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The Determinants of AI Adoption and Its Impact on Employee Engagement: Evidence from Egyptian Organizations

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Abstract

This study examines the determinants of Artificial Intelligence (AI) adoption and its influence on employee engagement in Egyptian organizations, utilizing the Technology–Organization–Environment (TOE) framework. Based on survey data from 210 professionals across various industries and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), the findings reveal that relative advantage, compatibility, and top management support significantly drive AI adoption. In contrast, complexity, security/privacy concerns, organizational readiness, competitive pressure, and external and government support do not show significant effects. Furthermore, AI adoption demonstrates a positive but modest impact on employee engagement, suggesting the presence of other contributing factors. These results reflect the unique socio-economic conditions in Egypt, where internal organizational factors outweigh external influences in shaping technology adoption. The findings have practical implications for organizations and policymakers, emphasizing the need to prioritize internal drivers—such as leadership commitment, perceived benefits, and system compatibility—when promoting AI adoption. Additionally, organizations should align AI initiatives with employee needs and workplace culture to enhance engagement outcomes.

Keywords: Artificial Intelligence Adoption, Employee Engagement, Technology–Organization–Environment Framework, Egypt

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1. Introduction

The rapid advancement of Artificial Intelligence (AI) has transformed organizational operations across the globe, offering unprecedented opportunities for efficiency, innovation, and competitive advantage (Na et al., 2022). In developing economies like Egypt, AI adoption presents challenges and opportunities, shaped by socio-economic conditions, technological infrastructure, and workforce readiness (Kamel, 2021). Understanding the factors that drive AI adoption in such contexts is critical for businesses seeking to harness its potential while navigating implementation barriers.
The Technology–Organization–Environment (TOE) framework provides a robust theoretical lens for examining technology adoption, accounting for technological characteristics, organizational dynamics, and external environmental influences (Tornatzky and Fleischer, 1990). Prior research has identified key determinants of AI adoption, including perceived benefits, compatibility with existing systems, top management support, and external pressures such as competitive or regulatory forces (Lutfi et al., 2022; Faustine and Rachmawati, 2024). However, the relative importance of these factors may vary across industries and national contexts, particularly in regions where digital transformation is still evolving.

Employee engagement, a cornerstone of organizational performance, reflects employees' emotional and psychological investment in their work (Rožman and Tominc, 2024). While AI has the potential to enhance engagement by automating repetitive tasks and enabling more strategic roles, its impact depends on how effectively it is integrated into workflows and perceived by employees (Goswami et al., 2023). In Egypt, where digital transformation is a national priority under Vision 2030, a comprehensive national strategy aimed at achieving sustainable development and improving the quality of life for all Egyptians by the year 2030, exploring the interplay between AI adoption and employee engagement offers timely insights for policymakers and business leaders (Oxford Business Group, 2022).

This study examines the determinants of AI adoption and its implications for employee engagement in Egyptian organizations. Egypt presents a compelling context for studying AI adoption due to its ongoing national digital transformation agenda, which is spearheaded by the Ministry of Communications and Information Technology (MCIT) and aims to build a digital Egypt by enhancing digital infrastructure, fostering innovation, and promoting digital skills across sectors (MCIT, 2025). These efforts are complemented by the country's economic diversification strategies and young, tech-savvy population. As part of Egypt Vision 2030, the government has prioritized the integration of digital technologies across public and private sectors, aiming to boost efficiency and innovation (Oxford Business Group, 2022). However, the country still faces structural challenges, such as unequal access to digital infrastructure, limited technological readiness in certain industries, and varying levels of managerial commitment to innovation (Kamel, 2021). These unique socio-economic and institutional dynamics make Egypt an ideal setting to explore the internal and external drivers of AI adoption, particularly in relation to their influence on employee engagement within organizations.

2. Literature Review

2.1. Theoretical Framework

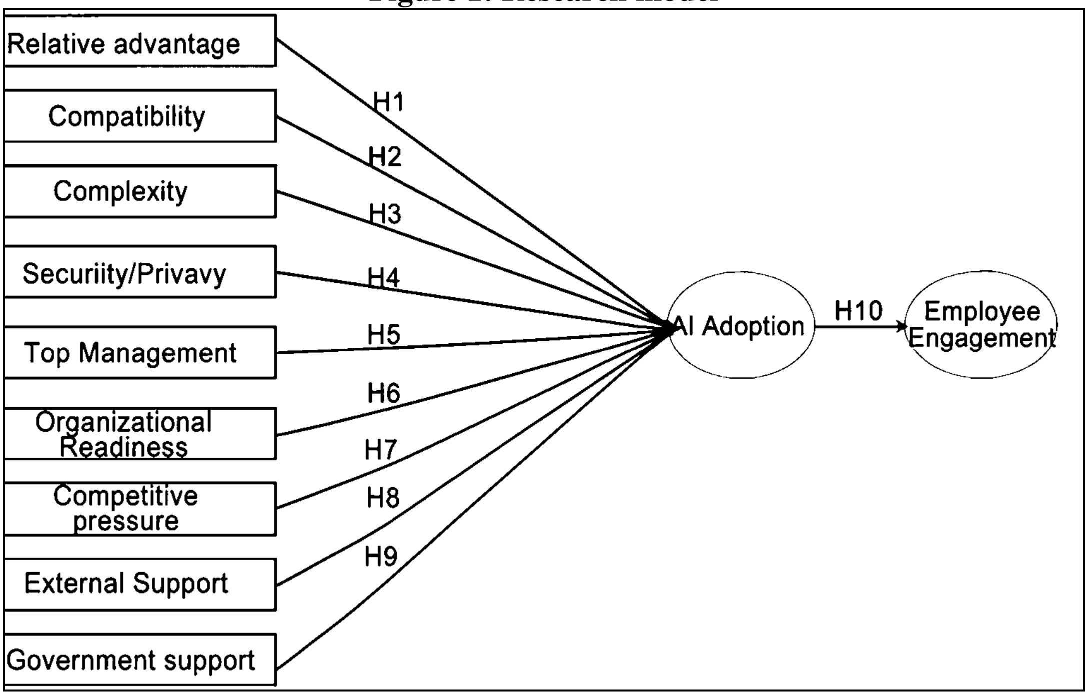
This study adopts the Technology–Organization–Environment (TOE) framework, originally proposed by Tornatzky and Fleischer (1990), as the principal theoretical model to examine Artificial Intelligence (AI) adoption within Egyptian organizations. Although the TOE framework has been applied globally, it is particularly appropriate for Egypt's context, where organizations share several structural similarities with those in other emerging economies—such as resource constraints, evolving digital infrastructures, and dependence on external support—yet also face unique challenges like regulatory variability, regional digital disparities, and informal organizational practices (Kamel, 2021; Oxford Business Group, 2022). These features make the TOE model both relevant and flexible for capturing the technological, organizational, and environmental determinants influencing AI adoption in Egyptian organizations. The TOE framework provides a suitable structure for analyzing the technological, organizational, and environmental factors that influence innovation uptake in firms. Factors such as relative advantage, compatibility, and complexity are considered in the technological context, while the organizational context includes top management support and organizational readiness. The environmental context captures external influences like competitive pressure, government support, and vendor availability (Tornatzky and Fleischer, 1990; Faustine and Rachmawati, 2024).

This framework has been validated across various settings, particularly in developing economies. For example, Faustine and Rachmawati (2024) employ the TOE framework to examine AI adoption in Tanzanian HRM practices, highlighting its effectiveness in capturing the interplay between internal and external adoption drivers. Similarly, Horani et al. (2023) conduct a systematic literature review on business analytics adoption and identify organizational readiness and top management support as key influencing factors. Kumar et al. (2022) apply the TOE model to analyze technology adoption in Indian retail outlets, finding that technological compatibility and environmental pressures significantly shape adoption decisions. Mujahed et al. (2021) explore mobile banking adoption among Palestinian SMEs, emphasizing the importance of technological readiness and perceived ease of use. Agarwal (2022) affirms TOE's relevance as a "generic" and adaptable model for evaluating AI integration, particularly in organizational contexts where resource constraints and strategic alignment are crucial considerations.

To enrich the theoretical foundation of this study, insights from the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and Innovation Diffusion Theory (IDT) are integrated to provide a comprehensive perspective on AI adoption dynamics, particularly at the individual level. TAM emphasizes perceived usefulness and ease of use as key drivers of individuals' attitudes and intentions toward technology adoption (Davis, 1989), offering insights into how employees' perceptions of AI's benefits and usability may shape its acceptance. TRA highlights the role of personal attitudes and subjective norms in influencing behavioral intentions (Ajzen and Fishbein, 1980), suggesting that social influences within Egyptian organizations could affect employees' willingness to adopt AI. IDT explains how innovations spread within a social system, identifying adopter categories (e.g., innovators, early adopters) and communication channels that influence adoption rates (Rogers, 1983). These models complement the TOE framework by providing a theoretical lens for understanding individual-level factors that contextualize employees' responses to AI adoption, particularly in relation to employee engagement, although the empirical analysis focuses on TOE-based constructs.

The TOE framework is particularly well-suited for this study; its strength lies in its comprehensive consideration of the technological, organizational, and environmental contexts that influence technology adoption. Given Egypt's evolving digital infrastructure and distinct socio-economic landscape, the TOE framework provides an appropriate and context-sensitive lens for examining the determinants of AI adoption and its implications for employee engagement. This study adopts the specific set of determinants outlined by Faustine and Rachmawati (2024), which include relative advantage, compatibility, complexity, security and privacy concerns, top management support, organizational readiness, competitive pressure, and external and government support, as illustrated in Figure 1.

Figure 1: Research model



Relative advantage refers to the perceived superiority of a particular technology over existing methods or systems within an organization, encompassing anticipated benefits such as improved efficiency and performance (Kurup and Gupta, 2022). However, adopting such technologies may be hindered if viewed as overly complex or challenging to implement (Almaiah et al., 2022). Boonsiritomachai et al. (2016) note that adopting new technologies often begin with recognizing their relative advantage. Organizations that perceive new technologies as more effective than their current practices are more inclined to adopt them successfully. Therefore, this study posits the following hypothesis:

H1. Relative advantage influences the adoption of AI.

Compatibility refers to how much a new technology aligns with an organization's current systems, values, and operational practices. It plays a crucial role in shaping technology adoption decisions by influencing how easily innovations can be integrated into existing workflows (Chong and Lim, 2022). Organizations may enhance their internal processes and policies to foster better alignment, facilitating smoother AI implementation. Research has shown that compatibility supports the advancement and acceptance of AI technologies (Neumann et al., 2022). Technical fit and organizational commitment are key elements that determine compatibility (Jöhnk et al., 2021). When AI systems are well-matched with existing technological infrastructures, they can reduce uncertainty and improve functional efficiency (Gangwar, 2018). Based on this, the following hypothesis is proposed:

H2. Compatibility influences the adoption of AI.

Complexity refers to the perceived challenges, risks, and obstacles associated with implementing and using AI technologies (Jöhnk et al., 2021). High levels of complexity can hinder adoption, as organizations may struggle with system usability, integration, and scalability. Conversely, successful AI implementation often requires streamlined processes and user-friendly interfaces to minimize resistance (Xu et al., 2023). The practical ease with which technology is deployed, including job completion time, system integration, data handling capabilities, and interface design, can significantly influence adoption outcomes. Flexibility and accessibility are also essential, as technologies that are intuitive and easily accessible are more likely to be adopted by organizations. Furthermore, the increasing role of automation and digital tools may shape the perceived complexity of AI solutions (Almaiah et al., 2022). Therefore, the study proposes the following hypothesis:

H3. Complexity influences the adoption of AI.

Security and privacy concerns refer to the perceived risks of utilizing digital technologies for workplace operations and data transmission (Jöhnk et al., 2021). These concerns are often central to decisions regarding technology adoption, particularly when handling sensitive information. According to Yabanci (2019), technological implementation can raise apprehensions about data confidentiality, trust, and system accessibility, especially in human-computer interaction. These perceived vulnerabilities can lead to doubts about whether AI systems are safe and appropriate for performing work-related tasks and exchanging organizational information (Kaur et al., 2021). In light of this, the study proposes:

H4. Security/privacy influences the adoption of AI.

Support from top management plays a crucial role in successfully integrating AI. It is foundational for driving technological innovation and managing organizational change (Lutfi et al., 2022). Leadership involvement reflects how seriously an organization values innovation, particularly in committing necessary resources and framing strategic priorities. Strong managerial support helps mitigate resistance to change and fosters an environment conducive to technology adoption. Thus, the study advances the following hypothesis:

H5. Top management support influences the adoption of AI.

Organizational readiness refers to the availability of internal systems, structures, and resources—such as technology, infrastructure, and human capital—that enable the effective implementation of innovations like AI (Alam et al., 2016). HR professionals play an important role in assessing their organization's preparedness by evaluating knowledge levels, commitment, resource allocation, and the ability to integrate new technologies successfully (Chong and Lim, 2022). For AI to be effectively adopted, an organization must have the necessary infrastructure, relevant expertise, and financial capacity (Pillai and Sivathanu, 2020). Readiness is thus considered a key enabler of successful AI adoption. Accordingly, this study hypothesizes:

H6. Organizational readiness influences the adoption of AI.

Competitive pressure reflects the influence of rival firms and the broader market environment on an organization's technology adoption decisions (Almaiah et al., 2022). In today’s globalized business climate, organizations must continuously evaluate their strategies, draw insights from competitors, and innovate to stay relevant (Shet et al., 2021). When competitors implement advanced AI solutions, they may gain operational and strategic advantages, compelling others in the industry to adopt similar technologies to maintain competitiveness (Nguyen et al., 2022). Based on this, the study posits:

H7. Competitive pressure influences the adoption of AI.

External support refers to assistance provided by third-party entities—such as consultants, technology vendors, and service providers—to facilitate the adoption of emerging technologies like Artificial Intelligence (AI). This support often includes training programs, technical guidance, and post-deployment services to ease organizations' challenges during the implementation process (Horani et al., 2023). Since AI is still regarded as a relatively novel technology, the proactive engagement of solution providers during its introduction is crucial in shaping user acceptance (Malik et al., 2021). For successful integration, vendors are expected to provide comprehensive support across all stages—from initial training to post-implementation maintenance (Singh and Pandey, 2024). In some cases, departments may require tailored AI solutions that align with the organization’s specific functional needs, making the role of external providers even more vital. Based on this, the following hypothesis is proposed:

H8. External support influences the adoption of AI.

Government involvement, including regulatory frameworks, incentive structures, and policy guidelines, can either facilitate or hinder the adoption of advanced technologies within organizations (Horani et al., 2023). Regulatory policies may act as enablers by providing clear technical standards and supportive legislation or create barriers through restrictive compliance requirements (Dincbas et al., 2021). Moreover, financial incentives such as subsidies, grants, tax benefits, and access to infrastructure and technical resources can play a significant role in motivating firms to adopt AI (Chong and Olese, 2017). Recognizing this, the study presents the following hypothesis:

H9. Government support influences the adoption of AI.

Implementing Artificial Intelligence (AI) in organizational settings has significantly influenced how employees engage with their work. AI offers tools that automate routine tasks, enhance decision-making, improve communication, and provide real-time support, reshaping traditional work environments and increasing operational efficiency (Rožman and Tominc, 2024). As AI technologies are integrated into daily operations, they help reduce administrative burdens and enable employees to focus on more meaningful, creative, and strategic aspects of their roles, ultimately fostering higher levels of engagement. Studies have shown that AI adoption has a significant impact on productivity and employee morale (Xu et al., 2023), through the optimisation of workflows and the facilitation of continuous monitoring (Singh and Pandey, 2024). AI-driven systems also allow organizations to tailor learning and development opportunities, recognize real-time performance, and facilitate flexible work arrangements. According to Rožman and Tominc (2024), the successful adoption of AI has shown a positive and significant impact on employee engagement, regardless of gender, in entrepreneurial environments. Their research underscores AI's potential in creating inclusive, efficient, and innovation-driven workplaces. Given these insights, the present study proposes the following hypothesis:

H10. The adoption of AI influences employee engagement.

3. Research Methodology

The questionnaire is developed based on a validated instrument by Faustine and Rachmawati (2024) and Rožman and Tominc (2024) to ensure alignment with the study's hypotheses. However, the items are adapted to be more generalizable across various departments, rather than limited to the Human Resources context. Several items are excluded based on concerns related to factor loadings and validity. Accordingly, Table 1 in the appendix presents the final set of variables and measurement items retained after these modifications to ensure relevance and methodological rigor.

A structured questionnaire, administered in both English and Arabic, is employed to investigate the hypothesized relationships presented in the conceptual model (see Figure 1). The study aims to examine the determinants of artificial intelligence (AI) adoption in Egypt and its influence on employee engagement. The sample size is determined by the recommendations of Hair et al. (2013), which suggest a range of five to ten respondents per questionnaire item. Given that the questionnaire comprises 33 items, the minimum required sample is calculated using the lower bound ($33 \times 5 = 165$). The final sample exceeds this threshold, comprising 210 valid responses. A 5-point Likert scale is used to capture respondents' perceptions, ranging from 1 "strongly disagree" to 5 "strongly agree" (Goswami et al., 2023). A total of 213 responses are collected; however, after excluding incomplete submissions, 210 are retained for analysis. The response rate is calculated by dividing the number of completed questionnaires (210) by the total number of individuals contacted (213), resulting in a high response rate of 98.6%, which is considered highly effective for survey-based research (Fowler Jr., 2009). The next step is to take into account the unit of analysis and the sampling technique.

As noted by Sekaran and Bougie (2016), the unit of analysis in research can be defined at the individual, dyadic, or group level. This study focuses on individuals, specifically employees in various industries. The sample represents a subset of the broader population, selected to draw inferences that can be generalized to the entire population, in line with the principles outlined by Tabachnick et al. (2019). Sampling must address two key components: the sample size and the sampling method. The sample size is determined according to the guidelines proposed by Hair et al. (2013), which recommend a ratio of 5 to 10 respondents per questionnaire item. Given that the instrument contains 33 items, the sample size adheres to this rule. Regarding the sampling technique, this study employs a combination of purposive and convenience sampling, rather than a probability-based approach (Cooper and Schindler, 2014). Purposive sampling is used to identify respondents with relevant experience and characteristics aligned with the research objectives, thereby enabling the selection of information-rich cases (Campbell et al., 2020). Convenience sampling is also utilized to access participants who are readily available and willing to respond, which is practical given time and resource constraints often encountered in field data collection (Etikan et al., 2015).

Inferential statistics are a key component in hypothesis testing within research (Sekaran and Bougie, 2016). This study employs Structural Equation Modeling using Partial Least Squares (PLS-SEM), facilitated by the SmartPLS 4 software. The evaluation of PLS-SEM encompasses three main stages: assessment of the measurement model (outer model), the structural model (inner model), and hypothesis testing, as recommended by Maroufkhani et al. (2022).

In assessing the measurement model, particularly for reflective constructs, several criteria are considered: indicator reliability, discriminant validity, and internal consistency. Indicator reliability is examined using outer loadings, with ideal values falling between 0.4 and 0.7. Indicators within this range may be excluded if doing so enhances composite reliability or the Average Variance Extracted (AVE), but the theoretical importance of the indicators must also be weighed (Hair et al., 2014). Discriminant validity ensures that each construct is distinct from others, typically evaluated through cross-loadings and the Fornell-Larcker criterion. Indicators are expected to show higher loadings on their assigned construct than on any other, and the AVE for each construct should surpass its squared correlation with other constructs (Agarwal, 2022). Internal consistency is gauged using composite reliability, where values above 0.6 are generally accepted as sufficient (Hair et al., 2019). These metrics collectively establish the validity and reliability of the measurement model in PLS-SEM analyses.

The structural (inner) model is assessed to determine the model's predictive accuracy and strength. Multicollinearity is checked using the Variance Inflation Factor (VIF), with values above 10 or a tolerance below 0.10 suggesting potential issues. The coefficient of determination (R^2) reflects the proportion of variance in the dependent variable explained by the independent variables, with higher values indicating a more robust model. Path coefficients ranging from −1 to +1 indicate the magnitude and direction of relationships between constructs—values nearing +1 imply strong positive relationships, while those near −1 indicate strong negative relationships (Maroufkhani et al., 2022). These indicators are fundamental in evaluating the structural model's overall validity and explanatory power.

4. Results

4.1. Demographic Results

Data are collected from 213 respondents encompassing a broad spectrum of demographic and professional characteristics, including variations in age, gender, job title, industry, sector, educational attainment, and area of residence. The respondents from different industries, including agriculture, manufacturing, trade, transportation, financial services, public administration, education, business services, technology, healthcare, construction & engineering, hospitality, real estate, automotive, and others, whether public or private sector, in different residential areas in Egypt. After excluding incomplete and invalid questionnaires, 210 valid responses are retained for data analysis. The demographic characteristics of the respondents are presented in Table 2.

Table 2: Demographic characteristics

Characteristics	**Frequency (n = 210)**
Gender	
Male	132
Female	78
Age	
15-30	88
34-40	53
41-64	69
Education	
Average non-university qualification	3
University Graduate/ Bachelor’s degree holder	132
Postgraduate degree holder	75
Job Title	
HR Professionals	105
IT Professionals	14
CEO	12
Finance Professionals	15
Marketing Professionals	7
Sales Professionals	15
Operations Professionals	10
Customer Service Professionals	8
Project Management Professionals	5
Administrative Professionals	2
Academic Professionals	11
Others	6

4.2. Factor Loadings

In assessing the outcomes obtained from the PLS-SEM analysis, the evaluation begins with examining the measurement model (Hair et al., 2014). A key component of this process is the assessment of indicator reliability (Hair et al., 2013). Reliability is established when factor loadings exceed 0.5, indicating that the construct accounts for at least 50% of the indicator's variance (Hair et al., 2014). In this study, all item loadings surpass this threshold, confirming the individual items' reliability (see Table 3).

Table 3: Factor Loading

Variables	Items	Factor loading
Relative Advantage (RA)	RA3	0.842
	RA4	0.891
Compatibility (CB)	CB1	0.912
	CB2	0.892
	CB3	0.793
Complexity (CO)	CO1	0.760
	CO2	0.840
	CO3	0.884
Security/ Privacy (SP)	SP1	0.839
	SP2	0.805
	SP3	0.862
Top management (TM)	TM1	0.918
	TM2	0.923
	TM3	0.903
	TM4	0.880
Organization Readiness (OR)	OR1	0.815
	OR2	0.945
	OR3	0.766
Competitive Pressure (CP)	CP2	0.848
	CP3	0.914
External Support (ES)	ES1	0.773
	ES2	0.857
	ES3	0.790
Government Support (GS)	GS1	0.887
	GS2	0.911
AI adoption (AI)	AI1	0.834
	AI2	0.804
Employee Engagement (EE)	EE3	0.782
	EE4	0.731
	EE5	0.838
	EE6	0.867
	EE7	0.819
	EE8	0.774

4.3. Discriminant Validity

The purpose of assessing discriminant validity is to ensure that the indicators associated with one construct are not highly correlated with indicators from other constructs (Hair et al., 2019). This study evaluates discriminant validity using two established approaches: the Heterotrait–Monotrait (HTMT) ratio and the Fornell-Larcker criterion. The HTMT method considers values below 0.90 indicative of acceptable discriminant validity (Gold et al., 2001; Teo et al., 2008; Henseler et al., 2015). As presented in Table 4, all HTMT values are within the acceptable range. Consequently, the measurement model can be considered to have satisfactory discriminant validity. Additionally, the Fornell-Larcker criterion was applied to assess discriminant validity, as shown in Table 5. This method involves comparing the Average Variance Extracted (AVE) of each construct with its correlations to other constructs. Discriminant validity is established when a construct's AVE is greater than its correlations with all other latent variables.

Table 4: HTMT

	AI	CB	CP	CO	EE	ES	GS	OR	RA	SP	TM
AI											
CB	0.852										
CP	0.339	0.357									
CO	0.498	0.609	0.039								
EE	0.478	0.510	0.225	0.230							
ES	0.429	0.400	0.455	0.108	0.401						
GS	0.566	0.457	0.493	0.275	0.402	0.533					
OR	0.151	0.194	0.393	0.463	0.161	0.243	0.073				
RA	0.799	0.553	0.365	0.298	0.316	0.460	0.381	0.102			
SP	0.278	0.286	0.124	0.461	0.139	0.102	0.159	0.333	0.215		
TM	0.848	0.784	0.454	0.317	0.530	0.427	0.644	0.156	0.396	0.168	

Table 5: Forner Larcker

	AI	CB	CP	CO	EE	ES	GS	OR	RA	SP	TM
AI	0.819										
CB	0.566	0.867									
CP	0.209	0.280	0.882								
CO	-0.324	-0.487	-0.022	0.830							
EE	0.324	0.450	0.183	-0.196	0.803						
ES	0.272	0.327	0.341	-0.068	0.334	0.808					
GS	0.357	0.370	0.374	-0.212	0.333	0.429	0.899				
OR	-0.102	-0.169	0.277	0.370	-0.146	0.160	-0.056	0.845			
RA	0.466	0.416	0.250	-0.239	0.254	0.334	0.272	0.070	0.867		
SP	-0.178	-0.224	0.041	0.363	-0.120	-0.077	-0.130	0.267	-0.166	0.835	
TM	0.587	0.702	0.366	-0.275	0.484	0.382	0.544	-0.145	0.314	-0.148	0.906

4.4. Composite Reliability and Average Variance Extracted

Following the assessment of internal consistency reliability, the next step involves calculating composite reliability, with acceptable values typically ranging from 0.6 to 0.7, as Hair et al. (2011) recommended. Subsequently, the evaluation of the measurement model proceeds with the examination of convergent validity for each construct indicator (Hair et al., 2019). Convergent validity is commonly measured using the Average Variance Extracted (AVE), which reflects the degree to which a construct correlates with its observed variables, thus verifying their association with the underlying factor. An AVE value of at least 0.5 is considered adequate (Hair et al., 2011; Agarwal, 2022; Faustine and Rachmawati, 2024). As shown in Table 6, all constructs in the current study exhibit AVE values above the 0.5 threshold, suggesting that each construct explains over 50% of the variance in its corresponding indicators.

Table 6: Composite Reliability and Average Variance Extracted

	Composite reliability	Average variance extracted
AI adoption	0.803	0.671
Compatibility	0.901	0.752
Competitive Pressure	0.875	0.778
Complexity	0.868	0.688
Employee Engagement	0.916	0.645
External Support	0.849	0.652
Government Support	0.894	0.808
Organizational Readiness	0.882	0.715
Relative Advantage	0.858	0.752
Security/Privacy	0.874	0.698
Top Management	0.948	0.821

4.5. Structural Model

Following the validation of the measurement model, the structural model is assessed using key indicators such as the coefficient of determination (R^2) and the statistical significance of the model paths (Hair et al., 2019). Tables 7 and 8 present the findings from these evaluations. The absence of multicollinearity is confirmed by all Variance Inflation Factor (VIF) values being below the threshold of 3 (Agarwal, 2022). Regarding predictive power, the model exhibits a moderate level of explanatory strength for AI adoption ($R^2 = 0.459$), while the explanatory power for employee engagement is relatively weak ($R^2 = 0.105$), in line with interpretative guidelines by Hair et al. (2011).

Table 7: Variance Inflation Factor

	AI	CB	CP	CO	EE	ES	GS	OR	RA	SP	TM
AI					1.000						
CB	2.621										
CP	1.430										
CO	1.621										
EE											
ES	1.431										
GS	1.647										
OR	1.423										
RA	1.332										
SP	1.204										
TM	2.572										

Table 8: R-squared

	R-square
AI adoption	0.459
Employee Engagement	0.105

4.6. Significance Testing

The outcomes of hypothesis testing, based on the calculated t-values and p-values, are summarized in Table 9.

Table 9: Significance Testing

	T values	P values	Decisions
H1: Relative Advantage -> AI adoption	4.331	0.000***	Supported
H2: Compatibility -> AI adoption	1.715	0.086*	Supported
H3: Complexity -> AI adoption	1.149	0.251	Rejected
H4: Security/Privacy -> AI adoption	0.237	0.812	Rejected
H5: Top Management -> AI adoption	4.162	0.000***	Supported
H6: Organizational Readiness -> AI adoption	0.132	0.895	Rejected
H7: Competitive Pressure -> AI adoption	0.839	0.401	Rejected
H8: External Support -> AI adoption	0.277	0.781	Rejected
H9: Government Support -> AI adoption	0.361	0.718	Rejected
H10: AI adoption -> Employee Engagement	4.538	0.000***	Supported

*Note: *p < 0.10, **p < 0.05, and *** p < 0.01 (two-tailed test).*

5. Discussion

This study employed the Technology–Organization–Environment (TOE) framework to investigate the factors influencing the adoption of artificial intelligence (AI) in relation to employee engagement within the Egyptian context. The results of the hypothesis testing show that a number of variables have a significant impact on AI adoption in the context of employee engagement. The first hypothesis (H1) posits that the organizational element of perceived relative advantage has a substantial impact on AI adoption. This finding is consistent with prior research by Faustine and Rachmawati (2024), Almaiah et al. (2022), and Na et al. (2022), who identified relative advantage as a critical driver of technological adoption. These findings indicate that employees in Egypt are more likely to adopt AI technologies when they perceive its relative advantages.

The second hypothesis (H2) posits that the organizational factor of compatibility significantly affects the adoption of AI, indicating that the alignment of AI technologies with existing organizational systems and workflows is a critical determinant of their adoption. This aligns with the findings of Tuffaha and Perello-Marin (2022) and Park and Kim (2019), who emphasize that compatibility plays a crucial role in the successful implementation of technological innovations across various sectors. Accordingly, when employees in Egypt perceive AI systems as compatible with their current work processes, they are more likely to support and adopt such technologies.

The fifth hypothesis (H5) posits that top management support significantly affects the adoption of AI, highlighting the crucial role played by leadership in fostering an environment conducive to technological innovation. This is consistent with Lutfi et al. (2022), who find that top management support is a key organizational factor influencing the adoption of AI. Accordingly, when top management provides strong support, employees in Egypt are more likely to endorse and adopt such technologies.
The tenth hypothesis (H10) posits that the adoption of AI significantly influences employee engagement in Egypt, suggesting a positive relationship between AI adoption and employee engagement. This is consistent with the findings of Rožman and Tominc (2024), who find that AI adoption contributes to enhance employee engagement. However, in the present study, the explanatory power of AI adoption with respect to employee engagement is modest, as indicated by an R^2 value of 0.105. This suggests that AI adoption accounts for approximately 10.5% of the variance in employee engagement, implying the presence of other influential factors beyond AI adoption alone.

The study found that hypotheses H3, H4, H6, H7, H8, and H9 are not supported, suggesting that factors such as Complexity, Security/Privacy, Organizational Readiness, Competitive Pressure, External Support, and Government Support may not directly influence AI adoption among employees in Egypt. Instead, only Top Management Support, Relative Advantage, and Compatibility emerge as significant determinants. These findings reflect Egypt’s unique socio-economic and cultural context.

For instance, while AI systems are often perceived as complex, employees develop strong mental models through organizational training and ERP use, which helps reduce perceived complexity (Elbanna, 2010; Elbanna and Linderoth, 2015). Security and privacy concerns are often overshadowed by economic priorities and weak enforcement, leading employees to prioritize usage despite risks (Hassounah et al., 2020).

In contexts such as Egypt, organizational readiness may play a limited role in AI adoption, as employees can independently access and use cloud-based AI tools. This aligns with broader findings that some enterprises can overcome resource limitations through accessible digital technologies (Lokuge and Duan, 2021; 2023).In Egypt, the impact of competitive pressure on digital innovation appears weaker in traditional sectors like agriculture and retail, where adoption remains slow due to infrastructural and readiness barriers (Kamel, 2021).Vendor support can be too costly, motivating employees to engage in self-learning and peer networks instead (Abdullahi et al., 2021).

Lastly, although Egypt Vision 2030 sets out an ambitious framework for digital transformation, Oxford Business Group (2022) notes that significant investments in information and communication technology infrastructure and digital services are still underway, suggesting a lag between policy formulation and on-the-ground implementation, potentially inhibiting employee-level AI uptake. Consequently, employees' decisions to adopt AI are shaped primarily by Top Management Support, Relative Advantage, and Compatibility, enabling them to navigate and overcome structural and resource-related barriers.

6. Limitations and Future Possibilities

Despite offering valuable insights, this study is not without limitations. First, the use of a non-probability sampling technique, such as purposive and convenience sampling, may limit the generalizability of the findings to the broader Egyptian workforce. Second, the study relies solely on self-reported perceptions, which may be subject to bias or social desirability effects. Third, the cross-sectional nature of the data restricts the ability to make causal inferences about the relationships among the variables. Fourth, the study does not explicitly examine the influence of industry-specific differences, as the unit of analysis focuses on individual employees across various industries. While this approach supports generalizability across sectors, industry-specific factors, such as technological maturity or competitive dynamics, may moderate the relationships between AI adoption determinants and employee engagement, particularly in Egypt's diverse economic landscape. Finally, the explanatory power of AI adoption on employee engagement, although statistically significant, is relatively low, indicating the presence of other influential factors not captured in this study.

Future studies should consider longitudinal research designs to better assess causal relationships and dynamic changes in AI adoption and engagement over time. Additionally, qualitative or mixed-method approaches could provide richer insights into the contextual and cultural factors shaping employee responses to AI integration. Expanding the study to include other developing countries or sector-specific analyses would also allow for comparative assessments and enhance the generalizability of the results. Specifically, future research could explore how industry affiliation moderates the relationships tested in this study, such as the impact of technological infrastructure or sector-specific competitive pressures on AI adoption. Finally, incorporating additional organizational and psychological variables, such as digital literacy, resistance to change, or job design, could help explain more variance in employee engagement and offer a more comprehensive understanding of AI's organizational implications.

Moreover, future research should not only investigate whether specific factors influence AI adoption but also examine the extent of that influence. For instance, multi-group analyses could compare the strength of predictors like top management support or compatibility across sectors, firm sizes, or employee roles. This approach would provide more granular insights into which factors exert the greatest influence in specific organizational contexts, offering actionable implications for both policymakers and practitioners seeking to promote effective AI integration.

7. Conclusion

This study explores the factors influencing the adoption of Artificial Intelligence (AI) and its impact on employee engagement within Egyptian organizations, using the Technology–Organization–Environment (TOE) framework. The findings underscore the significant role of organizational-level variables—specifically, relative advantage, compatibility, and top management support—in driving AI adoption. Notably, AI adoption is found to positively influence employee engagement, although it accounts for a relatively modest proportion of its variance. Several anticipated predictors, such as complexity, security/privacy concerns, organizational readiness, competitive pressure, external support, and government support, do not significantly influence AI adoption in this context.

These results reflect Egypt's distinct socio-economic landscape, where informal learning, managerial support, and practical alignment of AI tools with organizational routines appear more critical than external or systemic factors. This insight highlights a potential shift in how organizations in emerging economies approach technology integration, placing greater emphasis on internal adaptability rather than reliance on policy or vendor support. From a theoretical standpoint, the study contributes to the growing body of literature adapting the TOE framework to non-Western contexts. Practically, the findings suggest that organizations aiming to increase AI adoption and enhance employee engagement should focus on strengthening leadership commitment, aligning AI with existing systems, and clearly communicating the tangible benefits of AI tools. Rather than waiting for policy changes or external incentives, firms can make meaningful progress by cultivating internal readiness and fostering a culture of innovation. As AI continues to evolve, understanding its social, organizational, and psychological dimensions, particularly in developing economies, will be critical to ensuring it is ethical, inclusive, and effective deployment.

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The authors have no relevant financial or non-financial interests to disclose or competing interests to declare relevant to this article's content.

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Appendix

Table 1: Research Variable Measurement

Variables	Items	Sources
Relative Advantage (RA)	RA3: AI adoption in our department helps in lowering costs. RA4: AI adoption contributes to attracting and expanding new services for employees.	Faustine & Rachmawati (2024)
Compatibility (CB)	CB1: AI adoption in our department is consistent with our organization’s practices. CB2: AI adoption in our department fits with our organizational culture. CB3: It is easy to incorporate AI into our department practices.	Faustine & Rachmawati (2024)
Complexity (CO)	CO1: Learning to use AI tools in our department is difficult for our employees. CO2: AI tools in our department and technologies are high to maintain. CO3: AI tools in our department are difficult to operate.	Faustine & Rachmawati (2024)
Security/ Privacy (SP)	SP1: AI adoption in our department creates data security and privacy concerns. SP2: Implementing AI in our department creates vulnerabilities in the access control of the organization’s information assets. SP3: Implementing AI in our department creates risks through excessive dependency on external vendors (AI tool developers).	Faustine & Rachmawati (2024)
Top management (TM)	TM1: Our top management promotes the use of AI in our department. TM2: Our top management creates support for AI adoption within the organization. TM3: Our top management promotes AI adoption as a strategic priority in our department. TM4: Our top management is interested in the news about AI adoption, specifically in our department.	Faustine & Rachmawati (2024)
Organization Readiness (OR)	OR1: Lacking financial resources has prevented our organization from fully adopting AI in our department. OR2: Lacking needed IT infrastructures has prevented our organization from adopting AI. OR3: Lacking skilled resources/labor prevents our organization from fully exploiting AI.	Faustine & Rachmawati (2024)

Competitive Pressure (CP)	CP2: Our organization is pressured by competitors to adopt AI in our department. CP3: Our organization would adopt AI in response to competitors' actions.	Faustine & Rachmawati (2024)
External Support (ES)	ES1: Community agencies/vendors/AI tools developers can provide the required training for AI adoption in our department. ES2: Community agencies/vendors/AI tools developers can provide Effective technical support for AI adoption in our department. ES3: Community agencies/vendors/AI tools developers actively market AI adoption in our department.	Faustine & Rachmawati (2024)
Government Support (GS)	GS1: The government policies encourage us to adopt new information technology, especially in our department. GS2: The government provides incentives for adopting AI, such as offering technical support, training, and funding for AI technologies.	Faustine & Rachmawati (2024)
AI adoption (AI)	AI1: Our organization has already adopted AI in our department. AI2: AI adoption encourages the integration of our department practices with other functions.	Faustine & Rachmawati (2024)
Employee Engagement (EE)	EE3: Using AI enhances employee effectiveness. EE4: Employees are engaged in the quality of their work. EE5: Employees complete their work with passion. EE6: Employees are engaged in achieving successful business results. EE7: Employees are aware of the importance of innovation for our company, and they help to develop the enterprise. EE8: Employees are enthusiastic in their work.	Rožman& Tominc (2024)