INTERNATIONAL JOURNAL OF
SOCIAL SCIENCES BULLETIN
ISSN: (E) 3007-1917 (P) 3007-1909

Volume 4, Issue 3, 2026

# ARTIFICIAL INTELLIGENCE ADOPTION IN PAKISTANI BUSINESSES: THE INFLUENCE OF TRANSFORMATIONAL LEADERSHIP ON ORGANIZATIONAL READINESS

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**DOI:** https://doi.org/10.5281/zenodo.21505767

| Received | Accepted | Published |
|---|---|---|
| 01 January 2026 | 17 March 2026 | 31 March 2026 |

## ABSTRACT

*To successfully implement AI, efforts must go beyond technology investments to foster leadership that can rally organizational resources, deepen employee engagement, and ensure ongoing digital transformation. This study was conducted based on T-O model, having studied the impact of transformational leadership and organizational readiness on the adoption of artificial intelligence in Pakistani organizations, and the mediation role of organizational readiness. A quantitative cross sectional survey was conducted on 450 employees / managers of Engro Corporation, Foodpanda Pakistan and TCS Pakistan. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for analyzing the data and 5,000 bootstrap resamples were applied. Transformational leadership had significant positive effects on the organizational readiness ($\beta = 0.963$, $t = 275.701$, $p < .001$) and direct effect on the adoption of AI ($\beta = 0.371$, $t = 6.278$, $p < .001$). Organizational readiness also was a significant predictor of adoption ($\beta = 0.588$, $t = 10.106$, $p < .001$). Moreover, the indirect effect of transformational leadership via organizational readiness was significant ($\beta = 0.566$, $t = 10.101$, $p < .001$), indicating partial mediation. For organizational readiness, the model explained 92.7% of the variance, and for artificial intelligence adoption, the model explained 90.4% of the variance, with high predictive relevance values for both endogenous constructs. The results of this study suggest that transformational leadership is not only directly influencing the technology change toward AI adoption, but also cultivating the strategic alignment, employee readiness, managerial support, infrastructure, and organizational skills needed for the deployment. However, the extensive overlap in measurement of constructs and the co-linearity of constructs must be interpreted with caution. The study is important for the evolving body of literature on artificial intelligence within the context of the emerging economies because it introduces organizational readiness as a key instrument for the successful conversion of leadership vision to significant AI adoption.*

***Keywords:*** *artificial intelligence adoption, transformational leadership, organizational readiness, TOE framework, digital transformation, Pakistani businesses.*

**INTRODUCTION**

AI has shifted from a burgeoning technology to a powerful tool for the organization to leverage for decision making, enhanced operational efficiency, customer service, innovation, and competitive positioning. AI is being applied in predictive analysis, process automation, customer personalization, fraud detection, supply-chain management and knowledge intensive decision support. But the purchase of AI technologies doesn't guarantee that an organization is creating value. The utility of their benefits hinges on the leadership, human resources, technological systems, strategic vision, and cultural attitudes that companies have to embrace AI in their daily operations (Binsaeed et al., 2023; Chintalapati & Pandey, 2022). (Ahmad et al., 2023) showed that the capacity to use AI in the organization can be beneficial for creativity and firm performance, but this requires a coordinated and combined effort between technological and human and organizational resources. Likewise, Jöhnk et al., (2021) stated that it is important to understand what organizations have, their skills, and their dedication before going for the grand-scale implementation of Artificial Intelligence (Aftab et al., 2026; Ahmad et al., 2021; Rajbhandari et al., 2022).

Especially in developing economies, where organizations, facing pressures to be digitally competitive, are constrained by limited infrastructure, financial resources, technical expertise, and institutional support, the need for AI adoption is more evident. Recently, Pakistan has been focusing on AI as the cornerstone of its digital-development initiatives. The National Artificial Intelligence Policy 2025 recognizes AI as a crucial tool for the growth of a knowledge economy, fostering innovation, enhancing sectoral productivity, empowering human talent, and promoting responsible utilization of intelligent technologies. However, the availability of a national policy doesn't guarantee that adoption will take place at the organizational level. From policy aspiration to business-level implementation, organizations must ensure that they are ready internally and have leaders who can lead their employees through the technological uncertainty (Ahmed et al., 2026; Dr. Hira, 2021; Ersoy & Ehtiyar, 2023).

There is limited existing evidence from Pakistan that suggests the adoption of AI is limited and very dependent on the organizational context. In a study of the use of AI in Pakistani university libraries, (Ahmed Raza Khan & Professor Dr. Aijaz Ali Khoso, 2022) revealed that the use of AI was still in its infancy and was influenced by financial resources, technological practices, organizational size, employee knowledge, data management, and privacy concerns. Likewise, (Hafeez et al., 2026) noted that insufficient information technology infrastructure, financial limitations, worker reluctance, ethical issues, and data-security risks are some of the significant challenges for business-level AI use. Their study also showed that visionary leadership, an innovative culture, modern technological systems and a clear, strategic direction can be important enablers for adoption. These studies highlight that the integration of AI in Pakistan is not just about adopting technology; it's a transformative journey that involves leadership, employee buy-in, strategic alignment, and institutional readiness. The T-O framework is an appropriate theoretical approach to studying such organizational adoption decisions. Technological innovations are influenced by three interrelated contexts: the technological context (availability, compatibility, complexity, and benefits of technology), the organizational context (leadership, resources, structure, capabilities, culture, and preparedness of employees), and the environmental context (competition, regulation, government support, and industry pressures) (Akhtar et al., 2023). The TOE framework is a theory that offers an organizational-level perspective on adoption, making it appropriate for examining business-to-business AI adoption.The TOE framework is an organizational-level adoption theory and thus can be applied to businesses when studying their use of AI.

While all three TOE dimensions have the potential to impact technological innovation, management can directly shape and control conditions in the organizational domain and thus it is of particular importance. The latest studies indicate that eight factors are essential for AI readiness: Information technology infrastructure, Data quality, Strategic vision, Financial resources, Employee competencies, Collaborative culture, Organization capabilities, Top-management support. In a systematic review of 52 studies, (Ali et al., 2022) identified 23 factors affecting AI readiness and determined that infrastructure, leadership support, resources, compatibility, data quality, organizational culture, and financial capacity are some of the most important. (Haibat et al., 2025) also presented a multi-dimensional model of AI readiness, suggesting that readiness needs to be continuously evaluated as the organization progresses from experimentation to wider implementation of AI.

In this organizational setting, transformational leadership can offer the behavioral and strategic bedrock to support AI-led change. Transformational leadership is a style of leadership that involves communicating an inspiring vision, motivating employees to work towards a shared vision, allowing intellectual experimentation, acting as a believable role model, and meeting the developmental needs of employees. The four principles that make up its principle dimensions, idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration are especially important when an organization implements a new technology that can lead to uncertainty, change of routine, and new skills for employees (Ashergawi et al., 2026). Strengthening readiness includes articulating the need for AI, establishing AI initiatives to support organizational goals, fostering a culture of questioning and challenging traditional practices, and framing technological shifts as an opportunity, not a threat. They can also bolster staff confidence through training and development, resource provision, fostering psychological safety and personal commitment to technology innovation. Based on 30 studies, 39 independent effect sizes and 12,240 participants included in a (Asim et al., 2023) meta-analysis, transformational leadership showed a positive relationship with readiness, commitment, and openness to organizational change, and a negative relationship with resistance and cynicism. The results indicate that transformational leadership can influence employee participation in technology-based change by influencing both the willingness and perceived capability of employees to participate.

Digital-transformation research adds to the relevance of transformational leadership. (Huma et al., 2025) determined that digital transformational leadership was positively related to organizational agility and digital transformation, such that organizational agility played a role as a medium through which digital transformational leadership created a wider technological transformation. Transformational leaders define a common digital vision, foster quick learning, drive cross-organizational collaboration and explore new and different technologies. These practices are crucial for successful AI implementation as AI systems often demand new roles, decision-making frameworks, data-sharing protocols, and established workflows. Recent studies have directly shown the link between transformational leadership and AI-related actions. Based on 525 employees, (Irsa et al., 2026) found that transformational leadership had a positive effect on the use of AI by employees. A perception of organizational support is a part of this relationship, suggesting that employees are more inclined to use AI when their leaders foster a supportive atmosphere, valuing them and providing them with appropriate tools and resources to leverage the technology. The evidence reviewed indicates that transformational leadership can directly impact AI adoption by fostering experimentation, and indirectly by establishing favorable organizational conditions for this (Dr. Hira, 2021; Ersoy & Ehtiyar, 2023; Islam et al., 2022; Jabeen, 2025).

Therefore, it is hypothesized that transformational leadership will increase organizational readiness. The Vision of the leader can drive the collective commitment to implementing AI and intellectual stimulation can motivate the employees to master new skills and try out new processes to incorporate AI. Individualized consideration allows leaders to meet employee fears, lack of ability, and resistance; idealized influence creates trust towards the direction of change. Transformational leaders can also obtain financial resources, support technology investments, create implementation plans, and encourage a technical-non-technical partnership. These behaviours reinforce the human, infrastructural, strategic and cultural elements of readiness (Islam et al., 2020; Jhamb & Sethi, 2026). Adopting AI is already an essential precondition. The term organizational readiness for change is used by (Jamil et al., 2025) to refer to a shared psychological state within which organizational members are willing to accept a change in organization and feel they have the capacity to make it happen. So there is a sense of readiness which involves change commitment and change efficacy. Within the AI world, it's not just about positive attitudes from employees, but about the availability of financial resources, competent employees, proper data, supportive infrastructure, leadership commitment, implementation strategies, innovation-driven culture, and alignment of AI initiatives with organizational goals. With high readiness, employees are more likely to take the initiative to introduce change, work together to implement it, persevere through obstacles, and help it become part of the institution (Khan et al., 2025; Li et al., 2023).

Empirical research consistently has shown that readiness is one of the top drivers for implementation of AI. Using the TOE framework, (Li et al., 2025; Memon et al., 2026) found that senior management support, government support and employees' attitudes were among the most important conditions that enable organizational readiness for AI. The research showed that to successfully introduce AI, organizations must have tangible resources and additional favorable human responses. In the same way, current studies reveal that businesses with poor infrastructure, data silos, a lack of technical expertise, ineffective governance, and unclear strategic goals are less likely to take AI initiatives beyond the experimental phase. Leadership intentions can then be considered as the mechanism of organizational readiness to implement AI. While transformational leaders can generate enthusiasm and direction, making the vision happen without the requisite resources, infrastructure, capabilities, employee commitment and implementation procedures likely is not to be. Leadership sets the intent and impetus of technology change, readiness provides the organizational resources through which technology change is put into practice. From this perspective, transformational leadership can influence AI adoption in two ways: directly and indirectly through organizational readiness (Jabeen, 2025; Khan et al., 2025; Li et al., 2023; Memon et al., 2026).

Although AI adoption has increased, there are still a few areas that need to be addressed. First, leadership has received a relatively lesser level of attention compared to other factors, such as technological capability, data quality, perceived usefulness, and external pressure, that are associated with organization-wide readiness for AI. Secondly, most research on the direct link between transformational leadership and the use of AI has been carried out outside of Pakistan, and often focuses on the use of AI by individual employees instead of collective organizational use. Third, the research in Pakistan has focused mainly on specific industries or specific challenges, with very limited quantitative research on the combined effect of leadership and readiness on the adoption of AI in major business organizations. Lastly, the organizational readiness–transformational leadership–AI adoption nexus is not sufficiently explored in emerging-economy contexts (Islam et al., 2020; Jabeen, 2025; Naimat et al., 2025; Nguyen et al., 2022).

To fill these gaps, the present study brings together the three theories of transformational leadership, organizational readiness, and the organizational aspects of TOE. It defines AI usage as the application of AI technologies in the business processes, daily routines, decision-making, investments, services, efficiency and future competition strategies. It analyzes employees and managers of three different organizations: Engro Corporation, Foodpanda Pakistan, and TCS Pakistan, reflecting various business environments, yet all tasked with the shared need for AI-powered transformation. The study investigates both direct and mediated relationships between leadership and AI adoption, and offers insights into both the nature of the relationship and the conditions that need to be built within the organization to support the use of AI.

**Research Objectives**

- To examine the influence of transformational leadership on organizational readiness for AI adoption in Pakistani businesses.
- To determine the direct effects of transformational leadership and organizational readiness on the adoption of artificial intelligence.
- To investigate whether organizational readiness mediates the relationship between transformational leadership and AI adoption.

**Research Hypotheses**

**H1:** Transformational leadership has a significant positive influence on organizational readiness for AI adoption.

**H2:** Transformational leadership has a significant positive influence on artificial intelligence adoption.

**H3:** Organizational readiness has a significant positive influence on artificial intelligence adoption.

**H4:** Organizational readiness significantly mediates the relationship between transformational leadership and artificial intelligence adoption.

**Methodology**

The study used quantitative cross sectional research design with the Technology–Organization–Environment (TOE) Framework (Tornatzky & Fleischer, 1990) to investigate the effect of transformational leadership on organizational preparedness to use Artificial Intelligence (AI) in Pakistani companies. The respondents were internal managers and employees from organizations that have adopted or are considering adoption of AI technologies. The data were gathered from three prominent Pakistani players: Engro Corporation, Foodpanda Pakistan, and TCS Pakistan, since these entities have been taking strides towards the integration of digital technologies and AI-powered solutions into their operations. The respondents were selected by stratified random sampling technique and 450 employees/managers were responded to the study, with 150 employees/managers per organization. Primary data were gathered by using a structured questionnaire on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The items from the questionnaires for the measurement of transformational leadership and organizational readiness were adopted from the previously validated studies. The results of the collected data were analyzed with IBM SPSS Statistics 29 and with SmartPLS 4. Demographic information of the respondents was summarized using descriptive statistics. The reliability and validity of measurement model were determined by Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (Sohrab Khan et al.), the Fornell-Larcker Criterion and the Heterotrait-Monotrait (HTMT) ratio. Partial Least Squares Structural Equation Modeling (PLS-SEM) with bootstrapping (resampling 5,000 times) was used to test the following proposed hypotheses. For the structural model, the path coefficients (β), t-value, p-value, coefficient of determination ($R^2$), effect size ($f^2$), predictive relevance ($Q^2$), and the Standardized Root Mean Square Residual (SRMR) were also assessed. The study adhered to ethical standards and respondents were assured of confidentiality and anonymity; they all provided consent to participate.

**Results**

The successful implementation and integration of AI is not just a technological success, but a testament to the synergistic effect of visionary leadership, organizational readiness, and an institutional environment that translates strategic vision into actionable innovation. In this context, the empirical results offer an in-depth analysis of the respondents' profiles, data quality, the validity and reliability of the measurement model, and the strength of the hypothesized connections between transformational leadership, organizational readiness, and AI adoption. Table 1 shows the demographic profile of the sample used in the study and it suggests that the study sample was broadly representative and diverse. The respondents were spread out by gender, age, levels of education, organization affiliation, hierarchy and span of years on the job so that different parts of the work force contributed to the study. There were nearly equal numbers of men and women so that both male and female employees were represented. Likewise, the respondents in various age groups represented the perspectives of workers across the spectrum of their careers. The educational profile was highly qualified with the majority having a Bachelor's or Master's degree and those with advanced research qualifications. The cross-organizational relevance of the study was also reinforced by having equal representation from each organization, including Engro Corporation, Foodpanda Pakistan and TCS Pakistan, to prevent any single organization from disproportionately influencing the findings. The respondents also held different levels of seniority from senior managements to staff level and had different amounts of professional experience. The diversity of the members of the various levels of the analysis resulted in more credibility and representativeness of the findings of the analysis.

**Table 1 Demographic characteristics of respondents**

| Variable | Category | n | % |
|---|---|---|---|
| **Gender** | Male | 220 | 48.9 |
| | Female | 230 | 51.1 |
| **Age** | 20-29 | 141 | 31.3 |
| | 30-39 | 158 | 35.1 |
| | 40-49 | 99 | 22.0 |
| | 50+ | 52 | 11.6 |
| **Education** | Bachelor | 150 | 33.3 |
| | Master | 208 | 46.2 |
| | MPhil/MS | 68 | 15.1 |
| | PhD | 24 | 5.3 |
| **Organization** | Engro Corporation | 150 | 33.3 |
| | Foodpanda Pakistan | 150 | 33.3 |
| | TCS Pakistan | 150 | 33.3 |
| **Position** | Senior Management | 104 | 23.1 |
| | Middle Management | 74 | 16.4 |
| | Supervisor | 101 | 22.4 |
| | Officer | 95 | 21.1 |
| | Staff | 76 | 16.9 |
| **Experience** | <5 | 109 | 24.2 |
| | 5-10 | 99 | 22.0 |
| | 11-15 | 131 | 29.1 |
| | >15 | 111 | 24.7 |

**Note.** Percentages are based on N = 450 and may not total exactly 100 because of rounding.



After the demographic assessment, the construct-level descriptive statistics in Table 2 showed a consistent pattern of positive descriptives for all major study variables. The average scores of transformational leadership, organizational readiness and AI adoption were relatively similar and towards the upper end of the measurement scale. This trend indicates that the overall sentiment among respondents was that their organizations were displaying supportive and inspiring leadership, having a favourable level of preparedness for technological change and a positive orientation toward the use of artificial intelligence. The fairly similar standard deviations suggest that the participants' perception was reasonably consistent for the three constructs. In addition, the negative skewness scores show that responses were skewed mostly toward the agreement categories, supporting the high mean scores which reflected a favourable pattern. The kurtosis values were close to zero, suggesting that there were no significant departures from normality, unusually peaked or flat distributions.

**Table 2 Construct-level descriptive statistics**

| Construct | Items | M | SD | Skewness | Kurtosis | Min | Max |
|---|---|---|---|---|---|---|---|
| **Transformational Leadership** | 12 | 3.945 | 0.764 | -0.705 | -0.066 | 1.583 | 5.000 |
| **Organizational Readiness** | 18 | 3.949 | 0.775 | -0.755 | 0.042 | 1.722 | 5.000 |
| **AI Adoption** | 8 | 3.941 | 0.780 | -0.613 | -0.220 | 1.625 | 5.000 |

**Note.** Construct scores are respondent-level means across the relevant indicators. Kurtosis is reported as excess kurtosis.

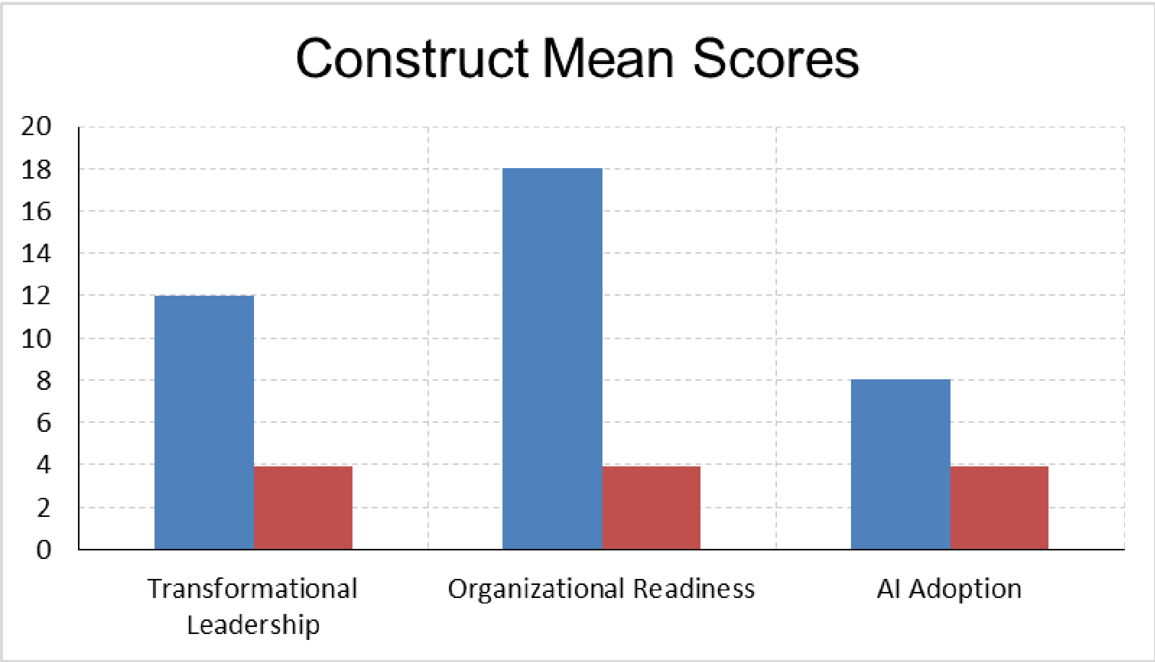


**Figure 1 Construct Mean Scores**

These results are further supported by the item-level descriptive results displayed in Table 3. The mean scores of the individual indicators were mostly positioned in the middle of the five-point scale, indicating favourable perceptions of the behaviours, capabilities, and practices depicted by the scales of transformational leadership, organizational readiness, and AI adoption. The fairly homogeneous standard deviations suggest that there was an adequate level of dispersion of responses and no real indication of any significant inconsistencies. Furthermore, all of the indicators showed negative skewnesses, thus indicating that favored responses were more frequent than unfavored responses. All the indictors were found to have a kurtosis acceptable to the standard limits, without any serious irregularities in their distribution. The overall tendency toward agreement was also mirrored in the number of items that covered the full range of response, with positive and negative perspectives being captured in nearly all items. These results indicated the individual indicators had sufficient variability and stable distributional characteristics, which justified their use in the next step of reliability, validity, and structural-model analyses.

**Table 3 Item-level descriptive statistics**

| Item | M | SD | Skew. | Kurt. | Min | Max |
|---|---|---|---|---|---|---|
| **TL1** | 3.942 | 0.921 | -0.625 | -0.154 | 1 | 5 |
| **TL2** | 3.958 | 0.988 | -0.639 | -0.395 | 1 | 5 |
| **TL3** | 3.927 | 0.968 | -0.667 | -0.164 | 1 | 5 |
| **TL4** | 3.953 | 0.920 | -0.631 | -0.074 | 1 | 5 |
| **TL5** | 3.931 | 0.896 | -0.349 | -0.806 | 2 | 5 |
| **TL6** | 3.936 | 0.945 | -0.618 | -0.212 | 1 | 5 |
| **TL7** | 3.949 | 0.946 | -0.595 | -0.341 | 1 | 5 |
| **TL8** | 3.938 | 0.913 | -0.529 | -0.374 | 1 | 5 |
| **TL9** | 3.962 | 0.918 | -0.619 | -0.098 | 1 | 5 |
| **TL10** | 3.978 | 0.951 | -0.643 | -0.238 | 1 | 5 |
| **TL11** | 3.924 | 0.957 | -0.552 | -0.379 | 1 | 5 |
| **TL12** | 3.947 | 0.947 | -0.636 | -0.131 | 1 | 5 |
| **OR1** | 3.931 | 0.954 | -0.634 | -0.158 | 1 | 5 |
| **OR2** | 3.920 | 1.022 | -0.731 | -0.055 | 1 | 5 |
| **OR3** | 3.949 | 0.915 | -0.582 | -0.216 | 1 | 5 |
| **OR4** | 4.002 | 0.947 | -0.667 | -0.338 | 1 | 5 |
| **OR5** | 3.969 | 0.974 | -0.679 | -0.204 | 1 | 5 |
| **OR6** | 3.938 | 0.913 | -0.635 | 0.065 | 1 | 5 |
| **OR7** | 3.924 | 0.967 | -0.651 | -0.309 | 1 | 5 |
| **OR8** | 3.938 | 0.988 | -0.738 | -0.086 | 1 | 5 |
| **OR9** | 3.898 | 0.943 | -0.499 | -0.445 | 1 | 5 |
| **OR10** | 3.982 | 0.969 | -0.775 | 0.178 | 1 | 5 |
| **OR11** | 3.936 | 0.933 | -0.697 | 0.139 | 1 | 5 |
| **OR12** | 3.951 | 0.940 | -0.613 | -0.213 | 1 | 5 |
| **OR13** | 3.933 | 0.958 | -0.645 | -0.159 | 1 | 5 |
| **OR14** | 3.976 | 0.977 | -0.771 | -0.049 | 1 | 5 |
| **OR15** | 3.964 | 0.938 | -0.530 | -0.526 | 1 | 5 |
| **OR16** | 4.009 | 0.925 | -0.714 | 0.007 | 1 | 5 |
| **OR17** | 3.927 | 0.933 | -0.532 | -0.372 | 1 | 5 |
| **OR18** | 3.940 | 0.969 | -0.736 | 0.132 | 1 | 5 |
| **AI1** | 3.949 | 0.981 | -0.680 | -0.161 | 1 | 5 |
| **AI2** | 3.973 | 0.898 | -0.560 | -0.289 | 1 | 5 |
| **AI3** | 3.933 | 0.941 | -0.510 | -0.531 | 1 | 5 |
| **AI4** | 3.924 | 0.969 | -0.645 | -0.083 | 1 | 5 |
| **AI5** | 3.942 | 0.928 | -0.574 | -0.215 | 1 | 5 |
| **AI6** | 3.933 | 0.988 | -0.646 | -0.302 | 1 | 5 |
| **AI7** | 3.929 | 0.960 | -0.495 | -0.564 | 1 | 5 |
| **AI8** | 3.940 | 0.936 | -0.551 | -0.368 | 1 | 5 |

**Note.** All items were measured on a five-point scale from 1 = strongly disagree to 5 = strongly agree.

The measurement model was evaluated beginning with the reliability and convergent validity. The Cronbach's alpha and composite reliabilities for transformational leadership, organizational readiness, and AI adoption were significantly higher than the recommended level as reported in Table 4. Results showed that all the items in each construct performed well and measured the same theoretical construct. The composite reliability values are also high, confirming the reliability and consistency of measuring scales. Additionally, the average values of VEs were above benchmark values, indicating that each construct accounted for more variance in their indicators than variance due to measurement error. Overall, these results indicate high internal consistency for all three constructs, and acceptable convergent validity.

**Table 4: Reliability and convergent validity**

| Construct | Items | α | CR | AVE | √AVE | Decision |
|---|---|---|---|---|---|---|
| **Transformational Leadership** | 12 | 0.953 | 0.959 | 0.662 | 0.814 | Established |
| **Organizational Readiness** | 18 | 0.970 | 0.972 | 0.660 | 0.812 | Established |
| **AI Adoption** | 8 | 0.931 | 0.943 | 0.675 | 0.821 | Established |

**Note.** α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

The quality of the measurements was further confirmed through examination of outer loadings, the significance of the bootstrap, confidence intervals, and examining indicator-level collinearity. Each indicator had a strong loading in the theoretically assigned constructs and was above the generally accepted criterion for a reliable indicator (as portrayed in Table 5). This means that every item contributed to the measure of the construct being measured in a meaningful way. The bootstrap results also confirmed that all outer loadings were statistically significant with no outer loadings having a confidence interval containing zero. The results of this study validate the statistically stable statistical relationships between the indicators and the constructs, and indicate that these relationships were not simply random occurrences. The variance inflation factors for the outer values were also below the threshold values indicating that there was no problematic multicollinearity in the indicators. Overall, the evidence suggests that the indicators used in the measurement are statistically relevant, stable and sufficient.

**Table 5 Outer loadings, bootstrap significance, and outer VIF**

| Item | Construct | Loading | SE | t | 95% CI | VIF |
|---|---|---|---|---|---|---|
| **TL1** | TL | 0.814 | 0.017 | 48.62 | [0.779, 0.845] | 2.615 |
| **TL2** | TL | 0.828 | 0.016 | 52.87 | [0.794, 0.855] | 2.730 |
| **TL3** | TL | 0.780 | 0.019 | 41.74 | [0.741, 0.815] | 2.286 |
| **TL4** | TL | 0.834 | 0.015 | 55.59 | [0.803, 0.862] | 2.802 |
| **TL5** | TL | 0.807 | 0.017 | 48.87 | [0.774, 0.838] | 2.527 |
| **TL6** | TL | 0.840 | 0.015 | 56.89 | [0.809, 0.867] | 2.917 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **TL7** | TL | 0.793 | 0.017 | 45.43 | [0.758, 0.825] | 2.330 |
| **TL8** | TL | 0.820 | 0.015 | 53.04 | [0.788, 0.848] | 2.617 |
| **TL9** | TL | 0.793 | 0.019 | 42.22 | [0.755, 0.827] | 2.354 |
| **TL10** | TL | 0.811 | 0.017 | 48.63 | [0.777, 0.842] | 2.555 |
| **TL11** | TL | 0.820 | 0.016 | 50.63 | [0.787, 0.848] | 2.632 |
| **TL12** | TL | 0.823 | 0.016 | 52.39 | [0.791, 0.851] | 2.635 |
| **OR1** | OR | 0.797 | 0.017 | 46.06 | [0.760, 0.828] | 2.573 |
| **OR2** | OR | 0.817 | 0.016 | 49.79 | [0.784, 0.847] | 2.746 |
| **OR3** | OR | 0.799 | 0.018 | 44.98 | [0.762, 0.832] | 2.617 |
| **OR4** | OR | 0.803 | 0.017 | 47.53 | [0.767, 0.833] | 2.617 |
| **OR5** | OR | 0.823 | 0.016 | 50.69 | [0.790, 0.852] | 2.909 |
| **OR6** | OR | 0.816 | 0.017 | 48.13 | [0.781, 0.847] | 2.756 |
| **OR7** | OR | 0.810 | 0.017 | 47.48 | [0.775, 0.841] | 2.757 |
| **OR8** | OR | 0.822 | 0.016 | 51.08 | [0.788, 0.852] | 2.915 |
| **OR9** | OR | 0.815 | 0.016 | 49.52 | [0.781, 0.845] | 2.742 |
| **OR10** | OR | 0.809 | 0.018 | 46.16 | [0.773, 0.842] | 2.714 |
| **OR11** | OR | 0.814 | 0.018 | 46.17 | [0.776, 0.846] | 2.769 |
| **OR12** | OR | 0.795 | 0.018 | 44.92 | [0.758, 0.827] | 2.564 |
| **OR13** | OR | 0.824 | 0.016 | 50.13 | [0.790, 0.855] | 2.941 |
| **OR14** | OR | 0.834 | 0.015 | 54.25 | [0.801, 0.861] | 3.004 |
| **OR15** | OR | 0.812 | 0.016 | 49.53 | [0.777, 0.842] | 2.802 |
| **OR16** | OR | 0.826 | 0.016 | 50.81 | [0.792, 0.857] | 2.867 |
| **OR17** | OR | 0.801 | 0.016 | 50.58 | [0.768, 0.831] | 2.712 |
| **OR18** | OR | 0.806 | 0.018 | 45.39 | [0.770, 0.838] | 2.611 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **AI1** | AI | 0.838 | 0.016 | 54.06 | [0.806, 0.866] | 2.589 |
| **AI2** | AI | 0.820 | 0.016 | 52.14 | [0.788, 0.849] | 2.396 |
| **AI3** | AI | 0.818 | 0.016 | 50.55 | [0.785, 0.849] | 2.404 |
| **AI4** | AI | 0.819 | 0.016 | 49.95 | [0.786, 0.850] | 2.379 |
| **AI5** | AI | 0.819 | 0.016 | 51.59 | [0.787, 0.848] | 2.376 |
| **AI6** | AI | 0.814 | 0.016 | 49.47 | [0.781, 0.844] | 2.350 |
| **AI7** | AI | 0.820 | 0.016 | 51.39 | [0.787, 0.848] | 2.393 |
| **AI8** | AI | 0.822 | 0.016 | 50.00 | [0.788, 0.851] | 2.429 |

**Note.** All loadings were significant at $p < .001$ based on 5,000 bootstrap resamples.

The measurement model was found to be highly reliable and to have good convergent validity; however, an important limitation was revealed in its discriminant-validity assessment. Table 6 shows that the square root of the average variance extracted is lower than the correlations of transformational leadership, organizational readiness, and AI adoption on the Fornell–Larcker results.

**Table 6 Fornell–Larcker criterion**

| Construct | TL | OR | AIA |
|---|---|---|---|
| **Transformational Leadership** | 0.814 | 0.963 | 0.937 |
| **Organizational Readiness** | 0.963 | 0.812 | 0.945 |
| **AI Adoption** | 0.937 | 0.945 | 0.821 |

**Note.** Diagonal elements are the square roots of AVE; off-diagonal elements are construct correlations.

This pattern of results shows that the constructs shared more variance with each other than they had unique variance with their respective indicators. Supported by the heterotrait–monotrait ratios reported in Table 7, these ratios were also higher than the recommended thresholds for establishing construct distinctiveness. The results indicate that respondents viewed transformational leadership, organizational readiness, and AI adoption as not completely distinct concepts but as a phenomenon more closely related and empirically overlapping. Thus, even though the constructs showed good internal consistency and convergent validity, they failed to attain discriminant validity. This overlap is a serious measurement issue that gives rise to the concern that some of the structural relationships may be measuring the same content as opposed to entirely different theoretical effects.

**Table 7 Heterotrait–monotrait ratio**

| Construct | TL | OR | AIA |
|---|---|---|---|
| **Transformational Leadership** | 1.000 | 1.001 | 0.994 |
| **Organizational Readiness** | 1.001 | 1.000 | 0.994 |
| **AI Adoption** | 0.994 | 0.994 | 1.000 |

**Note.** Values below .85 or .90 are commonly used as evidence of discriminant validity.

A further assessment of inner-collinearity was provided in Table 8 and confirmed the results of discriminant-validity. When transformational leadership was used as the sole predictor of organizational readiness, there was no collinearity problem. When both transformational leadership and organizational readiness were used as predictors of AI adoption, however, there was a high degree of multi-collinearity. Variance Inflation Factors for the two predictors were much larger than the recommended cut-off level, indicating that the predictors shared a large amount of explanatory information. This is an extent of overlap that could result in instability in the estimated path coefficients and can be a problem when trying to isolate the unique contribution of each predictor. The direct effects of transformational leadership and organizational readiness on AI adoption should be interpreted with caution; thus, the combined explanatory influence of transformational leadership and organizational readiness can be recognized.

**Table 8 Inner variance inflation factors**

| Endogenous construct | Predictor | VIF | Assessment |
|---|---|---|---|
| **Organizational Readiness** | Transformational Leadership | 1.000 | Acceptable |
| **AI Adoption** | Transformational Leadership | 13.647 | Problematic |
| **AI Adoption** | Organizational Readiness | 13.647 | Problematic |

However, the findings from the structural model analysis as reported in Table 9 showed that all the direct relationships proposed were positive and significant even with the consideration of the issues of measurement and collinearity. Transformational leadership had a significant impact on organizational readiness, particularly noting that inspirational, intellectual stimulating, individualized, and strategic vision leadership was closely related to higher organizational readiness to transform technology. This finding underscores the importance of transformational leaders in creating an environment where employees, systems and resources are aligned with organizational change.

**Table 9 Direct, indirect, and total effects**

| Effect | β | SE | t | p | CI lower | CI upper | Decision |
|---|---|---|---|---|---|---|---|
| **TL → OR** | 0.963 | 0.003 | 275.701 | < .001 | 0.955 | 0.969 | Significant |
| **TL → AI** | 0.371 | 0.059 | 6.278 | < .001 | 0.253 | 0.483 | Significant |
| **OR → AI** | 0.588 | 0.058 | 10.106 | < .001 | 0.476 | 0.703 | Significant |
| **TL → OR → AI (indirect)** | 0.566 | 0.056 | 10.101 | < .001 | 0.458 | 0.678 | Significant |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **TL → AI (total)** | 0.937 | 0.006 | 146.111 | < .001 | 0.924 | 0.949 | Significant |

**Note.** Two-tailed bootstrap tests with 5,000 resamples and percentile 95% confidence intervals.

Furthermore, transformational leadership had a significant direct impact on the adoption of AI, suggesting that good leadership can help to drive acceptance and implementation of AI, by fostering a vision of the technology, promoting innovation, inspiring employees and minimizing change resistance. Organizational readiness also had a strong positive effect and a relatively high direct effect on AI adoption. The discovery highlights that, besides leadership goals, a suite of infrastructure, employee capability, financial and technological resources, managerial commitment and institutional preparedness is essential for AI adoption. All direct effects were statistically stable in the analysed dataset as none of the confidence intervals contained zero.

The mediation results shed further light on the relationship between transformational leadership and the adoption of AI. The indirect effect of transformational leadership on AI adoption by way of organizational readiness was statistically significant, as indicated in Table 9. The results show that transformational leadership contributes to the adoption of AI in part through the cultivation of the organizational conditions necessary for the implementation of technology. That is, they are leaders who seem to turn strategic vision into organizational readiness by augmenting resources, organizational capabilities, employee confidence and institutional support for change. The direct effect of transformational leadership on AI adoption was still significant, even after accounting for the role of organizational readiness, suggesting partial mediation. Transformational leadership thus seems to have a direct and indirect effect on AI adoption via organizational readiness. This mediation effect should, however, be considered provisional, because the high amount of overlap between the two types of variables, transformational leadership and organizational readiness, in the results obtained in terms of numbers makes it difficult to consider them as two independent components of the suggested mechanism. The direct and indirect relationships are displayed graphically in figure 2.

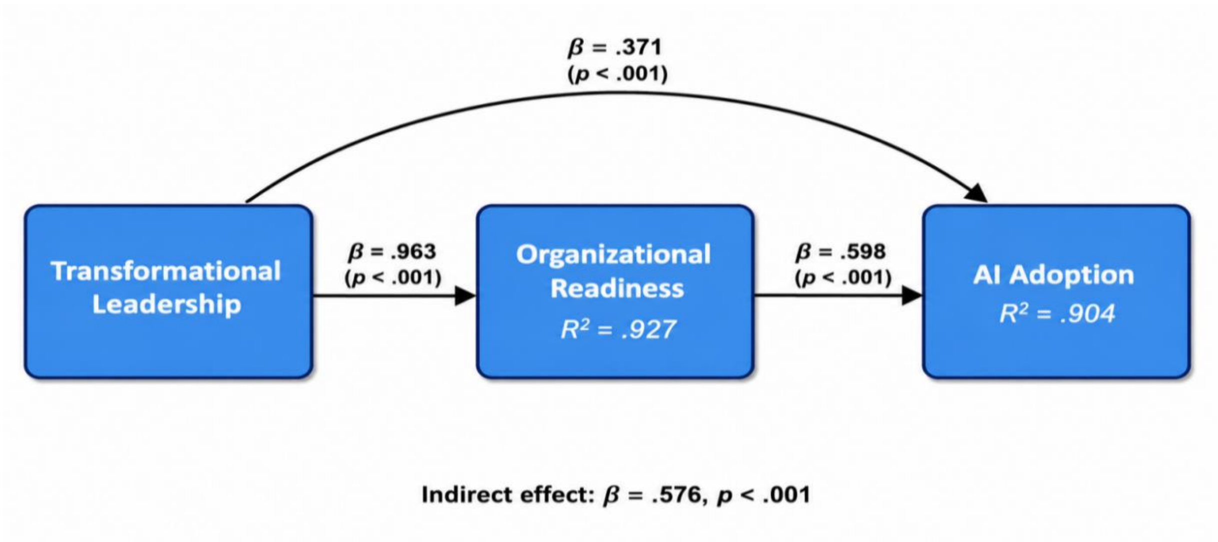


**Figure 2 Estimated structural model.**

The results of the explanatory power presented in Table 10 showed that the structural model had a very large percentage of variance in the endogenous constructs. However, transformational leadership accounted for a significant amount of variance in organizational readiness, and transformational leadership and organizational readiness together accounted for a significant amount of variance in AI adoption. The similarity between the adjusted and unadjusted coefficients indicates that the number of predictors in the model did not greatly boost the model's explanatory power. Additionally, the positive and relatively high predictive-relevance values suggest that the model had a good predictive power for organizational readiness and AI adoption in the dataset analyzed. The results indicated that the proposed framework provided a strong explanation of the processes involved in organizational preparedness and implementation of AI. Due to the markedly high values of explanatory power, however, caution should be taken in interpreting these values, as they may stem partly from the high empirical homogeneity of the constructs.

**Table 10 Explained variance and predictive relevance**

| Endogenous construct | $R^2$ | Adjusted $R^2$ | $Q^2$ |
|---|---|---|---|
| **Organizational Readiness** | 0.927 | 0.927 | 0.927 |
| **AI Adoption** | 0.904 | 0.903 | 0.902 |

The effect-size analysis in Table 11 further confirmed the relative importance of the proposed relationships. Leadership was a major driver of the findings related to organizational readiness and had an exceptionally high impact on organizational readiness, indicating that leadership is a critical component in preparing organizations for technological transformation. When it comes to AI adoption, organizational readiness had a medium unique contribution, while transformational leadership had a relatively low unique contribution. This is because this pattern posits a significant portion of the impact on AI adoption of transformational leadership could be mediated by organizational readiness. Transformational leaders are then likely to have the greatest impact when their strategic vision, encouragement, and innovation are translated into new skills, new processes, new resources, and new readiness. However, the effect sizes were not considered as perfectly separated causal contributions because of the significant collinear relations between the two concepts namely transformational leadership and organizational readiness.

**Table 11 Effect sizes**

| Endogenous | Predictor | $R^2$ incl. | $R^2$ excl. | $f^2$ | Magnitude |
|---|---|---|---|---|---|
| **Organizational Readiness** | Transformational Leadership | 0.927 | 0.000 | 12.647 | Large |
| **AI Adoption** | Transformational Leadership | 0.904 | 0.893 | 0.104 | Small |
| **AI Adoption** | Organizational Readiness | 0.904 | 0.878 | 0.263 | Medium |

The approximate model-fit assessment gave a good result also. The root mean square residual was not very different from that usually deemed acceptable, and showed that the average error between the observed and the synthetic correlations was slight. This result indicates that the structural model was well-suited to explain the observed data. Fit of the model does not rule out problems with discriminant validity and inner collinearity, however. A good fit statistic can indicate a correspondence between the proposed model and the data but is on its own not a proof that all constructs are conceptually and empirically different. The model-fit result should therefore be treated as supportive evidence towards model adequacy, and not as definitive.

Finally, the results of hypothesis testing summarized in Table 12 show that all four proposed hypotheses were statistically supported. This finding strongly backed H1, indicating that transformational leadership was a major factor in organizational readiness, and also significantly influenced AI adoption, thus supporting H2. The findings in regard to H3 indicated that the organizational readiness was a significant predictor of AI adoption. Moreover, the indirect effect of the transformational leadership on AI adoption fully mediated by organizational readiness strengthens H4 and substantiates that there is a partial mediation effect. Overall, the results form a strong statistical pattern: Transformational leadership strengthens organizational readiness, transformational leadership and organizational readiness drive the adoption of AI, and organizational readiness is an important channel through which leadership can influence technological transformation. The substantive results, however, are still provisional pending the resolution of the issues of discriminant validity and multi-collinearity. The statistical significance, explanatory power, predictive relevance and approximate model fit are all very positive, but can't be used to suggest completely separate construct-level relationships until future research provides for theoretical and empirical separation.

**Table 12 Summary of hypothesis decisions**

| Hypothesis | Relationship | β | t | p | Decision |
|---|---|---|---|---|---|
| **H1** | TL → OR | 0.963 | 275.701 | < .001 | Supported |
| **H2** | TL → AIA | 0.371 | 6.278 | < .001 | Supported |
| **H3** | OR → AIA | 0.588 | 10.106 | < .001 | Supported |
| **H4** | TL → OR → AIA | 0.566 | 10.101 | < .001 | Supported (partial mediation) |

**Note.** All decisions are statistical decisions for the supplied dataset; substantive conclusions remain conditional on resolving measurement overlap.



**Discussion**

This present study extends the knowledge on the adoption of artificial intelligence in the sense that technology transformation is not only a technical investment decision but an organizational and leadership process. The overall relationship pattern indicates that transformational leadership plays a role in AI adoption through the development of a convincing technological vision, fostering experimentation, and strengthening staff confidence and integrating AI into organizational resources and priorities. More significantly, the results show that the effect of leadership influence is more significant when translated to organizational readiness. This is in line with the central premise of the Technology–Organization–Environment (ToE) model: the decision to adopt technology is shaped by the dynamics between the technologies available and the ability of an organization to understand, absorb and make use of those technologies.

Transformational leadership and organizational readiness go together, helping to inspire the idea that readiness isn't just inherited from the current technological resources, but rather created through managerial behaviour. To enhance readiness, transformational leaders can establish a clear strategy for AI, gain the support of the workforce, foster learning, and provide the necessary financial and technical resources. This interpretation is consistent with (Noreen et al., 2023), who found strategic alignment, resources, knowledge, culture, and data and organizational commitment to be key dimensions of AI readiness. They point to the organization's readiness being triggered when the company's assets are purposefully aligned around particular AI use cases instead when the company simply has high-end technology.

The results also align with the results of (Philip, 2021) systematic review of 52 studies, which concluded that top-management support, collaborative culture, infrastructure, financial resources, data quality, and compatibility and organizational capability are key factors for AI readiness. Their synthesis reinforces the argument that leadership is at the centre of readiness, impacting resource allocation, strategic prioritization, interdepartmental collaboration and building an innovation supportive culture. The current research builds on this thought by suggesting that transformational leadership can serve as the motivational and behavioral underpinning for the development of these readiness conditions.

(Nurimansjah, 2023) highlight that digital transformational leadership enhances the agility of organizations and enables the wider process of digital transformation. Their research suggests that leadership doesn't necessarily drive transformation simply by communicating in a persuasive manner, but by enhancing the organization's abilities to detect technological opportunities, react quickly and reorganize resources. This is in line with a dynamic-capability view of readiness, in which transformational leadership aids in reconfiguring structures, knowledge, and employee competencies in response to AI-related change. Concluding a similar point, (Rajbhandari et al., 2022) illustrated that the influence of digital transformational leadership is transferred to digital transformation through digital strategy and digital culture. This reinforces the premise this leadership must be part of organizational arrangements before enduring technological change can be realized.

Particularly in developing countries, the need for leadership readiness is especially significant. (Saeed et al., 2023) examined the level of readiness of the textile and garment sector in Bangladesh with respect to the use of AI and big-data and found that there were weak organizational readiness due to lack of human, financial and employee-engagement readiness, while knowledge and leadership readiness were found to be moderate. The results of their study reconfirm the current research and indicate that the quality of leadership and the preparation of an organization are closely linked. However, they give them a helpful qualification: Visionary leadership can only succeed for so long if a company has poor budgets, lack of skills or poor employee engagement. Therefore, readiness should be considered as a multi-dimensional organizational readiness rather than as a psychological outcome of leadership.

The direct relationship between the transformational leadership on the one hand and the adoption of AI on the other hand aligns with the theory that employees act on leaders' attitudes and behaviour as a message about the legitimacy, usefulness and anticipated use of emerging technologies. AI-Capable leaders who show excitement about AI, encourage careful experimentation and savoring risks, can ease uncertainty and make AI-enhanced work "business as usual. Similarly, (Shafique et al., 2023; Shahzad et al., 2024) determined that transformational leadership positively influenced the use of AI among employees and that perceived organizational support mediated this relationship. The results indicate that when employees are supported in the following ways—by leadership persuading them of the benefits of AI, providing tangible help, offering rewards, and providing emotional and training support—then they're more likely to embrace it.

Similarly, (Tan et al., 2021) found that openness to AI was found to be most positively influenced by transformational leadership while less favourable adoption outcomes were found to be influenced by transactional leadership. Theoretically, this comparison is significant because rewards, monitoring, and formal compliance will not produce creativity, learning and adaptation that is needed for the implementation of AI. Transformational leadership seems more appropriate as it empowers employees to challenge some of the existing norms and consider AI as a tool to enhance performance instead of just a management mandate. (Sohrab Khan et al., 2025; Tjebane et al., 2022) came to a similar conclusion, highlighting the need for digital leaders to oversee all aspects of tech quality, organizational culture, AI proficiency, and employee trust. The Technology-Organization-People checklist illustrates that leadership can help the adoption process by organizing the social and technical aspects, and not just by focusing on the acquisition of technology.

However, more recent research evidence has revealed the transformational leadership effect is not always beneficial. (Subuhpoto et al., 2025) noted that the role of perceived organizational support in the indirect effect of transformational leadership on job satisfaction was weakened by a highly competitive workplace environment. When leadership encouragement is paired with very high levels of comparison, pressure or fear of replacement, employees might react negatively to AI projects. In these circumstances, AI use for employees could feel like job surveillance, or a means to job competition, instead of organizational growth. This certification is especially significant given that transformational leadership is not a technology-friendly type. This has to do with whether an organization has a vision that promotes responsible use of AI and whether the organization actually fosters learning and security for employees. A blend of leadership rhetoric and psychological safety, participation, and support can produce compliance, but not necessarily adoption.

The findings of the positive impact of organizational readiness on the adoption of AI align well with recent studies on AI adoption. In professional-services firms, (Ullah et al., 2026) discovered that AI readiness, innovation-management approaches, technological affordances, competition and regulation all influence adoption. Smaller organizations had less resources and more informal organizational structures, resulting in increased constraints with AI, while larger organizations had greater readiness and were more likely to adopt AI with fewer constraints. Thus, the present study supports the notion that the use of AI is more effective when the systems are compatible, employees are trained, funds are available, management supports it, and there is a clear implementation path.

This is supported by further evidence from the developing economies. According to (Wajid et al., 2025), Pakistani small businesses saw the potential in AI to enhance business efficiency, productivity, customer service and competitiveness, but were still grappling with challenges of technical knowledge, lack of resources and cultural resistance. Similarly, (Usman et al., 2026) found that AI applications were the least valuable in the context of value creation by the Pakistani SMEs which they argued was due to their high cost, technological complexity and regulatory issues. These studies reinforce the argument that readiness is not just a desired but an essential step toward successfully transforming interest in AI into valuable organizational practice. Companies can see the value of AI for their strategy but aren't able to implement it due to the lack of adequate infrastructure, technical expertise, governance and financing.

Concurrently, there is a difference between readiness and Pakistani SME research, as readiness can have a different process in organizational environments. The organizations analyzed in the current research are relatively experienced and have more advanced management systems and resources than most small enterprises in Pakistan, and are more exposed to digital technologies. Hence, in these firms, leadership and internal readiness could be more influential since basic infrastructure and financial resources are already relatively well established. But in smaller companies, other factors like access to technology, the willingness of vendors, and regulatory frameworks, could be the determining factor than leadership style. It is not a fair assumption, therefore, to draw conclusions on the transformational leadership as a dominant enterprise adoption factor for all kinds of Pakistani enterprises.

The organizational readiness is the most theoretically important result of the study. It proposes that transformational leadership affects AI adoption, at least in part, through an impact on the intentions of leadership that becomes implementable within an organization. Ambitions for a digital vision may be communicated from the leadership, but without the right infrastructure, knowledge, time, training, resources and strategic coordination, workers are unable to act upon this vision. Organizational readiness thus serves as a conversion process in which leadership behaviour turns into technological action. This argument aligns with (Zhen et al., 2021), who demonstrated that the effects of transformational leadership were mediated through perceived organizational support, which in turn mediated some portion of leadership's influence on AI usage. It is also in line with (Wang et al., 2023; Zainab et al., 2021) who linked organizational agility to digital transformational leadership and digital transformation, and (Aftab et al., 2026; Binsaeed et al., 2023; Chintalapati & Pandey, 2022) who found digital strategy and culture to be the mediation factors. Taken together, these studies suggest that leadership itself does not directly cause digital transformation; leadership is transmitted through the organization's capacities, perceptions of support, and strategic systems and adaptive structures.

It also further extends TOE by clarifying a process that is not explicitly discussed in the framework. The TOE framework highlights the technological, organizational and environmental determinants, but it is not necessarily a comprehensive explanation of the emergence and interaction of these determinants over time. The present study conceptualizes transformational leadership as an antecedent condition which contributes to the development of the organizational context and readiness as the proximal mechanism for the adoption. In this way, leadership is the agency of organizational preparation, and readiness is the ability by which the possibility of adoption is made possible.

However, the organisational explanation does not preclude technological and environmental factors. According to (Ali & Xie, 2021; Dr. Hira, 2021; Haibat et al., 2025; Irsa et al., 2026), the motivations and obstacles for AI adoption are significantly different across industries, with managerial support, data preparation, employee training, pressure from the market, government policy and organizational culture and security issues playing different roles in different sectors. (Jhamb & Sethi, 2026; Khan et al., 2025), also found that the benefits of regulation can be nullified even when firms are ready to implement it, and competition can encourage uptake among smaller firms. (Islam et al., 2022) applied the TOE framework as well, and they highlighted the interconnectedness of technological, organizational and environmental readiness in relation to organizational decisions concerning AI. So, the internal foundations of transformational leadership and organizational readiness are essential, but can be reinforced or undermined, depending on factors such as cost, data availability, regulatory uncertainty, competition, and government support.

An important caveat from the study is that there is a very close empirical relationship between transformational leadership, organizational readiness, and AI adoption. The assessment of measurement showed that there was a significant amount of overlap between the constructs and collinearity in the structural model. At a conceptual level, there is a difference between leadership, readiness and adoption: the former involves stimulating and guiding change, the latter involves the capacity and commitment of the organization to implement the change, while the former involves the actual integration and use of AI. If survey constructs capturing these concepts are seen as being almost synonymous, however, it becomes hard to know if they are reflecting three different phenomena in organizations or a more general phenomenon.

## Conclusion

The findings of this study suggest that the value of AI isn't just about the investment in technology, but about a multi-dimensional shift in the way that an organization functions, one that is driven by leadership, employee readiness, strategic positioning, infrastructure, and institutional commitment. Transformational leadership is key, setting a clear digital vision, fostering innovation, minimizing change resistance, nurturing employee growth, and rallying resources to AI efforts. Organizational readiness, on the other hand, builds on this leadership influence and transforms it into implementation by equipping the organization with technological capability, financial resources, human skills, management support, and adaptability, thereby paving the way for long-term use of AI.

The study broadens the T-O-E model by offering an important antecedent of organizational readiness (transformational leadership) and provides evidence of the role of organizational readiness as a vital potential pathway for the role of leadership in facilitating AI adoption. The results highlight that AI systems are just one component of the solution, as organizations must also dedicate resources to training their staff, investing in data and digital infrastructure, establishing governance frameworks, fostering interdepartmental collaboration, and defining implementation plans. These are fundamental for leveraging AI in everyday workflows, decision-making processes, service delivery, and even future competitiveness.

The study also emphasizes the importance of focusing on employee trust, ethical implementation, data protection, and the impact on existing workflows in responsible AI adoption. The results offer relevant theoretical and managerial implications, but some degree of caution must be exercised as there is a high level of overlap between the study constructs. Further investigations are warranted in the use of longitudinal and multi-source designs, further development of measures and an investigation of organizations of varying size and industry sectors. In sum, the most sustainable organizational benefits from AI are likely to stem from visionary leadership, as they relate to readiness, governance, and capability building.

**Practical Implications**

AI tools should be viewed as an organizational transformation initiative, not as a technology procurement. Develop transformational leadership skills, establish a clear AI vision, engage employees in the implementation, and mitigate resistance by providing training and ongoing support for Pakistani businesses. Digital infrastructure, data quality, workforce capabilities, cross-functional collaboration, ethical governance and cyber security are also investments that need to be made. Such organizations can start with purposeful pilot initiatives and then systematically roll out AI initiatives depending on the readiness of employees, the fit of the application in the operation, and on the strategic value.

**Limitations**

The cross sectional design restricts causal interpretation and fails to address the evolution of leadership, readiness and AI adoption over time. Data was collected using self-reported questionnaires; common-method and social-desirability biases may have occurred. Further, the study was conducted within the three big Pakistani organizations, which limited the generalizability of the findings to SMEs and public institutions and other industries. Because the relationships between the constructs are difficult to interpret because the discriminant validity is not established and there is a significant amount of collinearity, the results are not interpreted as definitive. Going forward, integration of more technological and environmental factors (from the TOE perspective) in the measurement scales, as well as the use of a longitudinal design and multi-source designs are suggested for future research.



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