Determinants of Organizational Sustainability Using Toe Model in Engineering, Electrical and Information Technology Industry: The Mediating Effect of AI Adoption

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Abstract: This study examines the determinants of organizational sustainability in Jordan's engineering, electrical, and information technology sectors. It explores how technological, organizational, and environmental factors influence organizational sustainability, and how AI adoption is a mediating variable in this regard. The research method used was a quantitative method, surveying 396 participants. The data were analyzed with SPSS and SmartPLS 4, which employs PLS-SEM. The results show that organizational and environmental aspects have the highest impact on sustainability. The factors with the most direct impact on sustainability are AI complexity (no impact) and AI compatibility, top management support, culture of innovation, regulatory pressure, and competitive pressure (all with an effect). Most relationships are mediated by AI, accentuating its importance in promoting organizational sustainability in emerging economies.

Key-Words: - Organizational Sustainability, AI Adoption, TOE Framework, Technological Factors, Organizational Factors, Environmental Factors, Jordan, PLS-SEM

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1 Introduction

The Engineering, Electrical and Information Technology Industry sector in Jordan has actively contributed towards the economy in the form of its share in GDP, employment opportunities, and exports [1]. According to [2] the industry is also assisted by its strategic geographical position, qualified workforce, and market access regionally and internationally. While the potential is there, the industry is also facing some headwinds: increased production costs, energy dependence, outdated technology, and heightened competition. Sustainability, as per [3] has received increasing attention in recent years with regard to productivity, efficiency, and global competitiveness. Yet, the use of second-generation technologies such as AI, leading to more sustainable organizations, though low, proves that more strategic innovation and better leadership are needed across the industry.

Based on the sustainability reports of Jordan Commercial Bank [4] and [5], it is evident that although companies in Jordan are formally committed to applying sustainability strategies that are in line with national and international frameworks, their application indicates a great extent of internal organizational constraints. Another related issue is the absence of a fully comprehensive organizational sustainability, which is about embedding environmental, social, and economic sustainability principles in strategies, operations, and leadership of an organization, and making sustainability a core driver of performance, not just a compliance exercise. This void is present whether sustainability is considered as environmental responsibility or as an opportunity to improve organizational performance. However, despite having sustainability roadmaps, many Jordanian companies seem to view sustainability as a top-of-the-pile ‘sustainability reporting' issue, rather than a cross-departmental and cross-board strategy [6].

As reported by [7], an important problem that one can notice is the lack of holistic assessment of the factors that hinder or enable Organizational sustainability in Jordan, which causes a lack of proper reporting of the sustainable practices followed within the organization. The same report highlighted a high level of corporate social responsibility (CSR) spending and HR reporting significant employee training hours; at the same time, it stated that no Jordanian company provided a broader framework

that clearly identifies how these efforts would translate into enhanced organizational sustainability and a foundation for long-term innovation capability, such as the use of AI technology.

2 Literature Review

Despite the fact that AI is increasingly regarded as a tool for more efficient, innovative, and sustainable practices, there are numerous potential opportunities for AI adoption success in Jordanian companies in the engineering, electrical, and IT sectors. One of the most significant problems is the shortage of qualified workers. A survey done by [8] of 364 Jordanian firms' owners recorded 56% of firms stating the requirement for new skills to enable the effective implementation of AI, while [9] surveyed 600 IT leaders located in the U.S., EMEA (Jordan is among these countries), and APAC regions, and stated that regional sources reported 38% of firms that list a lack of trained personnel as a significant barrier. This talent gap creates a major obstacle that hinders an organization's ability to effectively deploy, manage, and scale AI technologies.

Another major challenge is the cost of implementing AI, in addition to the lack of skills. Many organizations don't have the resources to invest in infrastructure, software, and skilled personnel to put AI-based systems in place. Moreover, 26% of companies in the Middle East and North Africa (MENA) believe that the tools are too costly, according to [9]. The financial barrier is even more pronounced in Jordan, with low organizational readiness and financial barriers creating a double burden. As per the Jordan's Artificial Intelligence Strategy and Implementation Plan, prepared by Ministry of Digital Economy and Entrepreneurship [10] which surveyed 18 public institutions, Jordanian companies have reported several issues in the adoption of AI, including low public awareness, the absence of a central body for managing AI, limited financial and technical support for start-ups, slow licensing procedures, unprepared data systems, insufficient Big Data infrastructure, weak research partnerships, and lack of a national data catalogue. Similarly, worldwide, A study conducted by [10] on 300 executives based in the US has established that 60% of firms have to turn to external sources to get the expertise, as the internal readiness is not up to mark; this clearly reflects the structural limitations and managerial deficiencies companies face when adopting AI technologies.

In addition, a lack of understanding about AI is a significant constraint to AI adoption in Jordan within the context of Leadership. However, the country's many managers and organization leaders are not very knowledgeable about the nature and potential of AI, which hinders strategic deployment and visionary leadership. On top of that, some workers are against the use of AI, making the situation even more difficult. In the report of the Ministry of [10] it has been mentioned that there is a lack of understanding about the nature of AI among managers or resistance by some employees of the organization. But a lack of understanding at the leadership level, combined with internal resistance, creates a practical obstacle that could stall or block the implementation of AI solutions and, consequently, impede the country's ability to maximize its use of AI to boost economic and social growth.

The report [11] indicates that, globally, around 42% of leaders who work as Chief Information Officers (CIOs) cannot see the business value of AI yet, as companies remain uncertain about the value of AI for their business; another 26% of companies are waiting to see some business use of AI that could be a success story. The uncertainty and delay in adoption frequently stem from this lack of clarity. To complicate matters further, some leaders don't have a clear strategy for using AI, aren't adept at integrating AI into their business units, or don't promote its use internally, further delaying progress.

All of these data concerns complicate AI's ability to deliver actionable insights. Facing cybersecurity and privacy risks is another key concern, with 600 IT leaders in Europe, the Middle East, and Africa (EMEA) polled, according to the report [9]. Moreover, 74% of businesses in MENA are facing security and compliance challenges, with data protection being the top two. In addition to these risks, the legal environment is unclear, and deployment is complicated. As of this writing, there are several governments around the world that have already started to develop ethics frameworks and digital strategies, but in the report published by [12] they surveyed 1 million US businesses and found that they already encounter numerous legal and potential regulatory barriers, including data governance and legal liability regarding AI-driven decision-making. Without clear policies, companies struggle to navigate risk.

There are several tangible hurdles for the adoption of AI in Jordan's Engineering, Electrical and IT sectors, and these are significant threats to sustainability aspirations. The lack of skilled personnel in the industry is another challenge, as 56% of Jordanian SMEs face the need for new skills in order to leverage AI effectively, including Jordanian IT businesses. This is consistent with the regional realities, as noted in [13] that human resource shortages are well documented. At the same time,

there is limited organizational readiness, inadequate infrastructure, legacy processes, and a lack of leadership support to adopt AI. Based on the results of the SME assessments done in Jordan [14], it has been found that SMEs, including IT companies, are not well equipped with advanced technologies. Another hurdle mentioned by [15] is that people are unaware of the strategic implications of AI. Adoption is being muddied by uncertain regulatory pressure. Jordanian companies also reference, as per [14], the absence of well-defined AI governance, ethical guidelines, as well as liability frameworks as a hindrance to the adoption of AI. This will need more than technical investment; a key and proactive policy environment and mindset will be necessary.

Despite extensive studies applying the Technology-Organization-Environment (TOE) framework in technology adoption for different industries, there is an apparent theoretical need for a nuanced understanding of the interaction between dimensions of TOE and technology adoption drivers such as AI adoption, particularly in the case of organizational sustainability. The majority of prior research focuses primarily on adoption success, including operational efficiency or user acceptance, leaving factors such as technological, organizational, and environmental elements and how they affect organizational sustainability untouched, as per several studies [16], [17], [18], [19]. Furthermore, the Diffusion of Innovations (DOI) theory has almost exclusively focused on the manner in which innovations are adopted and the attributes of innovations themselves; previous studies that considered DOI within the framework failed to fully incorporate technological context factors such as AI Compatibility, AI Complexity, and Innovation Culture [20], [21], and [22]. Similarly, the Resource-Based View (RBV) theory, useful to understand how firms use internal capabilities for competitive advantage, has been scarcely used as a complement to TOE and DOI to explain, from an integrative approach, how intangible assets (e.g., Top Management Support and Organizational Readiness) influence the achievement of Organizational Sustainability, as reported in several studies [23], [24], [25], and [26]. Moreover, the Institutional Theory was rarely integrated with theories like DOI, RBV, and TOE in the previous studies, where variables like Regulatory Pressure, Social Influence, and/or Competitive Pressure are linked with Organizational Sustainability, as per many papers [27], [28], [29], and [30]. Such a lack of use of theories together contributes to the absence of comprehensive models explaining the interaction of technological (AI complexity and compatibility), organizational (top management support, readiness and innovation culture), and environmental (regulatory pressure, social influence, competitive pressure) factors on sustainability in a single framework in both the lens of AI adoption as a mediator particularly in once marginalized sectors as engineering in emerging market economies such as Jordan, explained in many previous works [31], [32], [33], and [34]. The theoretical divide signals the need for a multi-theoretical and integrated analysis of the sustainability outcomes of the strategic use of technology adoption interventions in the organization.

Overall, this study will try to address these issues by bringing into focus the roles of the variables: Technological Factors (AI Complexity and AI Compatibility), Organizational Factors (Top management support, Organizational Readiness, and Innovation Culture), and Environmental Factors (Regulatory Pressure, Social Influence, and Competitive Pressure), as independent variables, with AI as a mediating variable. These are all related to Organizational sustainability in the field of Engineering, Electrical and Information Technology Industry Sector in Jordan.

3 Research Framework

The research is grounded in one core theory, which is the Technology-Organization-Environment (TOE) Framework, and three sub-theories, which are Diffusion of Innovations (DOI), Resource-Based View (RBV) Theory, and Institutional Theory (INT), which were selected to provide theoretical rationale for the study's variables. The overall structure of the model is based on the TOE Framework, according to which technological factors (AI complexity and AI compatibility), organizational factors (top management support, organizational readiness, innovation culture), and environmental factors (regulatory pressure, social influence, competitive pressure) determine organizational sustainability in Jordan. This model motivates internal and external factors shaping AI adoption as well as attending organizational consequences [17], [35], [36], [37], and [38].

DOI Theory is used to underpin AI complexity and AI compatibility as technological forces, with complexity and compatibility of innovation driving the adoption, in addition to innovation culture [38], [39], and [40]. Thus, using the RBV Theory to support Organizational Readiness and Organizational Sustainability, it can be shown that the exploitation of unique and valuable resources allows Engineering, Electrical and Information Technology Industry organizations to react to

external demands while preserving long-term competitive advantage and sustainability [41] and [42]. While Institutional Theory (INT) was selected to justify the selection of Regulatory Pressure, Top Management Support, Competitive Pressure, and Social Influence [27], [28], [29], and [30].

This study will attempt to overcome these problems by highlighting the roles of Technological Factors (AI Complexity and AI Compatibility), Organizational Factors (Top management support, Organizational Readiness, and Innovation Culture), and Environmental Factors (Regulatory Pressure, Social Influence, and Competitive Pressure) as independent variables, together with AI as a mediating variable. All of these variables are associated with Organizational sustainability among the Engineering, Electrical, and Information Technology industry sectors in Jordan. The research framework is illustrated in Figure 1. In this research, the following hypotheses are developed

H1: Technological factors have a significant positive effect on Organizational Sustainability.

H1a: AI Compatibility has a significant positive effect on Organizational Sustainability.

H1b: AI Complexity has a significant negative effect on Organizational Sustainability.

H2: Organizational factors have a significant positive effect on Organizational Sustainability.

H2a: Top management support has a significant positive effect on Organizational Sustainability.

H2b: Organizational Readiness has a significant positive effect on Organizational Sustainability.

H2c: Innovation Culture has a significant positive effect on Organizational Sustainability.

H3: Environmental factors have a significant positive effect on Organizational Sustainability.

H3a: Regulatory Pressure has a significant positive effect on Organizational Sustainability.

H3b: Social Influence has a significant positive effect on Organizational Sustainability.

H3c: Competitive Pressure has a significant positive effect on Organizational Sustainability.

H4: AI adoption mediates the relationship between the Technological Factors and Organizational Sustainability.

H4a: AI adoption mediates the relationship between AI complexity and Organizational Sustainability.

H4b: AI adoption mediates the relationship between AI compatibility and Organizational Sustainability.

H5: AI adoption mediates the relationship between the Organizational Factors and Organizational Sustainability.

H5a: AI adoption mediates the relationship between Top management support and Organizational Sustainability.

H5b: AI adoption mediates the relationship between Organizational Readiness and Organizational Sustainability.

H5c: AI adoption mediates the relationship between Innovation Culture and Organizational Sustainability.

H6: AI adoption mediates the relationship between the Environmental Factors and Organizational Sustainability.

H6a: AI adoption mediates the relationship between Regulatory Pressure and Organizational Sustainability.

H6b: AI adoption mediates the relationship between Social Influence and Organizational Sustainability.

H6c: AI adoption mediates the relationship between Competitive Pressure and Organizational Sustainability.

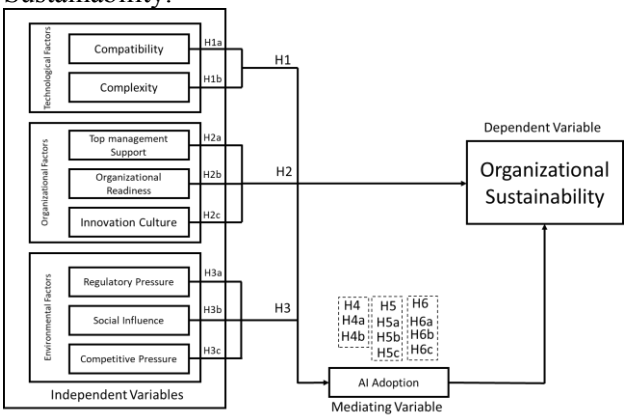


Fig. 1: The Study Framework

Source: Created by Author

4 Research Methodology

A quantitative research design was used in this study. This study's sample frame consists of the Jordan Chamber of Industry [43] reported 5,154 establishments in the Engineering, Electrical, and Information Technology Industry Sector in Jordan. The sector is an important part of Jordan's industrial and technological ecosystem, which is a strategic environment for examining the factors that influence the uptake of AI and organizational sustainability.

To make sure that every organization had an equal chance of being included in the study, a probability sampling technique was used, based on a systematic random sampling method to increase the representativeness of the sample. The list of all registered organizations in the sector was obtained from JCI and used as the sampling frame. The total

population (5,154) was divided by the desired sample size (396) to determine the sampling interval (13). As a result, 13 of these organizations were chosen to be surveyed.

This method is consistent with the usual practice of systematic sampling and will provide an unbiased and representative sample of participants drawn from the entire sector. The questionnaire was only open to those with a leadership position (CEOs, General Managers, Department heads, or senior executives). These will be selected based on their engagement in strategic decision-making, especially in the areas of AI implementation and sustainability projects in their respective organizations.

The data obtained from the 396 valid responses were analyzed with descriptive statistics, and preliminary analyses were performed in SPSS 30, while the evaluation of the hypothetical relationships was performed in Smart PLS 4 software using the structural equation modeling technique. Items of the questionnaire were adapted from existing measurement studies and are shown in Table 1 to be suitable for the context of IT SMEs in Jordan. The items of each construct were carefully examined and slightly modified to ensure clarity and relevance of each item and consistency with the objectives of the study.

Table 1. Instrument Development

Variable	Construct	References
AI Compatibility	4	[22], [44]
AI Complexity	6	[22]
Top management support	5	[45]
Organization Readiness	4	[46]
Innovation Culture	4	[47]
Regulatory Pressure	4	[48]
Social Influence	4	[49], [50]
Competitive Pressure	5	[51], [52]
AI adoption	5	[53]
Organizational Sustainability	9	[54]

Source: Created by Author

5 Data Analysis

5.1 Respondent Profile

The first segment of the instrument compiled information on the background profile of the respondents, which comprises their Age, Gender, Educational Level, and Years of experience. The characteristics of each demographic profile are described below in Table 2.

Table 2. Demographic Characteristics of Respondents (n = 396)

Item	Selection	Frequencies	Percentage
Age	Less than 25 YO	45	11.36
	26-35 YO	135	34.09
	36-45 YO	110	27.78
	46-55 YO	64	16.16
	56 YO and older	42	10.61
Gender	Male	265	66.92
	Female	131	33.08
Educational Level	Bachelor	203	51.26
	Master	106	26.77
	PhD	87	21.97
Years of Experience	less than 2 years	34	8.59
	2-4 years	127	32.07
	4-6 years	143	36.11
	More than 6 years	92	23.23

Source: Created by Author

The demographic profile of the respondents shows that the sample is well accomplished and experienced in both their profession and experience, as well as mature and well educated, which is suitable for the study of digital leadership and organizational sustainability in Engineering, Electrical and Information Technology sectors in Jordan.

As per age group, most of the respondents are between 26-35 years (34.09%) and 36-45 years (27.78%), respectively, with 61.87% of the respondents. This indicates that the majority of the respondents are active working-age people who are in a position to judge the sustainability and technology adoption of the organization, which has influence over decisions. The ages of respondents 46-55 years old (16.16%) and above 55 years old (10.61%) further reinforced the sample with input from high-experience and senior professionals.

In terms of gender, the respondents are mostly male (66.92%) and female (33.08%). This distribution is representative of the gender

distribution found in the engineering, electrical, and IT industry, which is typical of the region, thus improving the representativeness and external validity of the results.

In terms of educational attainment, over half of respondents have a Bachelor's degree (51.26%) and a significant number have postgraduate qualifications, such as a Master's degree (26.77%) and a PhD (21.97%). The high level of education suggests that these individuals possess adequate technical expertise and cognitive ability to grasp complex concepts like AI compatibility, AI complexity, digital leadership, and organizational sustainability, which are relevant in this context.

When it comes to work experience, the majority of respondents (36.11%) indicated that they had between 4 and 6 years of experience, followed by 2-4 years of experience (32.07%) and over 6 years of experience (23.23%). This is because more than 91% of the respondents have professional experience of at least two years, so their answers are based on experience in the organization and not only on theory. Few of the respondents have less than 2 years of experience (8.59%).

Overall, the respondents' profile indicates that the sample is sufficiently diverse and also competent and well-educated, justifying the reliability of the data and its use for testing the hypothesized relationships between technological, organizational, and environmental variables and digital leadership and organizational sustainability.

5.2 Measurement Model

The analysis was conducted in two stages: first, the measurement model was assessed to evaluate the reliability and validity of the constructs, followed by the structural model to examine the hypothesized relationships. CX and TMS recorded low Cronbach's Alpha values of 0.692 and below the acceptable threshold, Composite Reliability values below the recommended cut-off of 0.70, and Average Variance Extracted (AVE) values of 0.492 and 0.496 in the first run, all of which were below the recommended cut-offs of 0.70 for reliability and 0.50 for AVE [55]. Additionally, two items (CX2 and TMS4) had factor loadings below the acceptable threshold of 0.40. Therefore, a modification was made in the second run, and CX2 and TMS4 were removed to improve the scale. After their removal, the remaining items showed strong loadings ranging from 0.692 to 0.920, and the constructs achieved satisfactory reliability (Cronbach's Alpha ranging from 0.757 to 0.975; Composite Reliability ranging from 0.843 to 0.978) and convergent validity (AVE ranging from 0.573 to 0.831). Following this adjustment, all constructs met the recommended measurement criteria. (see Table 3).

Table 3. Convergent Validity Results

Items	Outer loadings	Cronbach's alpha	Composite reliability	AVE
AI1	0.895	0.930	0.931	0.782
AI2	0.871			
AI3	0.902			
AI4	0.878			
AI5	0.876			
CX1	0.770	0.828	0.836	0.591
CX3	0.790			
CX4	0.779			
CX5	0.732			
CX6	0.771			
CP1	0.807	0.849	0.854	0.623
CP2	0.774			
CP3	0.803			
CP4	0.797			
CP5	0.763			
CMP1	0.767	0.758	0.772	0.573
CMP2	0.747			
CMP3	0.809			
CMP4	0.702			
IC1	0.710	0.757	0.763	0.578
IC2	0.793			
IC3	0.744			
IC4	0.793			
ORE1	0.730	0.794	0.815	0.614
ORE2	0.797			
ORE3	0.818			
ORE4	0.788			
OS_EN1	0.913	0.975	0.975	0.831
OS_EN2	0.915			
OS_EN3	0.918			
OS_EV1	0.910			
OS_EV2	0.909			
OS_EV3	0.904			
OS_S1	0.908			
OS_S2	0.908			
OS_S3	0.920			
RP1	0.782	0.791	0.795	0.613
RP2	0.789			
RP3	0.764			
RP4	0.797			
SI1	0.740	0.795	0.834	0.613
SI2	0.840			
SI3	0.764			
SI4	0.786			
TMS1	0.767	0.796	0.804	0.619
TMS2	0.795			
TMS3	0.825			
TMS5	0.759			

Source: Created by Author

During the second step of the procedure, discriminant validity was assessed. This study was carried out with the purpose of determining the extent to which a certain construct is unique from other constructs. The degree of correlation that exists between the variables is an important aspect to consider when establishing validity. For the purpose of determining whether or not the constructs are legitimate, the square root of the average variance retrieved for each construct was utilized, as well as the correlations between the constructs themselves [56], [57]. In addition, the estimate provided by the model did not go much beyond 0.95, as stated in [57]. The results of the Fornell-Larcker Criterion are shown in Table 4 (Appendix). When the square root of each construct's Average Variance Extracted (AVE), displayed on the diagonal, is greater than its correlations with other constructs, displayed off-diagonal, discriminant validity is maintained. The square root of the average variance extracted (AVE) for each construct is greater than its correlations with all other constructs, as seen in Table 4 (Appendix), which demonstrates that the discriminant validity is sufficient [56].

Furthermore, the Heterotrait-Monotrait Ratio (HTMT) provides an estimate of the genuine correlation between two constructs, assuming that both were evaluated in a manner that was completely reliable or correct. Compared to the geometric mean of the average correlations between indicators that measure the same construct, the HTMT is the average of all correlations or cross-correlations between indicators that measure multiple constructs. This is in comparison to the average correlations between indicators that measure the same construct. The validity of discrimination may be evaluated using the HTMT. According to the research that has been done, the level of HTMT that is considered "acceptable" is 0.90. Please refer to Table 5 (Appendix) for further information.

5.3 Structural Model

The structural model represents the theoretical or conceptual aspects of the route model and illustrates those aspects. Within the PLS-SEM framework, the terms "inner model" and "structural model" are considered equivalent, as stated in [55]. This model accounts for both the latent variables and the paths that connect them to one another. The evaluation of the structural model will take place after the measurement model has been completed. In addition, [55] asserts that in order to conduct an evaluation of the structural model that is appropriate, it is essential to carry out four different actions. While these procedures are being carried out, the evaluation of the path coefficients (step 2), the assessment of collinearity (step 4), the evaluation of the coefficient f^2, and the estimation of the effect size (R^2) are all being carried out [55]. Table 6 (Appendix) and Figure 2 (Appendix), which are included in the appendix, present the findings in their entirety.

5.3.1 Assessment of the Structural Model for Collinearity Issues

Collinearity assessment is a vital assumption to ensure that multicollinearity does not exist. Collinearity diagnostics were performed to assess and identify multicollinearity among the predictors. This can be done by investigating the Variance Inflation Factor (VIF). The VIF should be 3.3 or lower, and not less than 1 [58]. Table 7 provides the multicollinearity test results and shows no VIF value above 3.3.

5.3.2 Assessing the Significance of Structural Model Relationships

The model's structural paths were evaluated to determine the significance of the path coefficients. The importance of these paths was assessed by examining the path coefficients and t-values. To test the hypothesis, PLS path modeling and bootstrapping were performed. The path coefficients and R^2 values were derived from the PLS analysis, while the t-values came from the bootstrapping process. As recommended [55], if the p-value is less than or equal to .05, the minimum acceptable t-value is 1.645. Additionally, the Beta value should be within -1 and +1; however, since the hypothesis in this study is positive, it should be positive. As shown in Table 6, all t-value scores meet the accepted level.

The analysis revealed several significant direct relationships. Specifically, H1 (TECH → OS) was significant ($\beta = 0.081$, $t = 2.946$, $p = 0.003$), indicating that technological factors positively influence organizational sustainability. At the dimensional level, H1a (CMP → OS) was supported ($\beta = 0.093$, $t = 3.460$, $p < 0.001$), whereas H1b (CX → OS) was insignificant ($\beta = 0.015$, $t = 0.623$, $p = 0.267$) and was therefore rejected. Furthermore, H2 (ORG → OS) showed a significant positive effect ($\beta = 0.128$, $t = 4.488$, $p < 0.001$). Its sub-dimensions, including H2a (TMS → OS) ($\beta = 0.094$, $t = 3.911$, $p < 0.001$), H2b (ORE → OS) ($\beta = 0.077$, $t = 3.082$, $p = 0.001$), and H2c (IC → OS) ($\beta = 0.097$, $t = 3.796$, $p < 0.001$), were all supported, confirming the importance of organizational factors in enhancing sustainability. In addition, H3 (ENV → OS) was also supported ($\beta = 0.111$, $t = 3.442$, $p = 0.001$), indicating

a significant influence of environmental factors. At the individual level, H3a (RP → OS) (β = 0.127, t = 4.852, p < 0.001), H3b (SI → OS) (β = 0.045, t = 1.808, p = 0.035), and H3c (CP → OS) (β = 0.107, t = 4.357, p < 0.001) were all found to be significant. Overall, the results demonstrate that technological, organizational, and environmental factors significantly contribute to organizational sustainability, with the exception of AI complexity, which did not show a significant direct effect.

5.3.3 The Coefficient of Determination (R^2)

Furthermore, [55] describes three levels of R^2 scores: .25, .50, and .75, representing weak, moderate, and substantial predictive accuracy. As shown in Table 7, the scores of R^2 for OS are considered at a substantial level.

Table 7. Coefficient of Determination (R^2)

Variable	R-square	R-square adjusted
AI	0.591	0.583
OS	0.798	0.793

Source: Created by Author

5.3.4 Assessment of the Effect Size (f^2)

The summary and inference on the f^2 estimate for independent (exogenous) constructs across the model are presented in Table 6. As recommended [20], an f^2 value below 0.02 indicates no effect. An f^2 value of 0.02 or higher is considered a weak effect, while values above 0.15 and 0.35 indicate medium and substantial effects, respectively [59]. For this classification, no impact was found for H1a (CX → OS), meaning that AI complexity does not contribute significantly to changes in organizational sustainability. Alternatively, H1b (CMP → OS) showed a weak to moderate effect size, indicating that variations in organizational sustainability can be partially attributed to being compatible with AI.

The overall technological construct had a weak ES, suggesting that technological factors as a whole are associated with sustainability, but have less impact than the other constructs.

The organizational factors showed a moderate effect size, with H2 (ORG → OS) indicating overall the importance of organizational capabilities. Specifically, the variables of top management support (H2a: TMS → OS) and innovation culture (H2c: IC → OS) had significant effect sizes, highlighting the importance of top management support and innovation culture in improving organizational sustainability. Meanwhile, the impact of ORE on OS was medium in size, indicating that organizational readiness had a moderate yet meaningful effect on sustainability outcomes.

In terms of environmental factors, H3 (ENV → OS) showed a moderate effect size and showed overall that external pressures are important. In individual cases, H3a (RP → OS) and H3c (CP → OS) showed significant effects, indicating that regulatory pressure, as well as competitive pressure, are significant factors affecting organizational sustainability. There was, however, a moderate effect size for H3b (SI → OS), indicating a moderate influence of social influence on sustainability performance.

5.3.5 The Mediating Assessment

Overall, in the current study, to assess the mediating effect of AI Adoption (AI) (namely H4, H4a, H4b, H5, H5a, H5b, H5c, H6, H6a, H6b, and H6c), the researcher employed PLS bootstrapping to examine both the direct and indirect effects through AI Adoption. The Bias-Corrected and Accelerated (BCa) confidence interval method was applied, as recommended by prior studies. Table 6 (Appendix) presents the results of PLS bootstrapping for both the direct and indirect effects.

As shown in Table 6 (Appendix), the current study proposed multiple hypotheses to evaluate the mediating role of AI Adoption. The mediating effect analysis conducted using SmartPLS revealed the following findings:

In H4, AI Adoption plays a significant mediating role in the relationship between Technological Factors (TECH) and Organizational Sustainability (OS), indicating mediation.

In H4a, AI Adoption plays a significant mediating role in the relationship between AI Complexity (CX) and Organizational Sustainability (OS), suggesting a meaningful indirect effect.

In H4b, AI Adoption plays a significant mediating role in the relationship between AI Compatibility (CMP) and Organizational Sustainability (OS), with a strong indirect effect observed.

In H5, AI Adoption plays a significant mediating role in the relationship between Organizational Factors (ORG) and Organizational Sustainability (OS).

In H5a, AI Adoption plays a significant mediating role in the relationship between Top Management Support (TMS) and Organizational Sustainability (OS).

In H5b, AI Adoption plays a significant mediating role in the relationship between Organizational Readiness (ORE) and Organizational Sustainability (OS).

In H5c, AI Adoption plays a significant mediating role in the relationship between Innovation Culture (IC) and Organizational Sustainability (OS).

In H6, AI Adoption plays a significant mediating role in the relationship between Environmental Factors (ENV) and Organizational Sustainability (OS).

In H6a, AI Adoption plays a significant mediating role in the relationship between Regulatory Pressure (RP) and Organizational Sustainability (OS).

In H6b, AI Adoption plays a significant mediating role in the relationship between Social Influence (SI) and Organizational Sustainability (OS).

However, in H6c, AI Adoption does not demonstrate a mediating role in the relationship between Competitive Pressure (CP) and Organizational Sustainability (OS), as this indirect path was not supported.

The findings suggest that, overall, AI Adoption acts as an important mediator between technological factors, organizational factors, and environmental factors, as well as organizational sustainability, with the majority of the relationships having significant indirect effects.

6 Discussion

Although the theoretical and empirical contribution of this research is substantial, it is important to recognize a few limitations in order to interpret the results as fairly as possible and to suggest directions for further research in this area. Such awareness of the limitations does not detract from the value of the study, but serves to strengthen the rigor of the study by setting limits for the interpretation of the findings.

First, this study used a cross-sectional research design that constrained the researcher from making causal inferences between the variables examined. While the proposed model and hypotheses were based on existing theories and had received sound statistical support, the data were gathered during a limited period of time. This may have resulted in the inability to fully capture the dynamic nature of the use of AI and the sustainability of the organization over time. The dynamics of the relationship between sustainability and digital transformation are a process of evolution, and longitudinal studies might help to gain more insights into how these relationships evolve over time, and how they change as AI technologies are developed.

Second, the study was based on self-reported data, obtained using a structured questionnaire, which may have led to common method bias and to subjective perception bias. Respondents' views on AI adoption, digital leadership, and sustainability outcomes could be influenced by personal attitudes, organizational norms, or social desirability. While careful statistical methods were used to ensure reliability and validity of data, perceptual measures were still used, which is a limitation. Future studies could consider using objective measures of performance and/or multi-source data to enhance measures.

Third, the study was limited to the Engineering, Electrical, and Information Technology industry sector in Jordan, which may limit the generalizability of the study results. A sectoral approach is one of the strengths of this study in filling a gap in the literature, but the results are not necessarily directly applicable to other industries or global contexts that have different regulatory frameworks, technological readiness, and culture. However, care must be exercised when generalizing the results to other sectors of society, such as healthcare, education, or services, and to other economies with varying degrees of digital infrastructure.

Fourth, while this study used a comprehensive framework that included technological, organizational, environmental, mediating and moderating variables, it did not take into account all those variables that could affect organizational sustainability. This study did not examine variables such as the size of organizations, financial resources, technological volatility, ethical AI management, and data quality. The model did not include these factors, which may reduce the extent to which the model explains the situation and imply potential avenues for further research to build upon the model.

Fifth, the measurement of digital leadership was through the lens of the respondents' perceptions of leadership behaviors and competencies, so this may not fully reflect the complexity of what leadership looks like in organizations. The level and type of leadership effectiveness may differ across different levels of hierarchy or functional areas, and future research could benefit from analyzing more than one leadership role or using mixed-method approaches to gain more nuanced understandings of digital leadership practices.

Lastly, despite the quantitative methodological orientation of the study, which was used to examine theoretical relationships and hypotheses, the contextual and behavioral processes driving them were not examined in detail. Qualitative or mixed-method studies might be used to support the findings and gain deeper insights into the how and why of the impact of AI adoption and digital leadership on

organizational sustainability, especially in complex and fast-changing technological contexts.

Another major drawback of the cross-sectional design is that it only provides a snapshot of organizational perceptions at one time, which fails to capture the dynamic and evolving process of AI adoption and organizational sustainability. Implementing AI and going digital usually takes place over time, with stages of experimentation, integration, and maturity. This means that the causal interpretations drawn from this study should be viewed with caution because it did not allow for examining the changes in the influence of leadership, changes in technological adaptation, and changes in sustainability outcomes over time. A longitudinal research design would yield stronger evidence of causality and enable future researchers to examine how AI adoption over time impacts sustainability performance at various stages of organizational development.

There is a second restriction that relates to having only one respondent per organization, which could be a source of single informant bias. This study gathered data from individual respondents, which may not necessarily reflect the perspectives of all organizational members regarding perceptions of AI adoption, digital leadership, and organizational sustainability. This can result in a partial or overly central understanding of organizational reality, especially when it comes to constructs like digital leadership and sustainability, which are understood differently in different parts of the organization and at different levels of the hierarchy. Future research should also look at obtaining data from more than one informant in a company, e.g., an overall average of senior managers, IT staff, and operational personnel, to strengthen the findings and make them more reliable.

Another constraint is the use of self-reported measures of an organization's sustainability outcomes. While perceptual measures are commonly employed in organizational studies, they do not always reflect the actual performance aspect of sustainability (such as cost saving, reduction of emissions, efficiency in energy use, or productivity gains). Social desirability bias, which can lead respondents to give overly positive ratings of sustainability performance, can also affect the results. This condition implies that the relationships reported are theoretical but may not be a true representation of operational results. Further research should include objective measures of sustainability or use archival data to more accurately and fairly measure organizational behavior.

Lastly, the results are applicable only in the particular context of the EIT sector in Jordan, where a unique institutional, technological, and economic environment exists. The emphasis on this context approach provides the internal validity of the study, but its results might be limited to other emerging economies, some of which might have different levels of digital infrastructure, regulatory maturity, organizational culture, and technological readiness. Hence, great care should be taken to extrapolate the results to other developing countries or sectors. The proposed model is recommended for replication in other national and sectoral contexts in future studies so that it can be validated and further developed in other emerging economy contexts.

To sum up: the scope of the present research is limited by these restrictions and is identified as a future research area. Overcoming these drawbacks in future studies would help to build a more complete body of knowledge around AI and organizational sustainability and bolster the strength of theory building in the field.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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APPENDIX

Table 4. Discriminant validity (Fornell and Larcker Criterion)

	AI	CX	CP	CMP	IC	ORE	OS	RP	SI	TMS
AI	0.884									
CX	0.336	0.769								
CP	0.262	0.005	0.789							
CMP	0.125	0.040	0.070	0.757						
IC	0.324	0.082	0.019	0.013	0.761					
ORE	0.317	0.048	0.041	0.037	0.005	0.784				
OS	0.874	0.353	0.291	0.123	0.327	0.302	0.812			
RP	0.240	0.039	0.013	0.021	0.058	0.046	0.285	0.783		
SI	0.276	0.032	0.003	0.022	0.083	0.102	0.158	0.024	0.783	
TMS	0.239	0.025	0.029	0.025	0.003	0.011	0.249	0.088	0.056	0.787

Source: Created by Author

Table 5. HTMT Discriminant validity

	AI	CX	CP	CMP	IC	ORE	OS	RP	SI	TMS
AI										
CX	0.379									
CP	0.292	0.064								
CMP	0.139	0.061	0.100							
IC	0.384	0.110	0.085	0.075						
ORE	0.362	0.076	0.092	0.093	0.063					
OS	0.817	0.386	0.316	0.136	0.379	0.332				
RP	0.277	0.080	0.063	0.072	0.116	0.092	0.322			
SI	0.312	0.064	0.070	0.080	0.114	0.145	0.170	0.081		
TMS	0.276	0.073	0.087	0.081	0.057	0.068	0.281	0.114	0.075	

Source: Created by Author

Table 6. Structural Model Path Coefficients

H	Path	Beta	STD Error	T-value	P-values	Decision	Confidence Interval		f^2	Effect Size	VIF	R^2
							5.00%	95.00%				
H1	TECH -> OS	0.081	0.028	2.946	0.003	Supported	0.028	0.137	0.226	Medium	1.159	0.798
H1a	CX -> OS	0.015	0.024	0.623	0.267	Rejected	-0.023	0.055	0.001	No Effect	1.028	
H1b	CMP -> OS	0.093	0.027	3.460	0.000	Supported	0.050	0.139	0.381	Substantial	1.188	
H2	ORG -> OS	0.128	0.029	4.488	0.000	Supported	0.070	0.181	0.377	Substantial	1.585	
H2a	TMS -> OS	0.094	0.024	3.911	0.000	Supported	0.057	0.135	0.387	Substantial	1.169	
H2b	ORE -> OS	0.077	0.025	3.082	0.001	Supported	0.038	0.120	0.291	Medium	1.333	
H2c	IC -> OS	0.097	0.026	3.796	0.000	Supported	0.056	0.139	0.371	Substantial	1.228	
H3	ENV -> OS	0.111	0.032	3.442	0.001	Supported	0.047	0.173	0.380	Substantial	1.494	
H3a	RP -> OS	0.127	0.026	4.852	0.000	Supported	0.086	0.173	0.401	Substantial	1.228	
H3b	SI -> OS	0.045	0.025	1.808	0.035	Supported	0.002	0.084	0.189	Medium	1.207	
H3c	CP -> OS	0.107	0.025	4.357	0.000	Supported	0.068	0.149	0.429	Substantial	1.199	
H4	TECH -> AI -> OS	0.190	0.027	6.937	0.000	Supported	0.137	0.244				
H4a	CX -> AI -> OS	0.058	0.025	2.337	0.010	Supported	0.023	0.093				
H4b	CMP -> AI -> OS	0.191	0.024	7.943	0.000	Supported	0.151	0.230				
H5	ORG -> AI -> OS	0.373	0.031	11.946	0.000	Supported	0.309	0.433				
H5a	TMS -> AI -> OS	0.182	0.024	7.583	0.000	Supported	0.140	0.219				
H5b	ORE -> AI -> OS	0.258	0.026	9.994	0.000	Supported	0.213	0.299				
H5c	IC -> AI -> OS	0.210	0.026	8.229	0.000	Supported	0.164	0.249				
H6	ENV -> AI -> OS	0.344	0.029	11.886	0.000	Supported	0.285	0.398				
H6a	RP -> AI -> OS	0.211	0.024	8.872	0.000	Supported	0.169	0.247				

H6b	SI -> AI -> OS	0.197	0.026	7.495	0.000	Supported	0.151	0.237				

Source: Created by Author

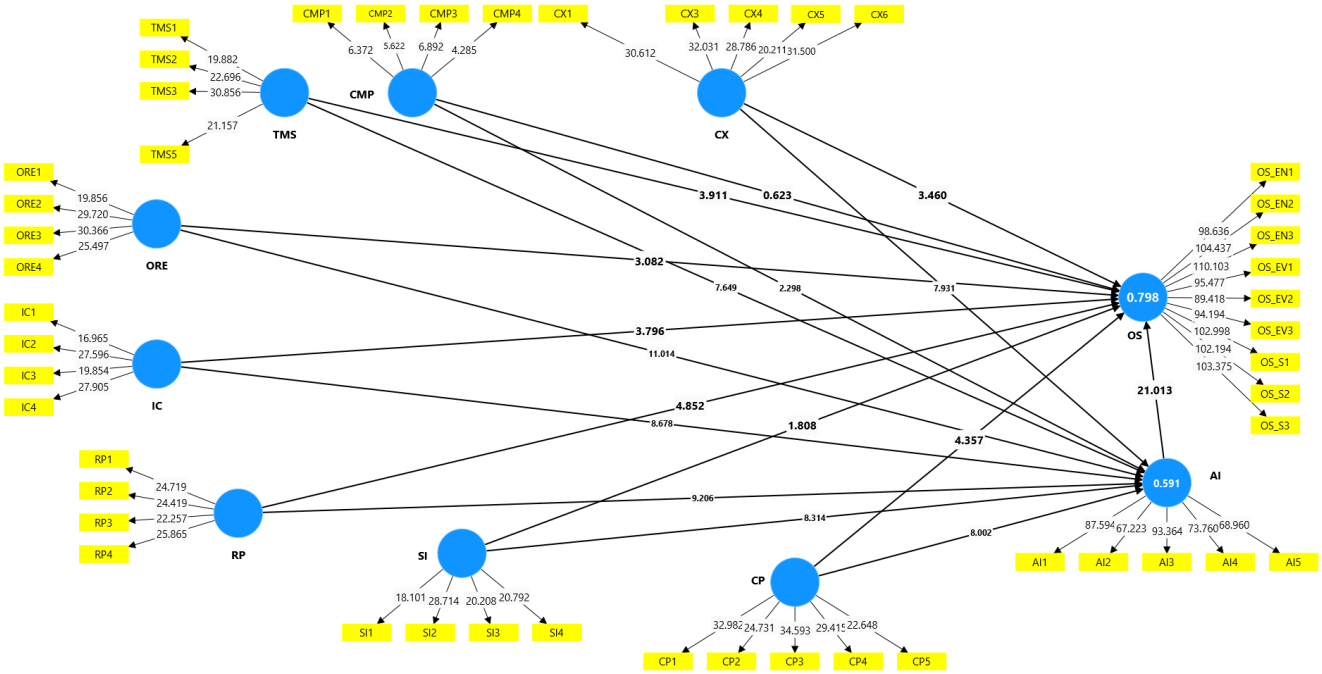


Fig. 2: The Study Framework
Source: Created by Author