organizational AI capability translates into positive employee-level outcomes, particularly in emerging economies where digital transformation is proceeding rapidly yet unevenly. The existing body of knowledge suffers from three interrelated deficiencies that collectively constitute a significant theoretical and practical void.

First, the dominant strand of AI research has concentrated on firm-level performance metrics—revenue growth, operational efficiency, and market positioning—while largely neglecting the individual-level psychological processes that serve as the micro-foundational conduits through which organizational AI resources generate value (Tambe et al., 2019; Felin, Foss, & Ployhart, 2015). This level-of-analysis gap means that the Resource-Based View (RBV), while

powerful in explaining why AI constitutes a strategic resource, offers limited guidance on how that resource is cognitively appraised, internalized, and enacted by individual employees.

Second, although theoretical arguments suggest that employee empowerment is a linchpin of successful digital transformation (Bouncken et al., 2025; English & Kenny, 2025), empirical evidence positioning empowerment as a specific mediating mechanism between AI capability and employee outcomes remains scarce. Without this evidence, practitioners lack a theoretically grounded roadmap for designing AI implementation strategies that genuinely empower rather than displace workers.

Third, and perhaps most critically for the present study, the vast majority of empirical AI research originates from advanced Western economies (Badawy, 2025; Mondal et al., 2024). This geographic concentration creates a dangerous assumption of universalizability. Emerging economies such as Egypt present a fundamentally different institutional, cultural, and infrastructural landscape: digital maturity is heterogeneous, hierarchical organizational cultures remain prevalent, and the pace of AI adoption is accelerating without commensurate development of supportive digital cultures (PwC, 2024; Elfar, 2026). Extrapolating findings from Silicon Valley or Western European contexts to Cairo or Alexandria risks producing misleading prescriptions. Understanding how AI capability operates within these distinct institutional settings is not merely a contextual add-on; it is a theoretical necessity for building generalizable knowledge about AI's human implications.

In Egypt specifically, the urgency of this problem is acute. National AI strategies are advancing rapidly, with a substantial majority of Egyptian CEOs reporting active plans for AI implementation (PwC, 2024). Yet the organizational and human infrastructure required to support responsible, empowering AI deployment lags the technological ambition. Without rigorous evidence on the empowerment pathways and cultural conditions that enable AI to enhance—rather than undermine—employee well-being and productivity, Egyptian organizations risk replicating the very implementation failures observed in more digitally mature contexts, but with fewer institutional safety nets.

1.2 Research Gaps

Building on the problem articulated above, this study identifies and addresses four specific gaps in the literature:

Gap 1 – The mechanism gap. Existing studies predominantly model direct associations between AI and organizational performance, leaving the individual-level psychological mechanisms largely unexplored (Tambe et al., 2019). The question of through what process AI capability influences employee performance and engagement remains theoretically underspecified and empirically untested.

Gap 2 – The empowerment mediation gap. While empowerment is widely acknowledged as important for digital transformation success (Bouncken et al., 2025), no prior study has empirically examined employee empowerment as a mediating mechanism linking AI capability to both performance and engagement simultaneously, particularly within a unified theoretical framework.

Gap 3 – The boundary-condition gap. The role of digital organizational culture as a moderator conditioning the strength of the AI–empowerment relationship is virtually unexamined (English & Kenny, 2025). This omission is consequential: if digital culture amplifies or constrains the empowerment effects of AI, then the same AI investment may yield dramatically different human outcomes depending on the cultural context in which it is embedded.

Gap 4 – The contextual gap. The geographic concentration of AI research in developed economies (Mondal et al., 2024; Badawy, 2025) leaves a critical void regarding emerging markets. Egypt, with its unique blend of rapid digital

ambition, evolving organizational cultures, and distinctive workforce characteristics, represents a theoretically rich yet empirically neglected context.

1.3 Theoretical Foundation

This study integrates the Resource-Based View (RBV) (Barney, 1991) with Psychological Empowerment Theory (Thomas & Velthouse, 1990; Spreitzer, 1995). RBV posits that sustainable advantage derives from valuable, rare, inimitable, and non-substitutable (VRIN) resources. AI capability constitutes precisely such a strategic resource (Mikalef & Gupta, 2021; Sandeep & Lavanya, 2026). However, because RBV primarily explains firm-level advantage, we integrate Psychological Empowerment Theory to bridge this level-of-analysis gap. While RBV frames AI capability as a valuable organizational resource (Chowdhury et al., 2024; Chang, 2026) enabled by complementary factors (Jafari et al., 2026), empowerment theory explains how this resource is cognitively appraised and internalized into employee-level meaning, competence, self-determination, and impact. This dual-theory integration explicitly links organizational resources to individual outcomes, addressing a common gap in RBV-based employee research.

1.4 Distinct Contribution Relative to Prior AI Capability Research

Mikalef and Gupta (2021) established AI capability's association with firm-level performance, but the psychological pathway through which this organizational resource is converted into individual employee outcomes remains largely unexamined. This study addresses that gap by positioning employee empowerment as a candidate micro-level conversion mechanism—a move consistent with calls to examine the micro-foundations of organizational capabilities (Felin, Foss, & Ployhart, 2015). Rather than simply relocating an existing organizational-level framework to a new country context, the theoretical contribution lies in explicitly modeling the individual-level mechanism (empowerment) and boundary condition (digital culture) through which an organizational AI resource may relate to employee-level outcomes. This represents a qualitative advance over prior work, not merely a geographic replication.

1.5 Research Questions

Guided by the identified gaps and theoretical framework, this study addresses the following research questions:

RQ1. Is AI capability associated with employee performance and employee engagement in Egyptian organizations?

RQ2. Does employee empowerment mediate the relationship between AI capability and employee outcomes (performance and engagement)?

RQ3. To what extent does digital organizational culture moderate the relationship between AI capability and employee empowerment?

RQ4. How do AI capability, employee empowerment, and digital organizational culture jointly relate to employee performance and engagement in an emerging-economy context?

1.6 Contributions of the Study

This study makes several contributions that align with JBR's mandate for research that is rigorous, relevant, and impactful.

Theoretically, it extends the Resource-Based View by articulating the individual-level micro-foundations of AI capability, demonstrating how organizational AI resources translate into individual outcomes through employee empowerment. It advances the digital transformation literature by identifying empowerment as a key mediating mechanism linking AI capability to both performance and engagement within a unified model. Furthermore, it enriches the understanding of digital organizational culture by empirically establishing its boundary-condition role in amplifying or constraining the

AI–empowerment nexus. By providing evidence from an emerging economy, the study addresses the prevailing geographical imbalance in AI scholarship (Mondal et al., 2024) and contributes to building more globally representative theory.

Practically, the findings offer actionable insights for managers seeking to translate AI investments into tangible employee empowerment. The study provides strategic guidance for cultivating digital organizational cultures that reinforce empowerment, alongside specific implications for HR practices during AI implementation in emerging markets. It delivers a robust measurement framework that enables organizations to track AI capability in tandem with employee-centered outcomes, facilitating a more effective and human-centric digital transformation.

Societally, by linking AI adoption to empowerment and engagement, the findings support responsible AI deployment that advances workforce development and sustainable economic growth in emerging economies—a contribution with direct relevance to policy makers and development practitioners.

1.7 Structure of the Study

The study is organized as follows: Section 2 reviews literature and develops hypotheses. Section 3 details methodology. Section 4 presents empirical findings. Section 5 discusses implications, and Section 6 concludes with limitations and future research.

2. Literature Review and Hypotheses Development

2.1 AI Capability and Employee Performance

AI capability is an organization's capacity to deploy AI through tangible resources, human skills, and intangible assets (Mikalef & Gupta, 2021). As a VRIN resource, it generates value by augmenting human cognition (Sandeep & Lavanya, 2026). However, translating this firm-level resource into individual performance requires examining how it alters task execution and cognitive load. AI capability enhances employee performance through three pathways. First, it accelerates decision-making by processing complex datasets and augmenting human judgment (Oliveira et al., 2025; Prasad & De, 2024). Second, automating routine tasks reduces cognitive load, freeing employees for high-value, strategic activities (Zhang et al., 2025). Third, AI-powered adaptive training builds employee competence over time (Ekuma, 2024). From an RBV perspective, AI generates performance returns through its interaction with human agents (Jafari et al., 2026). In Egypt, where firms are transitioning from manual to intelligent systems (Elfar, 2026; World Bank, 2023), the marginal contribution of AI capability to performance is particularly pronounced.

H1. *AI capability is positively associated with employee performance.*

2.2 AI Capability and Employee Engagement

Employee engagement reflects emotional, cognitive, and behavioral commitment to work (Macey & Schneider, 2008; Schaufeli et al., 2002). Within RBV, engagement is a human capital outcome reflecting how organizational resources foster psychological investment (Chowdhury et al., 2024). AI capability relates to engagement by automating mundane tasks, allowing employees to focus on meaningful work (Bankins & Formosa, 2023). It fosters continuous growth through personalized learning, strengthening affective commitment (Bankins et al., 2024), and improves work–life balance via intelligent scheduling (Ali & Siddiqui, 2026). Furthermore, AI systems providing real-time feedback enhance employees' sense of competence and impact (Spreitzer, 1995). However, this relationship is contingent on perception: AI viewed as a supportive tool boosts engagement, while AI perceived as a threat causes disengagement (Malik et al., 2022). This duality highlights the need to examine how AI is enacted, motivating our

focus on empowerment. In emerging economies, thoughtful AI adoption enhances engagement via improved tool access and skill development (Karthikeyan & Singh, 2025), though evidence in North Africa remains scarce.

H2. AI capability is positively associated with employee engagement.

2.3 The Mediating Role of Employee Empowerment

2.3.1 AI Capability and Employee Empowerment

Employee empowerment encompasses the authority, resources, and confidence to make decisions and exert influence (Spreitzer, 1995; Thomas & Velthouse, 1990), manifesting as meaning, competence, self-determination, and impact. Integrating RBV with empowerment theory, we argue AI capability acts as an enabling resource that alters structural and psychological work conditions. Specifically, AI enhances empowerment by providing real-time data that reduces information asymmetry and increases autonomy (Kibirige, 2025). It builds competence through adaptive training platforms (Ahn, 2024), particularly vital in emerging economies with limited formal training. Furthermore, by automating routine tasks, AI frees employees for high-impact activities (Ramachandran et al., 2022), while human–AI collaboration augments cognitive capacity and agency (Akinwalere & Chang, 2026). Thus, AI capability functions as a compensatory and augmenting resource that enhances empowerment cognitions.

H3. AI capability is positively associated with employee empowerment.

2.3.2 Employee Empowerment and Employee Outcomes

Empowered employees are theorized to exhibit higher performance because greater autonomy, competence, and intrinsic motivation support proactive goal attainment, adaptive problem-solving, and sustained effort (Wall et al., 2004; Marinova et al., 2017). From an RBV micro-foundations perspective, empowered employees represent the human mechanism through which organizational resources are converted into performance outcomes: the AI resource is only as valuable as the empowered individuals who deploy it (Felin, Foss, & Ployhart, 2015). Empirical evidence confirms positive associations between empowerment and performance, particularly in technology-enabled and knowledge-intensive environments (Marinova et al., 2017).

Empowerment is also theorized to enhance engagement by fostering psychological ownership, intrinsic motivation, and affective commitment (Spreitzer, 1995; Jose & Mampilly, 2015). Empowered employees who feel trusted, valued, and capable of influencing outcomes tend to report higher vigour, dedication, and absorption—the core dimensions of engagement (Schaufeli et al., 2002). Psychological Empowerment Theory provides the motivational logic here: when employees perceive their work as meaningful, feel competent, experience self-determination, and believe they can make an impact, they are more likely to invest discretionary cognitive and emotional energy in their roles.

H4a. Employee empowerment is positively associated with employee performance.

H4b. Employee empowerment is positively associated with employee engagement.

2.3.3 The Mediating Mechanism

Synthesizing the arguments developed above, we propose that employee empowerment serves as the psychological transmission mechanism—the micro-foundational conduit—through which organizational AI capability translates into individual-level performance and engagement. RBV explains the resource endowment (AI capability); Psychological Empowerment Theory explains the cognitive-motivational process through which that endowment is internalized and enacted. Without empowerment, AI capability remains a latent organizational asset; with empowerment, it becomes an active driver of individual outcomes.

This mediation logic addresses a critical gap identified by Tambe et al. (2019) and Felin et al. (2015): the absence of explicit individual-level mechanisms linking organizational technology resources to employee outcomes. By modelling empowerment as a partial mediator, we acknowledge that AI capability may also influence performance and engagement through direct pathways (e.g., task automation, decision support) while simultaneously operating through the empowerment mechanism.

H5a. Employee empowerment mediates the relationship between AI capability and employee performance.

H5b. Employee empowerment mediates the relationship between AI capability and employee engagement.

2.4 The Moderating Role of Digital Organizational Culture

Digital organizational culture (DOC) encompasses the shared values, beliefs, norms, and practices that support digital transformation, technology adoption, and innovation-oriented behaviours (Elbolok et al., 2025). Key dimensions include digital skills orientation, proactivity, entrepreneurial mindset, adaptability, continuous learning, transparency, trust, and collaborative experimentation (Kocak & Pawlowski, 2023; Aslam et al., 2026).

Within the RBV framework, digital organizational culture functions as a complementary intangible resource that determines the degree to which AI capability can be effectively leveraged (Barney, 1991; Jafari et al., 2026). A valuable resource generates competitive returns only when the organization possesses the complementary capabilities and cultural conditions to exploit it. Digital culture constitutes precisely such a complementary condition for AI capability.

The proposed moderating effect of DOC on the AI capability–empowerment relationship is theorized to operate through four mechanisms:

1. (a) Learning orientation. A culture that prioritizes continuous learning and skill development encourages employees to actively develop AI-related competencies, transforming AI from an imposed technology into a self-directed empowerment tool (Alakaş, 2024). In such cultures, employees perceive AI as an opportunity for growth rather than a threat to their role.
2. (b) Innovation climate. An organizational climate that rewards experimentation, tolerates intelligent failure, and encourages creative exploration of AI tools increases employees' sense of agency and self-determination—core empowerment cognitions (Aslam et al., 2026; Kolbjørnsrud, 2024).
3. (c) Trust and transparency. In cultures characterized by open communication, transparent decision-making, and trust in leadership, AI-related anxiety and fear of surveillance are reduced, enabling employees to engage with AI tools confidently and perceive them as empowering rather than controlling (Zhou et al., 2025; Deb Biswas & Sengupta, 2026).
4. (d) Collaborative mindset. A culture that values human–AI partnership rather than human-versus-AI competition facilitates the collaborative intelligence through which AI augments human capability (Kolbjørnsrud, 2024). This is particularly critical in hierarchical organizational cultures—common in many emerging economies—where top-down decision-making norms may otherwise inhibit the autonomy-enhancing potential of AI.

In emerging economies undergoing rapid but uneven digital transformation, the moderating role of DOC is expected to be especially pronounced. Organizations with strong digital cultures are better positioned to translate AI investments into empowerment because they provide the psychological safety, skill infrastructure, and normative support necessary for employees to embrace AI as an enabler (Maddula et al., 2018; World Bank, 2023). Conversely, in organizations with weak digital cultures, AI capability may be perceived as an external imposition, generating resistance rather than empowerment. This contingency logic implies that the same level of AI capability may yield

substantially different empowerment outcomes depending on the cultural context in which it is embedded—a proposition with significant theoretical and practical implications.

H6. Digital organizational culture moderates the relationship between AI capability and employee empowerment, such that the positive relationship is stronger when digital organizational culture is high.

2.5 Conceptual Model

Figure 1 presents the hypothesized moderated-mediation research model. The model proposes that AI capability relates to employee performance and engagement through two pathways: a direct pathway (H1, H2) reflecting the immediate task-level and cognitive benefits of AI, and an indirect pathway (H3 → H4a/H4b → H5a/H5b) operating through the psychological mechanism of employee empowerment. Digital organizational culture is modelled as a boundary condition (H6) that moderates the strength of the first stage of the indirect pathway (AI capability → empowerment), thereby influencing the overall indirect effect.

The model makes three distinctive theoretical contributions: (1) it specifies the individual-level mechanism (empowerment) through which an organizational-level resource (AI capability) generates employee outcomes, addressing the micro-foundations gap in RBV; (2) it identifies the cultural boundary condition (DOC) under which this mechanism is amplified or attenuated; and (3) it tests these relationships in an emerging-economy context (Egypt), contributing to the geographic diversification of AI-in-the-workplace research.

[Insert Fig. 1 *here]*

4. Methodology

4.1 Research Design and Context

This study employed a quantitative, cross-sectional survey design to test the hypothesized moderated-mediation model. The choice of a cross-sectional design was pragmatic and consistent with prior organizational behaviour research examining employee perceptions of technology, empowerment, and engagement (e.g., Warner & Wäger, 2019; Vial, 2019). While we acknowledge the inherent limitations of cross-sectional data for causal inference (discussed in Section 6), this design is appropriate for testing theoretically grounded associations and mediation/moderation mechanisms in field settings where experimental manipulation is neither feasible nor ethical.

4.1.1 Contextual Setting: Egypt as a Critical Case

The empirical context is Egypt, an emerging economy undergoing a comprehensive digital transformation under the national "Digital Egypt" strategy (Ministry of Communications and Information Technology, 2023). Egypt was selected not merely as a convenient data-collection site, but as a theoretically informative context for three reasons.

First, Egyptian organizations are at heterogeneous stages of digital maturity—from basic digitalization to AI-ready infrastructure (World Bank, 2023)—providing natural variation in AI capability and digital culture necessary for testing the hypothesized relationships.

Second, Egypt's institutional environment combines rapid technological ambition with evolving organizational cultures, hierarchical decision-making norms, and a workforce transitioning from traditional to digital skill sets (Elfar, 2026). This combination creates a context where the empowerment and cultural mechanisms theorized in this study are likely to be especially salient, making Egypt a critical case for testing boundary conditions (Flyvbjerg, 2006).

Third, while full AI implementation remains limited, Egyptian organizations are increasingly adopting AI-adjacent technologies: digital banking and fintech solutions (Central Bank of Egypt, 2023), robotic process automation (McKinsey & Company, 2024), Industry 4.0 and smart-manufacturing systems (World Economic Forum, 2023), digital payment and e-commerce platforms (Paymob, 2023), enterprise resource planning systems (SAP, 2023), and digital marketing/CRM tools (Salesforce, 2023). This technology continuum aligns with the digital transformation literature that treats adoption as a spectrum rather than a binary state (Vial, 2019; Warner & Wäger, 2019), ensuring that the sample captures meaningful variation in AI capability.

4.1.2 Sampling Strategy

A purposive sampling approach with sectoral quotas was employed, targeting organizations in the Cairo, Alexandria, and Giza governorates, where digital transformation initiatives and technology-intensive industries are most concentrated (Ministry of Communications and Information Technology, 2023). We adopted a non-probability, quota-based approach rather than probability sampling for two substantive reasons: (a) no comprehensive sampling frame of AI-adopting organizations exists in Egypt; and (b) the study's objective was to capture employees with direct experience of digital technologies, necessitating targeted rather than random selection.

Terminological clarification: We initially described this procedure as "stratified convenience sampling"; we have revised this terminology to purposive quota sampling, since stratified sampling implies probability-based selection, whereas the actual procedure was non-probability sampling organized around sectoral quotas to ensure representation across key industries.

The study targeted employees who regularly interact with digital technologies, automated systems, or intelligent digital tools in their daily work. Organizations were included if they met at least two of the following criteria: (1) implementation of digital management systems (ERP, CRM, HCM); (2) adoption of automation technologies (RPA, workflow automation); (3) use of data analytics and business intelligence tools; (4) deployment of digital banking or fintech solutions; (5) implementation of Industry 4.0 technologies (IoT, smart manufacturing); or (6) use of digital platforms for customer engagement. This multi-criterion inclusion strategy ensured that the sample captured organizations across the digital maturity spectrum, from early-stage digitalization to advanced automation, thereby enhancing the external validity of findings within the Egyptian context.

4.1.3 Sample Size Determination

Because the structural model was estimated using covariance-based SEM in AMOS, sample size adequacy was evaluated against maximum-likelihood estimation guidelines rather than the component-based heuristics used in partial least squares SEM. Following recommendations for ML-based CB-SEM (Kline, 2016), a minimum ratio of 10 respondents per estimated parameter is recommended, and models with more than 30 observed indicators typically require samples exceeding 300–400 to support stable maximum-likelihood estimation and adequate statistical power. With five latent constructs and a combined 55 observed indicators, the achieved sample of 387 falls within the recommended range and exceeds the minimum threshold of 300 for models of this complexity.

A post-hoc power analysis using G*Power 3.1 indicated that, with $n = 387$, $\alpha = .05$, and up to five predictors in the structural model, the study achieved statistical power of .99 to detect medium effect sizes ($f^2 = .15$), exceeding the conventional .80 threshold (Cohen, 1992). This high power minimizes the risk of Type II errors and ensures that the failure to detect an effect, where one exists, is unlikely.

4.1.4 Data Collection and Response Rate

Data were collected between January and March 2026 using a structured questionnaire distributed through both online platforms (Google Forms, SurveyMonkey) and physical copies to accommodate organizational preferences and internet accessibility variation. The dual-mode distribution strategy was designed to maximize response rates across organizations with differing digital infrastructure maturity.

The questionnaire was administered in Arabic following a rigorous translation–back-translation procedure (Brislin, 1970) to ensure conceptual equivalence between the English source and Arabic target versions. Two bilingual management scholars independently translated the instrument into Arabic, after which a third independent translator backtranslated it into English. Discrepancies were resolved through discussion until full consensus was reached.

Of 450 questionnaires distributed across 42 organizations, 412 were returned (91.6% response rate). After screening for incomplete responses (> 10% missing data) and unengaged response patterns (straight-lining, defined as identical responses across 10 or more consecutive items), 387 valid responses were retained, yielding a final usable response rate of 86%. This response rate is comparable to, and exceeds, those reported in similar digital-transformation studies in emerging markets (Warner & Wäger, 2019), suggesting that non-response bias is unlikely to be a serious concern.

4.1.5 Sample Characteristics

The final sample spanned five sectors: Banking and Financial Services (28.4%), Telecommunications (22.7%), Healthcare (18.6%), Manufacturing (16.8%), and Retail/E-commerce (13.5%). This sectoral distribution reflects the relative concentration of digital transformation activity in Egypt, where banking, telecommunications, and healthcare have been priority sectors under the Digital Egypt strategy (Ministry of Communications and Information Technology, 2023).

The demographic profile was as follows: 52.7% male and 47.3% female; 41.3% aged 25–34, 35.9% aged 35–44, 17.1% aged 45–54, 3.6% under 25, and 2.1% aged 55+; educational attainment of 58.4% Bachelor's degree, 24.8% Master's degree, 12.1% Diploma, and 4.7% PhD; and job tenure of 42.6% between 1–5 years, 31.5% between 6–10 years, 14.2% under 1 year, 8.5% between 11–15 years, and 3.2% over 15 years. In terms of job level, 54.3% were non-managerial, 32.8% middle management, and 12.9% senior management. The distribution across job levels ensures that the sample captures employee experiences at multiple hierarchical tiers, enhancing the generalizability of findings within organizational settings.

Organizational digital maturity was additionally assessed using a five-item scale adapted from Vial (2019): 18.6% of organizations were at an emerging stage (basic digitalization), 42.4% at a developing stage (integrated digital systems), 28.7% at a maturing stage (advanced automation and analytics), and 10.3% at a leading stage (AI-ready infrastructure). This distribution is consistent with Egypt's broader digital transformation landscape, where the majority of organizations are in the developing-to-maturing transition phase (World Bank, 2023; Ministry of Communications and Information Technology, 2023).

4.2 Measures

All constructs were measured using previously validated multi-item scales adapted from the existing literature to ensure content validity and comparability with prior research. Minor wording modifications were made where necessary to improve clarity and contextual fit for AI adoption in Egyptian organizations, while preserving the original meaning and psychometric integrity of the items. All measurement items were assessed using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The complete list of measurement items is presented in *Appendix Table A1*.

Control Variables. Consistent with prior digital transformation research, we controlled for age, gender, education level, job tenure, job level, and organizational sector, each of which may relate to employee performance and engagement in digital transformation contexts (Vial, 2019; Warner & Wäger, 2019). Including these controls reduces the risk of omitted-variable bias and ensures that the hypothesized relationships are not confounded by demographic or structural factors.

4.3 Common Method Bias Assessment

Given the cross-sectional and self-reported nature of the data, we implemented both procedural and statistical remedies to minimize and assess the potential impact of common method bias (Podsakoff et al., 2003).

4.3.1 Procedural Remedies

Respondents were assured of the anonymity and confidentiality of their responses to reduce evaluation apprehension and social desirability bias. The questionnaire was carefully structured into clearly labelled sections according to each construct to minimize item-context effects, while the order of items was varied across respondents to reduce potential order effects. All measurement items were written using clear, concise, and unambiguous language, avoiding double-barreled questions. The questionnaire was pilot tested with 30 employees prior to the main data collection to ensure clarity, comprehensibility, and the overall quality of the measurement instrument. Additionally, predictor and criterion variables were psychologically separated in the survey design by inserting a filler task between sections, reducing the likelihood that respondents would infer the study's hypotheses (Podsakoff et al., 2003).

4.3.2 Statistical Remedies

Four complementary statistical tests were conducted:

(1) Harman's single-factor test. A single-factor solution explained 31.4% of total variance, well below the 50% threshold, indicating that no single factor accounted for most of the covariance among items.

(2) Full collinearity assessment. Following Kock (2015), variance inflation factor (VIF) values were calculated for all constructs. VIF values ranged between 1.234 and 2.891, all below the conservative threshold of 3.3, suggesting that common method bias is not a serious concern.

(3) Marker variable test. A theoretically unrelated marker variable (satisfaction with office layout) was included in the survey. This marker was uncorrelated with all substantive constructs ($p > .05$), providing additional evidence against pervasive method bias.

(4) Single-factor CFA comparison. A single-factor CFA model showed poor fit ($\chi^2/df = 8.234$, CFI = .512, TLI = .498, RMSEA = .143) relative to the hypothesized five-factor measurement model (see Section 5.2). Furthermore, an unmeasured latent method factor did not meaningfully improve model fit (ΔCFI = .012, ΔRMSEA = .008). Collectively, these four tests provide converging evidence that common method variance is unlikely to account for the observed relationships.

4.4 Data Analysis Approach

Data were analyzed using covariance-based structural equation modeling (CB-SEM) in IBM SPSS AMOS 28.0 with maximum likelihood (ML) estimation. The choice of CB-SEM over partial least squares SEM (PLS-SEM) was deliberate and theoretically grounded: (a) the study's constructs and scales are well established in the literature, making a confirmatory, theory-testing approach appropriate; (b) ML-based CB-SEM provides an overall model-fit assessment (χ^2, CFI, TLI, RMSEA, SRMR) that allows the entire hypothesized structure to be evaluated simultaneously against the

covariance matrix of observed indicators; and (c) the sample size (n = 387) and indicator-to-sample ratio met the requirements for stable ML estimation (Kline, 2016). Additionally, CB-SEM is preferred when the research objective is theory confirmation rather than prediction, and when the measurement model requires rigorous evaluation of construct validity (Hair et al., 2019).

Analysis followed a two-step approach (Anderson & Gerbing, 1988). Step 1: A confirmatory factor analysis (CFA) evaluated the measurement model, including indicator reliability (factor loadings > .70), internal consistency reliability (composite reliability > .70), convergent validity (average variance extracted > .50), and discriminant validity (Fornell–Larcker criterion and heterotrait–monotrait ratio). Step 2: The structural model was estimated to test the hypothesized direct and indirect paths, with model fit evaluated against conventional thresholds.

4.4.1 Mediation Testing

Indirect effects (H5a, H5b) were tested using AMOS's bootstrapping procedure with 5,000 resamples to generate bias-corrected 95% confidence intervals (Preacher & Hayes, 2008). Bootstrapping is preferred over the Sobel test because it does not assume normality of the indirect effect distribution, which is typically skewed (Zhao, Lynch, & Chen, 2010). An indirect effect was considered significant when its confidence interval did not include zero. The variance accounted for (VAF) was calculated as a supplementary descriptive indicator of the proportion of the total effect explained by the indirect path, to characterize the mediation as full (VAF > 80%) or partial (VAF between 20% and 80%) (Hair et al., 2019).

4.4.2 Moderation Testing

Because AMOS does not natively estimate latent interaction terms for two continuous latent variables using the same information-preserving approach as PLS-SEM or Mplus's latent moderated structural equations (LMS), moderation (H6) was tested using multi-group SEM, consistent with recommended practice for CB-SEM moderation analysis (Byrne, 2016).

The sample was split into high and low digital-organizational-culture groups via a median split. While median splits are sometimes criticized for reducing statistical power, they are appropriate and widely used in multi-group SEM when the moderator is a latent construct and the primary objective is to test whether a structural path differs significantly across groups (Byrne, 2016). Additionally, the median split preserves interpretability and is consistent with prior digital culture research (e.g., Elbolok et al., 2025).

The AI capability → empowerment structural path was freely estimated in an unconstrained multi-group model and then constrained to equality across groups. A chi-square difference test ($\Delta\chi^2$, 1 df) between the constrained and unconstrained models was used to evaluate whether the path differed significantly by group. A significant $\Delta\chi^2$ indicates that the AI capability–empowerment relationship is moderated by digital organizational culture.

4.4.3 Model Fit Criteria

Model fit was evaluated against conventional CB-SEM thresholds: $\chi^2/df < 3.0$, GFI and AGFI > .90 (acceptable > .85), CFI and TLI > .90, RMSEA < .08 (with 90% confidence interval reported), and SRMR < .08 (Hu & Bentler, 1999; Kline, 2016). Missing data were minimal (< 2% for all items); mean imputation was applied to items with less than 5% missing data. Sensitivity analyses confirmed that the choice of imputation method did not materially alter the substantive conclusions.

5. Results

5.1 Descriptive Statistics and Correlations

Table 1 presents the descriptive statistics, standard deviations, and Pearson correlation coefficients for all study variables and control variables. Preliminary inspection of the correlation matrix revealed several patterns consistent with the hypothesized model. AI capability was positively and significantly associated with employee empowerment (r = .524, p < .01), digital organizational culture (r = .489, p < .01), employee performance (r = .487, p < .01), and employee engagement (r = .453, p < .01), providing initial support for the proposed direct relationships. Employee empowerment also showed significant positive correlations with digital organizational culture (r = .467, p < .01), employee performance (r = .531, p < .01), and employee engagement (r = .498, p < .01). Digital organizational culture was positively correlated with employee performance (r = .423, p < .01) and employee engagement (r = .445, p < .01), while employee performance exhibited a strong positive association with employee engagement (r = .512, p < .01).

Table 1
Descriptive Statistics and Pearson Correlations Among the Study Variables

Variable	M	SD	1	2	3	4	5	6	7	8	9	10
1. Gender	1.47	0.50	—									
2. Age	2.91	0.94	.06	—								
3. Education	2.84	0.73	− .03	.18**	—							
4. Organizational Tenure	2.76	1.02	.04	.54**	.15**	—						
5. Sector	1.58	0.49	− .02	.05	.07	.09	—					
6. AI Capability	5.23	1.12	.05	.08	.10*	.11*	.09	—				
7. Employee Empowerment	5.41	1.08	.04	.06	.09	.10	.07	.524**	—			
8. Digital Organizational Culture	5.18	1.15	.03	.07	.11*	.09	.05	.489**	.467**	—		
9. Employee Performance	5.36	1.04	.02	.09	.12*	.11*	.08	.487**	.531**	.423**	—	
10. Employee Engagement	5.29	1.11	.04	.08	.10*	.09	.06	.453**	.498**	.445**	.512**	—

Note. N = 387. Values below the diagonal are Pearson correlation coefficients. M = Mean; SD = Standard deviation. Gender was coded as 0 = female and 1 = male. Sector was coded as 0 = public and 1 = private. p < .05 (*), p < .01 (**), two-tailed.

[Insert Table 1 *here]*

Importantly, the control variables (gender, age, education level, organizational tenure, and sector) showed generally weak associations with the main study variables (most r values < .15), suggesting that the observed relationships among the focal constructs were unlikely to be substantially confounded by demographic characteristics. This pattern is consistent with prior digital transformation research indicating that technology-related outcomes are more strongly predicted by organizational and psychological factors than by demographic attributes (Vial, 2019).

5.2 Measurement Model (CFA) Assessment

Before testing the structural hypotheses, we evaluated the measurement model to ensure that the latent constructs were reliably and validly measured (Anderson & Gerbing, 1988). The hypothesized five-factor measurement model was estimated using AMOS with maximum likelihood estimation and demonstrated an acceptable-to-good fit to the data: $\chi^2(1,205) = 2,187.44$, $\chi^2/df = 1.816$, GFI = .901, AGFI = .887, CFI = .942, TLI = .936, RMSEA = .046 (90% CI [.043, .049]), and SRMR = .048. These values satisfy the conventional thresholds recommended by Hu and Bentler (1999) and Kline (2016), indicating that the hypothesized factor structure adequately represents the covariance structure of the observed data.

Table 1 and Fig. 2 present the standardized measurement model. All indicator loadings exceeded the recommended threshold of .70 (range = .750–.883), confirming indicator-level reliability. As reported in Table 2, all constructs exhibited satisfactory internal consistency reliability (Cronbach's α = .84–.92; Composite Reliability [CR] = .90–.94) and adequate convergent validity (Average Variance Extracted [AVE] = .65–.76), well above the recommended thresholds of .70 for CR and .50 for AVE (Fornell & Larcker, 1981).

Table 2
Measurement Model Assessment: Factor Loadings, Reliability, and Convergent Validity

Construct	Code	Factor Loading	Cronbach's α	CR	AVE
AI Capability – Tangible Data	TD1	.820	.90	.92	.66
	TD2	.828			
	TD3	.793			
	TD4	.812			
	TD5	.807			
	TD6	.797			
AI Capability – Technology	T1	.821	.92	.94	.67
	T2	.859			
	T3	.801			
	T4	.797			
	T5	.832			
	T6	.806			
	T7	.828			
AI Capability – Basic Resources	BR1	.870	.85	.91	.76
	BR2	.846			
	BR3	.822			
AI Capability – Business Skills	BS1	.803	.91	.93	.65
	BS2	.822			
	BS3	.761			
	BS4	.842			
	BS5	.805			
	BS6	.782			
	BS7	.818			
AI Capability – Technical Skills	TS1	.839	.92	.94	.68
	TS2	.864			
	TS3	.806			
	TS4	.817			

Note. Standardized factor loadings were obtained from the confirmatory factor analysis (CFA). Cronbach's alpha (α) assesses internal consistency reliability. Composite Reliability (CR) and Average Variance Extracted (AVE) were computed following the approach of Fornell and Larcker (1981). All factor loadings exceeded the recommended threshold of 0.70, Cronbach's α and CR values were greater than 0.70, and all AVE values exceeded 0.50, indicating satisfactory internal consistency reliability and convergent validity of the measurement model.

Construct	Code	Factor Loading	Cronbach's α	CR	AVE
	TS5	.794			
	TS6	.831			
	TS7	.824			
AI Capability – Inter-departmental Coordination	IC1	.815	.91	.93	.66
	IC2	.776			
	IC3	.836			
	IC4	.819			
	IC5	.774			
	IC6	.821			
	IC7	.812			
AI Capability – Organizational Change Capacity	OCC1	.809	.90	.92	.67
	OCC2	.826			
	OCC3	.840			
	OCC4	.825			
	OCC5	.818			
	OCC6	.826			
AI Capability – Risk Proclivity	RP1	.851	.84	.90	.71
	RP2	.848			
	RP3	.810			
Employee Empowerment	EE1	.857	.90	.92	.73
	EE2	.865			
	EE3	.865			
	EE4	.846			
Digital Organizational Culture	DOC1	.842	.90	.92	.70
	DOC2	.874			
	DOC3	.830			
	DOC4	.819			
	DOC5	.831			

Note. Standardized factor loadings were obtained from the confirmatory factor analysis (CFA). Cronbach's alpha (α) assesses internal consistency reliability. Composite Reliability (CR) and Average Variance Extracted (AVE) were computed following the approach of Fornell and Larcker (1981). All factor loadings exceeded the recommended threshold of 0.70, Cronbach's α and CR values were greater than 0.70, and all AVE values exceeded 0.50, indicating satisfactory internal consistency reliability and convergent validity of the measurement model.

Construct	Code	Factor Loading	Cronbach's α	CR	AVE
Employee Performance	EP1	.870	.91	.93	.73
	EP2	.853			
	EP3	.869			
	EP4	.825			
	EP5	.825			
Employee Engagement – Cognitive	EEC1	.849	.89	.92	.74
	EEC2	.867			
	EEC3	.842			
	EEC4	.864			
Employee Engagement – Emotional	EEE1	.865	.91	.93	.76
	EEE2	.875			
	EEE3	.883			
	EEE4	.866			
Employee Engagement – Behavioral	EEB1	.849	.87	.91	.69
	EEB2	.859			
	EEB3	.848			
	EEB4	.750			

Note. Standardized factor loadings were obtained from the confirmatory factor analysis (CFA). Cronbach's alpha (α) assesses internal consistency reliability. Composite Reliability (CR) and Average Variance Extracted (AVE) were computed following the approach of Fornell and Larcker (1981). All factor loadings exceeded the recommended threshold of 0.70, Cronbach's α and CR values were greater than 0.70, and all AVE values exceeded 0.50, indicating satisfactory internal consistency reliability and convergent validity of the measurement model.

[Insert Table 2 *here]*

[Insert Fig. 2 *here]*

5.2.1 Discriminant Validity

Discriminant validity ensures that conceptually distinct constructs are empirically distinct—that is, each construct captures unique variance not shared with other constructs (Fornell & Larcker, 1981). We assessed discriminant validity using two complementary approaches: the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT).

As presented in Table 3, the square root of the average variance extracted (AVE) for each construct exceeded its correlations with all other constructs, satisfying the Fornell–Larcker criterion. Furthermore, Table 4 confirms that all HTMT values remained below the conservative threshold of .85, well below the more liberal .90 cutoff, providing robust additional evidence that the constructs are empirically distinct (Henseler, Ringle, & Sarstedt, 2015).

Table 3

Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Construct	**1**	**2**	**3**	**4**	**5**
1. AI Capability	.826				
2. Employee Empowerment	.524	.798			
3. Digital Culture	.489	.467	.815		
4. Employee Performance	.487	.531	.423	.823	
5. Employee Engagement	.453	.498	.445	.512	.812

*Note. N = 387. Diagonal elements (in bold) represent the square root of the average variance extracted (AVE) for each construct. Off-diagonal elements represent the Pearson inter-construct correlations. For adequate discriminant validity, the diagonal value for each construct must be greater than its highest correlation with any other construct (*Fornell & Larcker, 1981*).*

Table 4

Discriminant Validity Assessment Using the Heterotrait–Monotrait Ratio (HTMT)

Construct	***1***	***2***	***3***	***4***	***5***
1. AI Capability	-				
2. Employee Empowerment	.642	-			
3. Digital Culture	.598	.571	-		
4. Employee Performance	.601	.655	.534	-	
5. Employee Engagement	.567	.612	.558	.634	-

Note. All heterotrait–monotrait (HTMT) ratios are below the conservative threshold of .85, providing robust evidence of discriminant validity (Henseler et al., 2015).

[Insert Table 3 *here]*

[Insert Table 4 *here]*

5.3 Structural Model Assessment and Hypothesis Testing

Having established the reliability and validity of the measurement model, we proceeded to test the structural hypotheses using the two-step approach recommended by Anderson and Gerbing (1988). The structural model demonstrated acceptable fit to the data: $\chi^2(1,214) = 2,264.91$, $\chi^2/df = 1.866$, CFI = .938, TLI = .931, RMSEA = .048 (90% CI [.045, .051]), and SRMR = .051. These fit indices are consistent with those of the measurement model, indicating that the hypothesized structural relationships adequately represent the data.

Figure 3 presents the structural model with standardized path coefficients, while Table 5 provides detailed results of the hypothesis testing. As shown, all hypothesized direct paths were statistically significant at $p < .001$, providing support for H1 through H4b. Specifically:

Table 5

Structural Model Assessment and Hypotheses Testing

Hyp.	Path	β	SE	t / C.R.	p	Decision
H1	AI Capability → Performance	.322	.067	5.104	< .001	Supported
H2	AI Capability → Engagement	.214	.071	4.197	< .001	Supported
H3	AI Capability → Empowerment	.402	.058	7.862	< .001	Supported
H4a	Empowerment → Performance	.341	.064	6.047	< .001	Supported
H4b	Empowerment → Engagement	.374	.069	5.130	< .001	Supported
—	Age → Performance	.087	.048	1.813	.070	Not significant
—	Tenure → Performance	.098	.051	1.922	.055	Not significant
—	Education → Engagement	.112	.049	2.286	.022	Significant

Note. N = 387. Model fit indices: $\chi^2(1,214) = 2,264.91$, $\chi^2/df = 1.866$, CFI = .938, TLI = .931, RMSEA = .048 [90% CI: .045, .051], SRMR = .051. Control variables (Age, Tenure, Education) were included in the structural model. "Not sig." = Not significant.

- H1 supported: AI capability was positively associated with employee performance (β = .322, *p* < .001), indicating that organizations with stronger AI capability tend to have employees who report higher performance. This finding is consistent with RBV logic: AI capability, as a strategic resource, generates performance returns through enhanced decision-making, task automation, and cognitive augmentation (Mikalef & Gupta, 2021).
- H2 supported: AI capability was positively associated with employee engagement (β = .214, *p* < .001), suggesting that AI-enabled work environments foster greater psychological investment and commitment among employees.
- H3 supported: AI capability was positively associated with employee empowerment (β = .402, *p* < .001), the strongest direct effect in the model, underscoring the centrality of AI capability as an enabling resource that enhances employees' sense of autonomy, competence, and impact.
- H4a supported: Employee empowerment was positively associated with employee performance (β = .341, *p* < .001).
- H4b supported: Employee empowerment was positively associated with employee engagement (β = .374, *p* < .001).

Regarding control variables, age and tenure showed no significant association with employee performance (β = .087, p = .070; β = .098, p = .055, respectively), suggesting that in digitally transforming Egyptian organizations, adaptation to AI-enabled work processes may depend less on cumulative experience than on access to AI tools and empowerment opportunities. Education, in contrast, was significantly associated with engagement (β = .112, p = .022), consistent with evidence that higher educational attainment is associated with greater digital readiness and capacity to leverage technology for meaningful work (Huang & Rust, 2021).

[Insert Table 5 *here]*

[Insert Fig. 3 *here]*

5.4 Mediation Analysis

To test the hypothesized mediating role of employee empowerment (H5a, H5b), we employed bootstrapping with 5,000 resamples to generate bias-corrected 95% confidence intervals, as recommended by Preacher and Hayes

(2008) and Zhao, Lynch, and Chen (2010). Bootstrapping is preferred over the Sobel test because it does not assume normality of the indirect effect distribution, which is typically skewed.

As shown in Table 6, both mediation hypotheses were supported:

Table 6
Mediation Analysis: Bootstrapped Indirect Effects

Mediation Path	Indirect Effect	SE	95% CI	VAF	Type
AI Capability → Empowerment → Performance	.176	.034	[.109, .243]	34.0%	Partial
AI Capability → Empowerment → Engagement	.161	.037	[.089, .233]	35.1%	Partial

Note. N = 387. Estimates are based on 5,000 bootstrap resamples with bias-corrected 95% confidence intervals (CI). VAF = Variance Accounted For. An indirect effect is considered statistically significant if the 95% CI does not contain zero (Preacher & Hayes, 2008).

- H5a supported: The indirect effect of AI capability on employee performance through employee empowerment was significant (indirect effect = .176, SE = .034, 95% CI [.109, .243]), with a Variance Accounted For (VAF) of 34.0%. This indicates partial mediation: empowerment explains approximately one-third of the total effect of AI capability on performance, while the remaining two-thirds operates through direct pathways such as task automation, decision support, and process efficiency.
- H5b supported: The indirect effect of AI capability on employee engagement through employee empowerment was likewise significant (indirect effect = .161, SE = .037, 95% CI [.089, .233]), with VAF = 35.1%, indicating partial mediation. This finding suggests that empowerment is a meaningful but not exclusive mechanism through which AI capability enhances engagement; other pathways, such as improved work–life balance, personalized development opportunities, and reduced cognitive load, may also contribute (Bankins et al., 2024).

The partial-mediation pattern is theoretically important. It confirms that employee empowerment is a significant psychological transmission mechanism linking organizational AI resources to individual outcomes, consistent with Psychological Empowerment Theory. However, it also acknowledges that AI capability's influence on employee outcomes is multifaceted, operating through both psychological (empowerment) and structural (process, technology) pathways simultaneously. This dual-pathway insight enriches the RBV micro-foundations perspective by demonstrating that strategic resources generate value through both human and technical mechanisms.

[Insert Table 6 *here]*

5.5 Moderation Analysis (Multi-Group SEM)

To test the hypothesized moderating role of digital organizational culture (H6), we conducted a multi-group SEM analysis, consistent with recommended practice for testing moderation with latent constructs in CB-SEM (Byrne, 2016). The sample was split at the median of digital organizational culture into high-DOC (n = 194) and low-DOC (n = 193) groups. While median splits are sometimes criticized for reducing statistical power, they are appropriate and widely used in multi-group SEM when the moderator is a latent construct and the primary objective is to test whether a structural path differs significantly across groups (Byrne, 2016).

In the unconstrained multi-group model, the AI capability → empowerment path was substantially stronger in the high-DOC group ($\beta = .612$, $p < .001$) than in the low-DOC group ($\beta = .300$, $p < .001$). This represents a more than two-fold

difference in path magnitude, indicating that the empowerment-enhancing effect of AI capability is substantially amplified in organizations with strong digital cultures.

To formally test the moderating effect, we compared an unconstrained model (path freely estimated across groups) with a constrained model (path fixed equal across groups). As shown in Table 7, constraining the AI capability → empowerment path to equality produced a statistically significant chi-square difference ($\Delta\chi^2(1) = 9.87$, $p = .002$), providing formal statistical evidence that the path coefficient differs significantly by the level of digital organizational culture and supporting H6.

Table 7

Moderation Analysis: Multi-Group SEM Invariance Testing (Digital Organizational Culture)

Model	χ^2	df	$\Delta\chi^2$	Δdf	p
Unconstrained (path free across groups)	1,942.10	2,410	—	—	—
Constrained (path fixed equal across groups)	1,951.97	2,411	9.87	1	.002

Note. N = 387 (High-DOC group: n = 194; Low-DOC group: n = 193). The constrained model fixes the path coefficient (AI Capability → Empowerment) to be equal across groups. A significant $\Delta\chi^2$ indicates that the path coefficient differs significantly between the high and low digital organizational culture (DOC) groups (Cheung & Rensvold, 2002), supporting H6.

[Insert Table 7 *here]*

Substantive interpretation. Although the difference in constrained versus unconstrained χ^2 is modest in absolute magnitude—a common occurrence when testing single-path invariance in large multi-group models (Cheung & Rensvold, 2002)—the substantive difference in standardized path coefficients ($\beta = .612$ vs. $\beta = .300$) indicates that the practical, real-world strength of the AI capability–empowerment relationship differs meaningfully across digital-culture contexts. In organizations with high digital organizational culture, AI capability is strongly and positively associated with employee empowerment, suggesting that a supportive digital culture creates the psychological safety, learning orientation, and trust necessary for employees to perceive AI as an enabling rather than threatening resource. Conversely, in organizations with low digital culture, the empowerment-enhancing potential of AI is substantially attenuated, likely because hierarchical norms, limited training infrastructure, and resistance to experimentation inhibit employees' ability to leverage AI for autonomous decision-making and skill development. This moderation finding carries significant theoretical and practical implications. Theoretically, it establishes digital organizational culture as a critical boundary condition that determines the degree to which AI capability translates into empowerment, extending RBV by identifying the cultural complementarity conditions under which strategic resources generate human capital returns. Practically, it suggests that AI investment alone is insufficient; organizations must simultaneously cultivate digital cultures to unlock the empowerment potential of AI—a finding particularly relevant for emerging economies where cultural transformation may lag behind technological adoption.

5.6 Explained Variance

The model explained a moderate-to-substantial proportion of variance in the endogenous constructs: employee empowerment ($R^2 = .342$), employee performance ($R^2 = .398$), and employee engagement ($R^2 = .361$). These values are consistent with moderate-to-substantial explanatory power by conventional benchmarks (Cohen, 1988), indicating that the hypothesized model captures meaningful variance in employee outcomes while acknowledging that additional factors (e.g., leadership style, job design, organizational climate) also contribute to performance and engagement.

6. Discussion and Conclusion

6.1 Discussion of Findings

This study set out to examine the human side of artificial intelligence adoption by investigating whether, how, and under what conditions organizational AI capability translates into employee performance and engagement. Drawing on the Resource-Based View (RBV) and Psychological Empowerment Theory and utilizing data from 387 employees across digitally transforming Egyptian organizations, the findings provide robust empirical support for all six hypothesized relationships.

First, confirming H1 and H2, AI capability is positively and significantly associated with both employee performance and engagement. In the context of emerging economies like Egypt, where organizations are rapidly transitioning from legacy systems to intelligent digital ecosystems (World Bank, 2023), these findings suggest that AI capability operates not merely as an operational efficiency tool, but as a strategic catalyst for human capital enhancement. Consistent with RBV logic (Barney, 1991; Mikalef & Gupta, 2021), when organizations invest holistically in AI—encompassing data infrastructure, technical skills, and change capacity—they create an environment where employees can perform at higher levels and engage more deeply with their work.

Second, the study confirms the critical mediating role of employee empowerment (H3, H4a, H4b, H5a, H5b). The partial mediation effects (VAF ≈ 34–35%) reveal that empowerment is a vital psychological transmission mechanism. AI capability enhances performance and engagement partly by providing employees with real-time informational access (increasing perceived control), AI-driven skill development (building competence), automation of mundane tasks (enhancing the meaning of work), and collaborative intelligence (expanding impact). This finding is crucial: it demonstrates that the value of AI is not realized solely through algorithmic superiority, but through its capacity to psychologically empower the human workers who deploy it. The partial nature of the mediation also acknowledges that AI influences outcomes through parallel structural pathways, such as direct process optimization and decision-support automation.

Third, and perhaps most consequentially for theory and practice, the study establishes digital organizational culture as a vital boundary condition (H6). The multi-group analysis revealed that the empowerment-enhancing effect of AI capability is more than twice as strong in organizations with high digital cultures (β = .612) compared to those with low digital cultures (β = .300). This finding underscores a critical reality: technology does not operate in a cultural vacuum. In environments characterized by continuous learning, psychological safety, and trust, AI is embraced as an enabling partner. Conversely, in cultures lacking these digital norms, the same AI investments yield significantly diminished human returns. This moderation effect is particularly salient in emerging markets, where rapid technological adoption often outpaces the evolution of supportive organizational cultures.

6.2 Theoretical Implications

This research makes three distinct contributions to the strategic management, information systems, and organizational behavior literatures, directly aligning with JBR's mandate for rigorous and impactful theory building.

First, *Unlocking the Micro foundations of the Resource-Based View (RBV).* Traditional applications of RBV have predominantly focused on macro-level, firm-performance outcomes (e.g., competitive advantage, market share). This study advances RBV by empirically articulating its micro foundations (Felin et al., 2015). We demonstrate exactly how an organizational-level strategic resource (AI capability) is converted into individual-level value (performance and engagement). By integrating Psychological Empowerment Theory, we provide the missing psychological link, showing

that strategic resources generate human capital returns only when they alter the cognitive and motivational states (meaning, competence, self-determination, impact) of the employees utilizing them.

Second, *Repositioning Employee Empowerment in the AI Discourse*. While much of the extant literature debates the "dark side" of AI (e.g., job displacement, algorithmic control, technostress), this study contributes to the "bright side" literature by identifying empowerment as a core mechanism of positive AI integration. We move beyond treating empowerment as a static trait or a generic HR outcome, positioning it instead as a dynamic, technology-enabled psychological state. This answers recent calls to explore the human-centric mechanisms of digital transformation (Vial, 2019; Warner & Wäger, 2019) and provides a nuanced counter-narrative to technological determinism.

Third, Establishing Digital Culture as a Crucial Boundary Condition. The study enriches the digital transformation literature by empirically validating the moderating role of digital organizational culture. While prior research has acknowledged culture's importance conceptually (Kane et al., 2019), this study quantifies its amplifying effect. We demonstrate that digital culture is not merely a "nice-to-have" backdrop, but a strict prerequisite—a complementary intangible resource—that determines the efficacy of tangible AI investments. Furthermore, by validating these dynamics in Egypt, we address the severe geographic bias in AI research (Huang & Rust, 2021), proving that while the mechanisms of AI empowerment are theoretically universal, their magnitude is highly context-dependent, shaped by local institutional and cultural realities.

6.3 Managerial and Policy Implications

For executives, HR leaders, and policymakers, particularly in emerging economies, this study offers a strategic roadmap for human-centric AI integration. We distil our findings into four actionable imperatives:

First, *Recalibrate AI Investment from "IT Procurement" to "Holistic Capability Building*." Managers must abandon the misconception that purchasing AI software equates to achieving AI capability. True capability requires a tripartite investment: tangible (data and infrastructure), human (AI literacy and analytical skills), and intangible (governance and change management). Budgets must be allocated equally across technology acquisition and the human upskilling required to leverage it.

Second, *Design AI Implementation for Empowerment, Not Just Efficiency.* To translate AI into engagement and performance, managers must deliberately design AI workflows that enhance the four dimensions of psychological empowerment.

- Meaning: Use AI to automate repetitive tasks, freeing employees for high-value, creative problem-solving.
- Competence: Deploy AI-driven, personalized learning platforms to continuously upskill the workforce.
- Self-Determination: Provide employees with autonomy in how they interact with and customize AI tools for their specific workflows.
- Impact: Ensure AI dashboards provide transparent, real-time feedback that allows employees to see the direct impact of their decisions.

Third, Cultivate Digital Culture as the "Operating System" for AI. The stark difference in empowerment outcomes between high- and low-culture organizations dictates that cultural transformation must precede or accompany technological deployment. Leaders must foster psychological safety, reward intelligent experimentation and treating AI-related failures as learning opportunities rather than punishable offenses. In hierarchical contexts common in emerging markets, middle managers must be trained to transition from "command-and-control" supervisors to "coaches and facilitators" of human-AI collaboration.

Fourth, Contextualize AI Strategies for Emerging Economies. Policymakers and business leaders in markets like Egypt should leverage national digital initiatives (e.g., "Digital Egypt") to build foundational digital literacy before deploying advanced AI. Furthermore, organizations should adapt global AI best practices to fit local cultural nuances, ensuring that technology serves to augment local workforce strengths rather than imposing alien work paradigms.

6.4 Limitations and Avenues for Future Research

While this study offers robust insights, its boundaries suggest several fruitful avenues for future research.

Methodological Limitations. First, the cross-sectional design precludes definitive causal claims; it is plausible that highly engaged and empowered employees are more likely to perceive their organizations as having high AI capability (reverse causality). Future research should employ longitudinal panel designs or Experience Sampling Methodology (ESM) to capture daily fluctuations in AI usage, empowerment, and engagement, establishing temporal precedence. Second, reliance on single-source, self-reported data introduces the risk of common method variance, despite our rigorous procedural and statistical remedies. Future studies should utilize multi-source data, pairing employee self-reports of empowerment and engagement with objective performance metrics or supervisor ratings.

Contextual and Conceptual Boundaries. While focusing on Egypt addresses a critical geographic gap, it limits immediate generalizability to other institutional contexts. Future research should conduct cross-national comparative studies across diverse emerging economies (e.g., comparing North Africa with Southeast Asia or Latin America) to isolate the effects of specific cultural and institutional dimensions (e.g., power distance, uncertainty avoidance) on the AI-empowerment nexus.

Expanding the Nomological Network. Finally, this study focused on a specific set of variables. Future research should explore alternative mediators, such as psychological safety, job crafting, and technostress, to capture the dual (positive and negative) impacts of AI. Additionally, scholars should disaggregate AI capability to examine whether specific AI types (e.g., generative AI vs. predictive analytics vs. robotics) differentially impact employee outcomes. Qualitative, ethnographic studies are also highly recommended to uncover the nuanced, lived experiences of employees navigating the cultural friction of AI adoption in traditional organizations.

6.5 Conclusion

As artificial intelligence fundamentally reconfigures the architecture of work, the organizations that will thrive are not necessarily those with the most advanced algorithms, but those that successfully integrate these technologies with their human capital. This study demonstrates that AI capability is a potent driver of employee performance and engagement, but its success is contingent upon two critical human factors: the psychological empowerment of the workforce and the presence of a supportive digital organizational culture. By providing novel empirical evidence from an emerging economy, this research underscores that the future of AI in the workplace is not a zero-sum game between human and machine. Rather, when guided by empowering leadership and embedded in a resilient digital culture, AI serves as a powerful catalyst for human potential, driving both organizational excellence and employee well-being in the digital age.

Declarations

Ethical approval

This study was conducted in accordance with the Helsinki Declaration and approved by the Scientific Research Ethics Committee of the Higher Institute for Administrative Sciences, Egypt (Code: HIAS/REC/26-006, dated February 16, 2026).

Consent to participate

All participants provided voluntary informed consent after receiving detailed written information about the study objectives, procedures, risks, and benefits, and after having the opportunity to ask questions.

Consent to publish

Not applicable.

Data availability statement

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Competing interests

The authors declare no competing interests.

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Figures

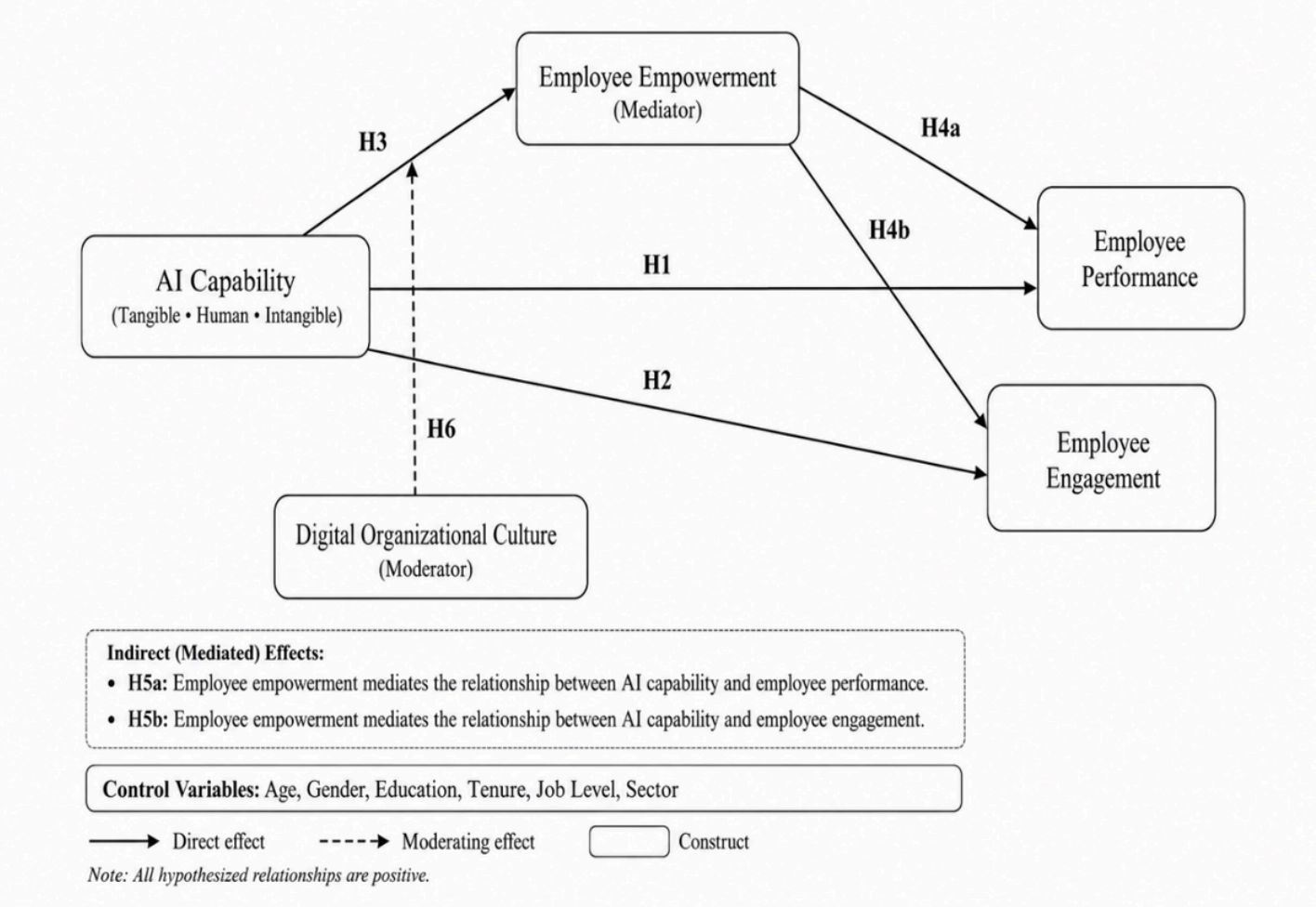


Figure 1

Model of the Study.

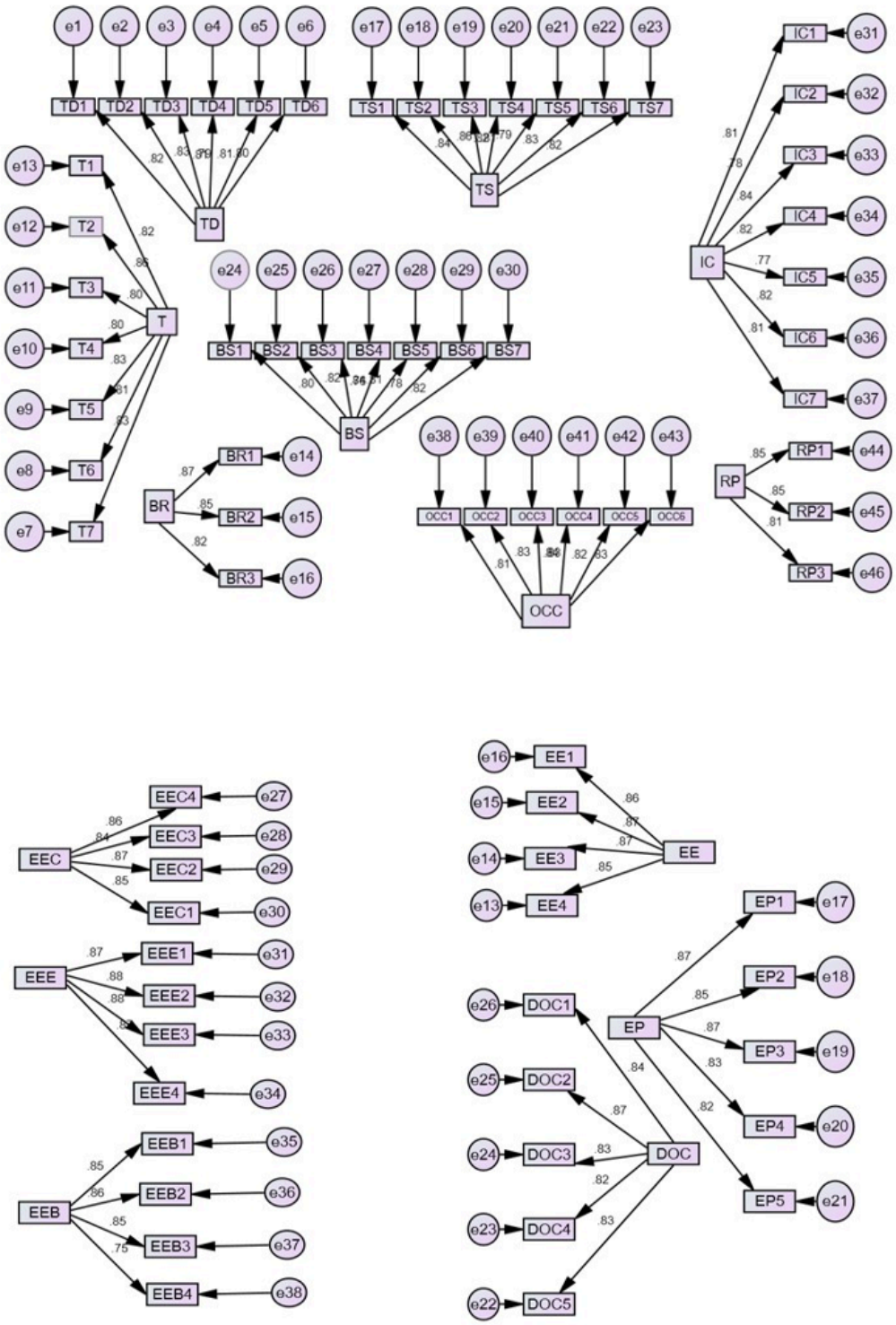


Figure 2

Measurement model with standardized factor loadings.

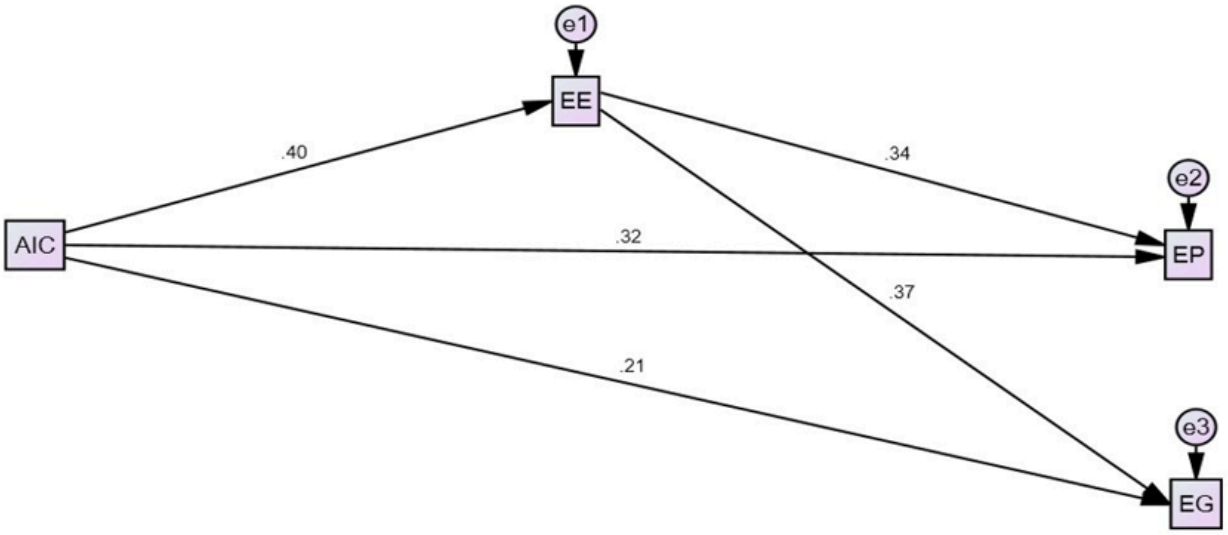


Figure 3

Structural model with standardized path coefficients.

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- SupplementaryMaterial.docx