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# From AI Readiness to Organizational Performance: The Mediating Role of AI Adoption in A Mena-Anchored Multi- Industry Study

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**Abstract:** *Organizations increasingly invest in AI readiness, yet evidence remains mixed on whether such readiness improves performance directly or only after AI is adopted in practice. This study examines how innovation and the structural determinants of AI affect perceived organizational performance, with AI adoption tested as a mediating mechanism. Drawing on the TOE/TOEH framework, dynamic capabilities theory, and the resource-based view, data were collected through a bilingual online questionnaire from 422 professionals, mainly from MENA organizations. The model was assessed using SPSS, SmartPLS 4, and PROCESS Model 4. Results show that structural determinants strongly predict AI adoption, and AI adoption significantly improves perceived organizational performance. However, structural determinants do not directly affect performance once AI adoption is included. AI adoption fully mediates the structural determinants-performance relationship, while innovation affects performance directly and is not mediated by AI adoption. The study clarifies how AI readiness becomes performance-relevant only through actual adoption.*
Keywords: AI adoption, AI readiness, structural determinants, innovation, organizational performance, MENA

## INTRODUCTION

Artificial intelligence (AI) has moved from being an emerging digital technology to becoming a strategic organizational capability. Firms increasingly use AI to automate tasks, improve decision-making, redesign processes, personalize services, and support data-driven business models. Yet the performance value of AI remains difficult to explain. Many organizations invest in data infrastructure, software platforms, vendor partnerships, and AI-related skills without seeing immediate performance gains. This tension creates a central management question: does AI readiness itself improve organizational performance, or does it become valuable only when it is converted into actual AI adoption?

This article addresses that question by examining the mediating role of AI adoption between the structural determinants of AI and perceived organizational performance. The article also includes innovation as a parallel organizational capability. Innovation is important because organizations may improve performance through product development, process redesign, service improvement, business model renewal, and learning even when AI adoption remains limited.

Including innovation in the model therefore makes it possible to compare two performance routes: a broad innovation route and an AI-readiness rout

The study is positioned in the literature on AI adoption, technology readiness, and organizational performance. Prior research has often examined innovation, AI readiness, AI adoption, and performance separately. Some studies focus on AI adoption drivers, others on the performance benefits of innovation or digital transformation, and others on AI-enabled performance outcomes. Fewer studies integrate innovation and structural determinants in the same empirical model while testing whether AI adoption is the mechanism through which readiness becomes performance-relevant.The empirical setting is a MENA-anchored multi-industry sample. This context is important because the region is experiencing fast AI policy development and digital transformation, while organizational AI maturity remains uneven. National AI strategies in countries such as Egypt, Saudi Arabia, and the United Arab Emirates create strong external momentum, but firms still differ in their infrastructure, leadership commitment, employee capability, and actual AI use. This makes the context suitable for testing whether structural readiness produces performance directly
or through adoption.

The article contributes by showing that structural determinants of AI are not performance-generating in themselves. Instead, they operate as readiness conditions that drive AI adoption, and AI adoption then transmits their effect to performance. The findings also show that innovation improves perceived organizational performance directly but does not significantly predict AI adoption once structural determinants are included. The strongest article-level claim is therefore that AI readiness becomes organizational value only when translated into actual AI adoption.

## Literature/Theoretical Underpinning

The theoretical foundation of the study combines the Technology-Organization- Environment framework, its human-centered TOEH extension, dynamic capabilities theory, the resource-based view, diffusion of innovation theory, and the Balanced Scorecard approach to performance. The TOE framework explains technology adoption through technological, organizational, and environmental conditions. In the AI context, recent studies argue that this framework should be extended to include human factors such as employee acceptance, AI literacy, trust, resistance to change, and learning orientation (Dönmez et al., 2025; Sánchez et al., 2025). This four-dimensional TOEH perspective is especially relevant because AI adoption depends not only on systems and strategy but also on people who use, trust, and embed AI in work processes.

Structural determinants of AI refer to the technological, organizational, environmental, and human conditions that make AI adoption possible. Technological determinants include infrastructure, compatibility, data quality, and system integration. Organizational determinants include leadership commitment, resources, governance, readiness, and culture. Environmental determinants include competitive pressure, customer expectations, regulation, and ecosystem support. Human determinants include digital skills, acceptance, trust, and learning capability. Collectively, these determinants represent AI readiness rather than AI use itself.

Dynamic capabilities theory helps explain why readiness alone may not be enough. Resources and structural conditions create potential value, but they must be transformed into operational capability before they produce performance outcomes (Teece, 2007). The resource-based view similarly argues that resources generate advantage when they are valuable, difficult to imitate, and effectively deployed (Barney, 1991). From this perspective, AI readiness is a resource condition, while AI adoption is the organizational mechanism that converts readiness into performance-relevant activityAI adoption is conceptualized here as the extent to which organizations deploy, integrate, and routinely use AI technologies in operational, managerial, and strategic activities. Adoption is therefore more than intention or acquisition. It includes adoption intensity, functional integration, depth of utilization, user acceptance and trust, and strategic embeddedness. This distinction is important because an organization may possess AI infrastructure or leadership support without integrating AI into decision-making, customer service, production, or strategic planning.

Innovation is included as a separate organizational capability. Innovation refers to the development and implementation of new products, processes, services, business models, digital practices, and sustainable or social initiatives. The literature consistently links innovation to organizational performance because innovation improves customer value, operational efficiency, learning, adaptability, and competitive differentiation (Bahoo et al., 2023; Farida & Setiawan, 2022; Jiao et al., 2024; Mariani et al., 2023). However, innovation is broader than AI adoption. An innovative firm may generate performance through channels that do not rely on AI, such as product improvement, process redesign, customer experience development, or business model innovation. Perceived organizational performance is operationalized as multidimensionaloutcome. Rather than relying only on financial indicators, this study follows the Balanced Scorecard tradition by considering financial, customer, internal process, learning and growth, and innovation and competitive advantage dimensions (Kaplan & Norton, 1996; Madsen, 2025). This approach is appropriate for AI and innovation research because performance benefits may appear first in speed, quality, learning, responsiveness, and competitive capability before they appear in formal financial measures.

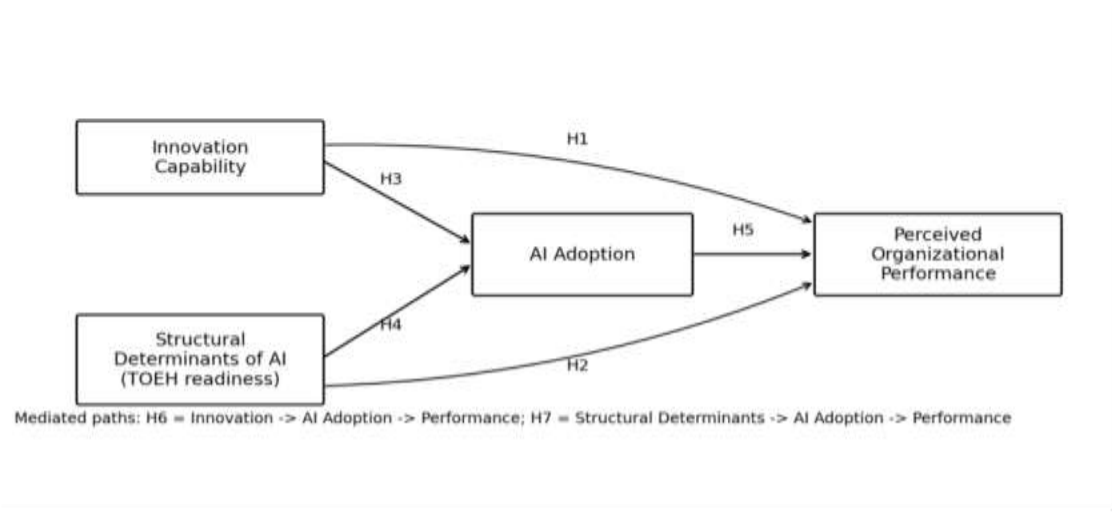


**Figure 1. Conceptual model and hypothesized relationships.**

The conceptual model therefore tests five direct relationships and two mediation relationships. Innovation and structural determinants are modeled as antecedents. AI adoption is modeled as the mediator. Perceived organizational performance is the dependent variable. The direct paths test whether innovation, structural determinants, and AI adoption influence performance, and whether innovation and structural determinants influence AI adoption. The indirect paths test whether AI adoptionmediates the innovation-performance relationship and the structural determinants-performance relationship.

H1. Innovation has a significant positive effect on perceived organizational performance.

H2. Structural determinants of AI have a significant positive effect on perceived organizational performance.

H3. Innovation has a significant positive effect on AI adoption.

H4. Structural determinants of AI have a significant positive effect on AI adoption.

H5. AI adoption has a significant positive effect on perceived organizational performance.

H6. AI adoption mediates the relationship between innovation and perceived organizational performance.

H7. AI adoption mediates the relationship between structural determinants of AI and perceived organizational performance.

## METHODOLOGY

The study adopted a positivist, deductive, mono-method quantitative design. A cross- sectional online survey was used because the research objective was to test theoretically specified relationships among latent constructs. The target population consisted of currently employed professionals able to report on their organizations' innovation orientation, AI readiness, AI adoption, and performance. Respondents were reached through professional networks and human resources contacts using non- probability convenience sampling with referral elements.

The final analytical sample included 422 valid responses. The sample was suitable for the study because it was concentrated in industries where AI adoption and digital transformation are substantively relevant. Manufacturing represented 22.3% of responses, energy 22.0%, and technology 17.1%, together accounting for more than 61% of the sample. Most respondents worked in very large organizations with 1,000 or more employees (67.8%), and the role distribution was dominated by management (50.2%), technical or operational roles (27.0%), and executive roles (15.6%). The sample was also experienced: 80.1% of respondents had more than ten years of professional experience. Geographically, Egypt accounted for 55.0%, the United Arab Emirates for 12.6%, and Saudi Arabia for 5.2%, making the sample strongly MENA- anchored while still multi-country.

The questionnaire contained 63 measurement items and five demographic questions. Innovation was measured by 18 items, structural determinants of AI by 14 items, AI adoption by 15 items, and perceived organizational performance by 16 items. All measurement items used a five-point

Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The questionnaire was prepared in English and Arabic to reduce language-related barriers and improve respondent accessibility.

Data analysis was conducted using IBM SPSS Statistics, SmartPLS 4, and PROCESS Macro Model 4. SPSS was used for data screening, descriptive statistics, reliability diagnostics, correlations, common method bias diagnostics, and group comparisons. SmartPLS 4 was used as the main PLS-SEM platform for assessing the measurement and structural models. PROCESS Model 4 was used as a robustness check formediation results. Statistical inference for the PLS-SEM model was based on bootstrapping with 5,000 subsamples.

**Table 1. Measurement constructs used in the questionnaire.**

| Construct | Dimensions/coverage | Items |
|---|---|---|
| Innovation | Product, process, organizational, business model, digital, sustainable and social innovation | 18 |
| Structural determinants of AI | Technological, organizational, environmental, and human determinants | 14 |
| AI adoption | Adoption intensity, functional integration, depth of utilization, user acceptance and trust, strategic embeddedness | 15 |
| Perceived organizational performance | Financial, customer, internal process, learning and growth, innovation and competitive advantage performance | 16 |

## RESULTS/FINDINGS

The data screening process confirmed the suitability of the dataset. No missing values were found across the demographic variables and the 63 measurement items. No cases were removed for inattentive responding. Item distributions showed no severe violations of univariate normality, and the final analytical sample remained N = 422.

Descriptive statistics indicate a meaningful readiness-adoption gap. Innovation received the highest composite mean (M = 4.135), suggesting that respondents generally perceived their organizations as innovation-oriented. Structural determinants of AI also received a moderate-to-high mean (M = 3.646). However, AI adoption had the lowest mean (M = 3.291), while perceived organizational performance stood at M = 3.633. This pattern suggests that organizations may be more innovative and structurally ready for AI than they are mature in actual AI deployment.

The measurement model demonstrated strong reliability and validity. Cronbach's alpha ranged from 0.928 to 0.968, composite reliability ranged from 0.938 to 0.972, and AVE ranged from 0.525 to 0.696. These values support internal consistency reliability and convergent validity. Discriminant validity was generally supported; however, the HTMT value for the structural determinants-AI adoption pair reached 0.850, which is acceptable under the 0.90 threshold but should be interpreted with caution because the constructs are conceptually close. Common method bias diagnostics did not indicate a major concern: Harman's single-factor test showed 44.50% variance for the first factor, below the 50% warning threshold, and full- collinearity

VIF values were below 5.0. All bivariate correlations among the composite constructs were positive and significant, with the strongest correlation observed between structural determinants and AI adoption (r = 0.804), foreshadowing the mediation pattern observed in the structural model.

**Table 2. Measurement model reliability and convergent validity.**

| Construct | Items | Cronbach alpha | CR | AVE |
|---|---|---|---|---|
| Innovation | 18 | 0.961 | 0.965 | 0.604 |
| Structural determinants of AI | 14 | 0.928 | 0.938 | 0.525 |
| AI adoption | 15 | 0.968 | 0.972 | 0.696 |
| Perceived organizational performance | 16 | 0.960 | 0.963 | 0.622 |

**Table 3. PLS-SEM direct effects.**

| Hypothesis/path | Beta | T | p | 95% CI | Decision |
|---|---|---|---|---|---|
| H1: Innovation -> POP | +0.427 | 6.343 | < .001 | [+0.285, +0.548] | Supported |
| H2: SDA -> POP | +0.049 | 0.566 | .571 | [-0.129, +0.214] | Not supported |
| H3: Innovation -> AIA | +0.021 | 0.435 | .663 | [-0.071, +0.113] | Not supported |
| H4: SDA -> AIA | +0.793 | 18.707 | < .001 | [+0.706, +0.875] | Supported |
| H5: AIA -> POP | +0.207 | 2.684 | .007 | [+0.059, +0.365] | Supported |

**Table 4. Explained variance and effect sizes.**

| Path | R2 of outcome | Adjusted R2 | f2 | Effect size |
|---|---|---|---|---|
| INN -> POP | .387 | .383 | 0.124 | Small-to-medium |
| SDA -> POP | .387 | .383 | 0.001 | Negligible |
| INN -> AIA | .655 | .653 | 0.001 | Negligible |
| SDA -> AIA | .655 | .653 | 0.759 | Large |
| AIA -> POP | .387 | .383 | 0.024 | Small |

**Table 5. Mediation analysis using bootstrapped indirect effects.**

| Hypothesis/path | Indirect effect | SE | 95% CI | Decision |
|---|---|---|---|---|
| H6: INN -> AIA -> POP | +0.004 | 0.011 | [-0.014, +0.029] | Not supported |
| H7: SDA -> AIA -> POP | +0.164 | 0.063 | [+0.049, +0.298] | Supported |

**Table 6. Decomposition of total effects and mediation type.**

| Path | Total effect | Direct effect | Indirect effect | Mediation type |
|---|---|---|---|---|
| INN -> POP | +0.432 | +0.427 (sig.) | +0.004 (ns) | Direct-only; no mediation |
| SDA -> POP | +0.213 | +0.049 (ns) | +0.164 (sig.) | Indirect-only; full mediation |

The direct-effect results show a clear pattern. Innovation significantly and positively influenced perceived organizational performance (β = +0.427, p < .001). Structural determinants of AI did not have a significant direct effect on performance (β = +0.049, p = .571). Innovation did not significantly predict AI adoption once structural determinants were included in the model (β = +0.021, p = .663). By contrast, structural determinants strongly predicted AI adoption (β = +0.793, p < .001), and AI adoption had a statistically significant positive effect on perceived organizational performance (β = +0.207, p = .007).

The mediation results provide the central finding of the article. AI adoption did not mediate the relationship between innovation and perceived organizational performance. The indirect effect was negligible and non-significant (β = +0.004, 95% CI [-0.014, +0.029]). In contrast, AI adoption significantly mediated the relationship between structural determinants of AI and perceived organizational performance (β = +0.164, 95% CI [+0.049, +0.298]). Because the direct effect of structural determinants on performance was not significant, this relationship is classified as indirect-only full mediation.

## DISCUSSION

The findings reveal two distinct performance routes. The first is a direct innovation route. Innovation contributes positively to perceived organizational performance without requiring AI adoption as an intermediary. This supports the view that innovation remains a broad strategic capability that improves performance through products, processes, services, learning, customer responsiveness, and business model renewal. The performance value of innovation is therefore wider than the AI agenda.

The second route is an indirect AI-readiness route. Structural determinants of AI do not improve performance directly. Their value appears only when they are translated into AI adoption. This is the strongest and most publishable contribution of the article. It shows that AI readiness should not be confused with AI value. Infrastructure, leadership support, data capability, governance, external pressure, and employee readiness create the conditions for adoption, but they do not become performance- relevant until AI is actually deployed, integrated, and used.

This finding contributes to the AI productivity debate. The performance benefits of AI are often assumed to follow from investment in technology and readiness conditions. The present results challenge that assumption. Structural readiness has a strong effect on AI adoption, but its direct effect on performance disappears once adoption is included. This suggests that readiness is a latent capacity, while adoption is the conversion mechanism. In dynamic capabilities terms, AI readiness is the resource platform, and AI adoption is the operational capability that transforms that platform into performance outcomes.

The non-significant innovation-AI adoption path is also theoretically important. Innovation and AI adoption are related at the bivariate level, but innovation does not explain unique variance in AI adoption after structural determinants are included. This indicates that an innovation-oriented organization does not automatically become an AI-adopting organization. AI adoption requires specific technological, organizational, environmental, and human foundations. Innovation creates a favorable climate, but structural readiness drives implementation.

The significant but modest AI adoption-performance effect also deserves careful interpretation. AI adoption is performance-enhancing, but its effect is smaller than that of innovation. This may reflect the maturity stage of AI adoption in many organizations. If AI remains confined to pilots, isolated tools, or limited functional use, its performance effect may be positive but not yet transformational. Stronger performance gains are likely when AI moves from experimentation to deep utilization, operational decision-making, and strategic embeddedness.

## Implication to Research and Practice

For research, the article contributes to the AI adoption literature by distinguishing readiness from adoption and showing that adoption mediates the readiness- performance relationship. This extends the TOE framework by supporting the relevance of the TOEH formulation in a MENA-anchored multi-industry sample. It also contributes to dynamic capabilities theory by showing how structural readiness becomes performance-relevant through an operational capability, namely AI adoption.

For C-suite executives, the findings suggest that innovation strategy and AI strategy should be integrated but not conflated. Innovation directly improves performance, while AI readiness improves performance indirectly through adoption. Leaders should therefore continue to invest in broad innovation capabilities while ensuring that AI- specific readiness conditions are converted into real use cases and embedded workflows.

For CIOs, CTOs, and digital transformation leaders, the results emphasize that AI readiness should be measured by adoption outcomes, not only by infrastructure or platform availability. Data architecture, system compatibility, governance, vendor partnerships, and cybersecurity are necessary, but they must support actual AI use in decisions, operations, customer interfaces, and strategic planning. For HR and people-strategy leaders, the human dimension of AI readiness is central. Employee acceptance, trust, digital competence, and learning orientation are not secondary issues. They determine whether AI remains a technical project or becomes a routinized organizational capability. Training, role redesign, change communication, and responsible AI practices should therefore accompany technical deployment.

For policymakers in the MENA region, the results suggest that national AI strategies should not focus only on technology investment and policy declarations. They should also support organizational adoption capacity through skills development, data governance frameworks, industry partnerships, regulatory clarity, and sector-level use-case diffusion. Regional AI competitiveness depends on the ability of firms to translate readiness into adoption and adoption into performance.

## CONCLUSION

This article examined how innovation and the structural determinants of AI influence perceived organizational performance, with AI adoption tested as the mediating mechanism. Based on 422 responses from a MENA-anchored multi-industry sample, the findings show that innovation directly improves perceived organizational performance, while structural determinants improve performance only indirectly through AI adoption. AI adoption fully mediates the structural determinants- performance relationship but does not mediate the innovation-performance relationship.

The central conclusion is that AI readiness is not enough. Organizations do not gain performance benefits merely by possessing AI-supportive infrastructure, leadership, resources, governance, external pressure, or human capability. These conditions become valuable when translated into actual AI adoption. The article therefore reframes AI adoption as the translation mechanism that converts structural readiness into organizational performance. At the same time, innovation remains an independent and broader route to performance that should not be reduced to AI deployment alone.

## Future Research

Future research should extend the model longitudinally to examine whether the performance effect of AI adoption strengthens over time as organizations move from early implementation to deeper integration. Cross-sectional evidence can identify associations consistent with the proposed mechanisms, but longitudinal data would provide stronger evidence of temporal ordering.

Future studies should also test the model in specific industries such as manufacturing, energy, banking, healthcare, and professional services. Industry-level research would clarify whether the strength of the readiness-adoption-performance pathway differs according to data intensity, regulation, customer interaction, and operational complexity.

Further research should incorporate objective performance indicators alongside perceptual measures. While perceptual organizational performance is appropriate for multi-industry survey research, financial and operational data would strengthen external validation. Finally, comparative studies across MENA countries and other regions would help determine whether the full mediation of structural determinants through AI adoption is context-specific or generalizable across institutional environments.

## Author Note and Declarations

Author Note: This manuscript is derived from the author's ongoing Doctor of Business Administration (DBA) dissertation titled "The Relationship between Innovation, Structural Determinants of AI and Perceived Organizational Performance:
The Mediating Role of AI Adoption." The dissertation has not yet been defended or published. This manuscript has been substantially rewritten and reframed as a standalone journal article focusing on the structural mediation mechanism through which AI adoption links AI readiness to perceived organizational performance.

Conflict of Interest: The author declares no conflict of interest.

Data Availability: The data supporting the findings of this study are available from the author upon reasonable request, subject to ethical and confidentiality considerations.

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