The Effect of Organizational AI Absorptive Capacity on Employees' Smart Work Environment Perception and Digital Innovative Behavior: The Moderating Role of Digital Transformational Leadership

NABIL ABUDARWISH, MOHAMMAD MUSA AL-MOMANI, MOHAMMED BASSAM NASSOURA, BILAL ALNASSAR, AHMAD AWADALLAH
Department of Business Information Technology
Zarqa University
Zarqa
JORDAN

Abstract: - This study investigates the effect of organizational artificial intelligence (AI) absorptive capacity on employees' perceptions of the smart work environment and how these perceptions influence their digital innovative behavior in the telecommunications industry, with Digital Transformational Leadership as a moderating variable. In this study, two important theoretical perspectives were utilized: Absorptive Capacity Theory, which highlights how organizations acquire, assimilate, and apply their knowledge related to AI, and Socio-Technical Systems Theory, which addresses the connection between technology and the social aspect of the working environment. A quantitative research design was used through partial least squares structural equation modeling (PLS-SEM). The data were gathered from 279 respondents working in the telecommunication industry in Jordan. These respondents worked for internet service providers, network operators, and mobile network operators. The findings show that organizational AI absorptive capacity has a strong positive effect on Smart Work Environment Perception ($\beta = 0.742$), which in turn enhances Digital Innovative Behavior ($\beta = 0.681$). Smart Work Environment Perception partially mediates the relationship between AI absorptive capacity and Digital Innovative Behavior (indirect effect $\beta = 0.506$), while Digital Transformational Leadership positively moderates the relationship between AI absorptive capacity and the smart work environment ($\beta = 0.276$) and between the smart work environment and Digital Innovative Behavior ($\beta = 0.241$). The current research adds value to the literature surrounding AI adoption within organizations by examining how technical capabilities and organizational leadership help foster Digital Innovative Behavior in the telecommunications industry.

Key-Words: - Organizational AI Absorptive Capacity, Smart Work Environment Perception, Digital Innovative Behavior, Digital Transformational Leadership, PLS-SEM, Telecommunications.

Received: February 11, 2026. Revised: April 19, 2026. Accepted: June 22, 2026. Published: November 2, 2026.

1 Introduction

Organizational business landscapes have witnessed revolutionary changes as a result of the emergence and development of modern artificial intelligence (AI) technologies and digital transformation [1]. Organizations use intelligent systems to make their operations more effective, efficient, and productive in terms of improving administration processes and making decisions. The industry that faces the biggest challenge in terms of transformation is the telecommunication industry since it operates using modern technologies.

Absorptive Capacity Theory [17] becomes crucial in the context of AI technologies because it explains how an organization can gain, incorporate, and utilize knowledge concerning new technologies in its business practices [2]. In other words, while adopting AI technologies becomes crucial for organizations' successful operation in the modern competitive environment, an equally important factor is the organization's capacity to assimilate these technologies.

Moreover, the emergence of the smart working environment represents one of the main outcomes of digital transformation [3]. This means that there is a data-driven environment that is characterized by the automation of processes and technological and human system fusion. This creates an environment that positively influences employee behavior and encourages employees to innovate and engage with digital technology. Digital innovation has been identified as one of the main behavioral outcomes in the digital age because of the ability of the employees to come up with ideas through the use of the technology and solving work-related challenges.

This shows that it has become very important for managers and researchers to consider the factors that influence this behavior. In this case, Digital Transformational Leadership is vital because of its ability to facilitate employees in innovating and adopting a smart work environment [4].

Consequently, this research becomes highly significant in relation to the telecommunications industry, which has been among the leading adopters of AI technology [5]. The objective of this study is to investigate the effect of organizational AI absorptive capacity on employees' perceptions of the smart work environment and on their Digital Innovative Behavior (hereafter AIAC, SWEP, and DIB, respectively). Also, the study will look at the moderating role played by Digital Transformational Leadership (DTL) in establishing such connections. The theories that have informed this study include Absorptive Capacity Theory and Socio-Technical Systems Theory. These theories help to establish the connection between technology and human resource management in a digitalized working environment [6].

The study also differs clearly from earlier work by members of the present author team, which examined the adoption of electronic commerce in small and medium enterprises [14], the integration of AI and business intelligence for enterprise performance [15], and the role of business intelligence in supply-chain optimization [16]. None of these studies examined AI absorptive capacity, smart work environment perception, Digital Transformational Leadership, or employee-level Digital Innovative Behavior, and the present study uses a different population, research model, and newly collected dataset. The remainder of the paper is organized as follows: Section 2 reviews the literature and develops the hypotheses; Section 3 describes the methodology; Section 4 presents the results; Section 5 discusses the findings; Section 6 outlines the contributions; and Section 7 concludes the paper.

2 Literature Review and Hypotheses Development

2.1 Smart Work Environment Perception and Digital Innovative Behavior

An intelligent working environment influences the Digital Innovative Behavior of employees through the relationship between technological systems and human beings in the organization. Through the use of smart systems, employees have access to sophisticated tools used for obtaining information and sharing knowledge [7]. These enable the employees to interact with the technology and make use of it to come up with innovations. Interaction between employees and the technological system stimulates innovative behavior, such as coming up with ideas on how to solve problems and making use of smart digital tools to perform better.

The reason behind such correlation can be explained based on the mechanism of Socio-Technical Systems Theory, whereby it states that the individual behavior in an organization emerges through the interaction of both the technological and social systems in the organization [8]. In this case, when there is a smart workplace which facilitates high integration of both these systems, the result is the creation of an exciting organizational setting, enabling individuals to participate and experiment in the organization. This leads to digital innovation within the organization. Accordingly, the following hypothesis is proposed:

H1: Smart Work Environment Perception has a positive effect on Digital Innovative Behavior.

2.2 Organizational AI Absorptive Capacity and Smart Work Environment Perception

The ability of the organization to assimilate AI technologies will affect the creation of the smart working environment in telecom organizations. Firstly, the organization learns about the technical knowledge concerning the implementation of AI technology, after which it becomes capable of understanding, integrating, and implementing this knowledge in its processes [9]. All this demonstrates the organization's way of converting technical knowledge into practical application in the working environment through process automation, information management, and creation of the digital infrastructure. Consequently, the resulting working environment turns into a smart environment based on data and technology.

The reason for this connection is rooted in the organizational absorptive capacity, a concept that operates in three sequential steps that include acquisition of external knowledge about AI, its internalization by means of comprehension and analysis and its application through the transformation into practical uses within the organization [10]. As a result of such interaction, technical knowledge is turned into organizational value via process optimization and digitization, creating the prerequisites for the smart work environment in telecommunications organizations. Hence:

H2: Organizational AI Absorptive Capacity has a positive effect on Smart Work Environment Perception.

2.3 The Moderating Role of Digital Transformational Leadership

Digital Transformational Leadership serves as a catalyzing force that shapes the interaction between the capacity for the acquisition and assimilation of AI knowledge in an organization and the creation of a smart work environment in the telecommunication sector [11]. Although the capacity of an organization to acquire and assimilate AI knowledge is essential in the creation of a smart work environment, its success highly relies on the type of leadership within the organization. Digital Transformational Leadership supports digital transformation through offering vision, inspiring employees, and creating a learning culture.

The reason for this relationship lies in the nature of Digital Transformational Leadership, which involves inspiration, intellectual stimulation, and the digital empowerment of employees. Digital Transformational Leadership, in other words, can be considered positively correlated with an organization's ability to apply and implement AI knowledge and technologies into tangible applications and intelligent systems in the workplace setting [12]. The more prominent the role played by Digital Transformational Leadership, the more pronounced the effect of the organization's AI absorptive capabilities on its smart work environment. Therefore:

H3: Digital Transformational Leadership positively moderates the relationship between Organizational AI Absorptive Capacity and Smart Work Environment Perception, such that the relationship is stronger when Digital Transformational Leadership is high.

Digital Transformational Leadership is also expected to shape how employees translate a smart work environment into innovative action. Even when smart tools and data-driven systems are available, employees may not experiment with them unless leaders articulate a clear digital vision, provide intellectual stimulation, and tolerate the risks that accompany experimentation [4], [12]. Consistent with Socio-Technical Systems Theory, leadership is part of the social subsystem that determines whether the technical subsystem is used creatively [8]. Hence:

H4: Digital Transformational Leadership positively moderates the relationship between Smart Work Environment Perception and Digital Innovative Behavior, such that the relationship is stronger when Digital Transformational Leadership is high.

2.4 The Mediating Role of Smart Work Environment Perception

The AI absorptive capacity within an organization has an impact on Digital Innovative Behavior since the required knowledge base and the technical capabilities have to be established at the organizational level first [10]. When technical knowledge is acquired and applied, it enables people to effectively use AI technologies in their everyday work. Such a development goes beyond the organizational level and allows people to think of new ideas and innovate in a digital manner.

The above statement is supported by the Absorptive Capacity Theory. According to this theory, knowledge transfer happens on several levels within an organization [13], [14]. First, there is the acquisition of external knowledge related to AI technology; then the internal assimilation and understanding take place; and finally, the knowledge becomes applied. Thus, when such a process of knowledge transfer takes place within an organization, it leads to people's ability to innovate digitally [15], [16]. Part of this effect is expected to be direct, while part is expected to be transmitted through the smart work environment that AI absorptive capacity creates. Accordingly:

H5: Organizational AI Absorptive Capacity has a positive direct effect on Digital Innovative Behavior.

H6: Smart Work Environment Perception mediates the relationship between Organizational AI Absorptive Capacity and Digital Innovative Behavior.

2.5 Conceptual Framework

Figure 1 presents the conceptual framework. Each box represents a latent construct and each arrow corresponds to one hypothesis. The solid horizontal arrows denote the direct effects AIAC → SWEP (H2) and SWEP → DIB (H1), and the curved arrow denotes the direct effect AIAC → DIB (H5). The sequence AIAC → SWEP → DIB constitutes the mediating relationship (H6), in which SWEP transmits part of the effect of AIAC to DIB. The two dashed arrows originating from DTL do not point to a construct but to the middle of the AIAC → SWEP and SWEP → DIB paths; they therefore represent moderating relationships (H3 and H4), in which DTL is expected to change the strength of these relationships rather than to affect a construct directly.

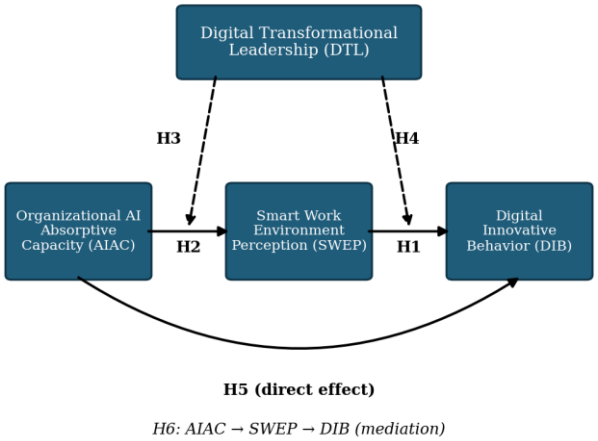


Fig. 1: Conceptual framework and research hypotheses
Source: created by the authors.

3 Methodology

A quantitative method was used in order to explore the inter-relationships among the variables of the proposed theoretical model. A descriptive-analytical, cross-sectional design was utilized to investigate the effect of AI absorptive capacity on the smart work environment and Digital Innovative Behavior, as well as the moderation of Digital Transformational Leadership on the above-mentioned relations. This method is appropriate to use in scientific research where hypotheses and cause-and-effect relationships need to be tested.

3.1 Research Population

The population under investigation consists of employees in Jordanian telecommunication companies such as ISPs, telecommunication network operators, and mobile communication network operators. This is due to the fact that this industry is highly dependent upon artificial intelligence technologies.

3.2 Sample, Sampling Procedure, and Respondents

The study was conducted in the telecommunications industry in the Hashemite Kingdom of Jordan among employees working in internet service providers, network companies, and mobile telecommunications service providers. The convenience sampling approach was used by distributing questionnaires among the target population and asking for their voluntary participation. Specifically, 300 questionnaires were distributed in January–February 2026, among which 290 were returned. After removing 11 questionnaires that could not be used for analysis or were filled out incorrectly, the final number of analyzed questionnaires equals 279, which is 93.00% of the initial sample.

Sample adequacy was assessed with two criteria. According to the ten-times rule, the sample should be at least ten times the largest number of structural paths pointing at any construct; with at most four predictors of DIB (AIAC, SWEP, DTL, and the SWEP × DTL interaction term), at least 40 observations are required. Using the more conservative inverse square root method [20], with the smallest path coefficient in the model (0.241) and a 5% significance level, the minimum sample size is $(2.486 / 0.241)^2 \approx 107$. The sample of 279 respondents exceeds both thresholds.

Of the 279 respondents, 61.3% were male and 38.7% female; 93 employees (33.3%) worked for mobile network operators, 79 (28.3%) for internet service providers, and 107 (38.4%) for network operators. Most respondents held a bachelor's degree (174 employees, 62.4%), had 5–10 years of work experience, and 58.4% occupied technical positions.

3.3 Questionnaire Development and Measures

In this study, data were collected using a structured questionnaire consisting of two parts: the first part collected the demographic and job characteristics of respondents, and the second part measured the four study constructs. All items were adapted from previously validated scales: AIAC was measured with 6 items adapted from [10], [17]; SWEP with 5 items adapted from [7], [8]; DIB with 6 items adapted from [4], [12]; and DTL with 5 items adapted from [11], [12]. All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was translated into Arabic using back-translation, reviewed by 5 academic experts for content validity, and pre-tested on a pilot sample of 30 employees who were not included in the final sample.

The data used in this study were collected specifically and independently for the present research and have not been used in any of the authors' previous publications or submissions, including [14]–[16].

3.4 Data Analysis

In order to analyze the data collected, Partial Least Squares Structural Equation Modeling (PLS-SEM) was performed using SmartPLS 4.1.0.6. Following the two-step approach recommended by Hair et al. [18], the measurement model was assessed first through indicator loadings, Cronbach's α, composite reliability (CR), average variance extracted (AVE), and discriminant validity using the Fornell–Larcker

criterion [19]; the structural model was then assessed to test the hypotheses. The significance of path coefficients was determined by bootstrapping with 5,000 subsamples, using percentile 95% confidence intervals and two-tailed tests at the 5% significance level. Collinearity among predictor constructs was examined with the variance inflation factor (VIF). Explanatory power was evaluated with R^2, effect sizes with Cohen's f^2 (0.02, 0.15, and 0.35 indicating small, medium, and large effects) [21], and predictive relevance with Stone–Geisser's Q^2, obtained using the blindfolding procedure with an omission distance of D = 7 [18], [22]. The mediating effect (H6) was tested by bootstrapping the indirect effect and classified following Zhao et al. [23]. The moderating effects (H3 and H4) were estimated by creating interaction terms using the two-stage approach in SmartPLS. This technique is appropriate for the analysis since the model includes mediating and moderating relationships.

3.5 Validity, Reliability, and Ethical Considerations

Validity and reliability were measured by using composite reliability, convergent validity, and discriminant validity in order to check the validity of the instrument used in measuring the constructs. Ethics were observed in this study since confidentiality of information provided by the respondents was assured, the data were used for research purposes only, and respondents could withdraw at any point of time. The study was reviewed and approved by the Scientific Research Ethics Committee at Zarqa University (approval No. 24/2025/117, dated November 26, 2025). Participation was voluntary, respondents were informed of the purpose of the study, and informed consent was obtained before the questionnaire was completed. No personally identifying information was collected.

4 Results

4.1 Measurement Model

The results from the validity and reliability test indicate that all study variables have very high degrees of internal reliability, with Cronbach's alpha values ranging from 0.874 to 0.903, above the minimum acceptable threshold of 0.70, thus indicating high internal consistency of items for each study variable. In addition, the composite reliability values of 0.911 to 0.932 indicate the very high level of consistency and reliability of the measurement instruments. With respect to convergent validity, all average variance extracted (AVE) values were above the minimum acceptable threshold of 0.50, with a range of 0.742 to 0.783. This implies that the items of each variable account for a substantial proportion of the variance in the variables. All indicator outer loadings ranged from 0.795 to 0.912, exceeding the recommended value of 0.708 [18].

Table 1. Reliability and convergent validity of the constructs

Construct	Items	Source	α	CR	AVE
AIAC	6	[10], [17]	0.891	0.924	0.783
SWEP	5	[7], [8]	0.874	0.911	0.742
DIB	6	[4], [12]	0.903	0.932	0.769
DTL	5	[11], [12]	0.886	0.918	0.756

Source: created by the authors.

Note: AIAC = Organizational AI Absorptive Capacity; SWEP = Smart Work Environment Perception; DIB = Digital Innovative Behavior; DTL = Digital Transformational Leadership; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Table 1. reports, for each construct, the number of items, the source of the adapted scale, and the three reliability and convergent-validity indicators. Cronbach's α ranges from 0.874 (SWEP) to 0.903 (DIB), and CR ranges from 0.911 (SWEP) to 0.932 (DIB); all values exceed the 0.70 threshold and remain below 0.95, the level above which item redundancy becomes a concern [18]. AVE ranges from 0.742 (SWEP) to 0.783 (AIAC), meaning that each construct explains roughly three-quarters of the variance of its own items, well above the 0.50 criterion. SWEP shows the lowest, and DIB and AIAC the highest, values on these indicators, but the differences are small, and the measurement model can therefore be used to estimate the structural model

Table 2. Discriminant validity (Fornell–Larcker criterion)

	AIAC	SWEP	DIB	DTL
AIAC	**0.885**			
SWEP	0.701	**0.861**		
DIB	0.612	0.744	**0.877**	
DTL	0.598	0.621	0.655	**0.869**

Source: created by the authors.

Note: Diagonal values (bold) are the square roots of the AVEs in Table 1; off-diagonal values are inter-construct correlations.

Table 2. assesses discriminant validity using the Fornell–Larcker criterion [19]. The diagonal values

are the square roots of the AVEs reported in Table 1 (√0.783 = 0.885 for AIAC, √0.742 = 0.861 for SWEP, √0.769 = 0.877 for DIB, and √0.756 = 0.869 for DTL), and the off-diagonal values are the correlations between constructs. Each diagonal value exceeds every correlation in its row and column. The highest correlation, between SWEP and DIB (0.744), is lower than both √AVE of SWEP (0.861) and √AVE of DIB (0.877); likewise, the correlation between AIAC and SWEP (0.701) is lower than 0.885 and 0.861, and the correlations of DTL with the other constructs (0.598–0.655) are lower than 0.869. Each construct therefore shares more variance with its own indicators than with any other construct, which supports discriminant validity

4.2 Structural Model

Before the structural relationships were evaluated, collinearity among the predictor constructs was examined. The inner-model VIF values ranged from 1.842 to 2.451 (Table 5), below the threshold of 3 [18], indicating that collinearity does not bias the path estimates.

Table 3. Coefficient of determination (R^2) and predictive relevance (Q^2)

Endogenous construct	**R^2**	**Q^2**	**Interpretation**
SWEP	0.551	0.402	Moderate R^2; large Q^2
DIB	0.673	0.463	Moderate R^2; large Q^2

Source: created by the authors.

Table 3. reports the explanatory power (R^2) and predictive relevance (Q^2) of the two endogenous constructs. R^2 was obtained from the PLS algorithm and represents the proportion of variance in each endogenous construct explained by the constructs that point to it. AIAC, together with DTL and the AIAC × DTL interaction term, explains 55.1% of the variance in SWEP (R^2 = 0.551), and AIAC, SWEP, DTL, and the SWEP × DTL interaction term jointly explain 67.3% of the variance in DIB (R^2 = 0.673). According to the guidelines of Hair et al. [18] (0.25 weak, 0.50 moderate, 0.75 substantial), both values indicate moderate explanatory power, with DIB approaching the substantial level. This is consistent with the view that digital innovation in telecommunication organizations is not determined by a single variable but results from the combined effect of organizational capability, the work environment, and leadership

Q^2 was obtained using the blindfolding procedure with an omission distance of D = 7, which omits part of the data, re-estimates the model, and predicts the omitted values. A Q^2 greater than zero indicates that the model has predictive relevance for a given construct, while values of 0.02, 0.15, and 0.35 indicate small, medium, and large predictive relevance, respectively [18]. The Q^2 values of 0.402 for SWEP and 0.463 for DIB are therefore above zero and indicate large predictive relevance. These values show that the model has predictive relevance for both endogenous constructs; they do not, however, by themselves show that the model's predictions are accurate in an absolute sense.

The findings indicate a high level of impact of organizational AI absorptive capacity ($\beta = 0.742$, $t = 12.315$, $p < 0.001$; H2) on Smart Work Environment Perception, since telecommunications companies that are more capable in terms of acquiring, analyzing, and utilizing their technical knowledge would be able to redesign the modern digital work environment accordingly. It seems that digital transformation in such organizations is not a chance process but is a result of the development of organizational competencies required for the assimilation of the technology. Another finding is that the smart work environment positively impacts Digital Innovative Behavior ($\beta = 0.681$, $t = 10.842$, $p < 0.001$; H1), because creating a data-driven, automated, and interconnected digital environment encourages harmonious interactions between employees and technologies, thus increasing their propensity to come up with innovative solutions.

In addition, the direct effect of AI absorptive capacity on Digital Innovative Behavior ($\beta = 0.389$, $t = 6.214$, $p < 0.001$; H5) implies that the effect of AI is not limited to altering the organizational environment; it also impacts employee behavior in a direct way. This means that having more technological and cognitive skills in organizations due to available knowledge and technology gives employees the ability to engage in innovation regardless of whether or not the organizational environment has changed.

In relation to the moderating effect of Digital Transformational Leadership, findings imply that it strengthens the relationship between AI absorptive capacity and smart work environment ($\beta = 0.276$, $t = 4.983$, $p < 0.001$; H3). This shows the impact that supportive Digital Transformational Leadership has on accelerating the process of translating technical knowledge to organizational settings. Similarly, Digital Transformational Leadership strengthens the relationship between smart work environment and Digital Innovative Behavior ($\beta = 0.241$, $t = 4.417$, $p < 0.001$; H4). The positive signs of both interaction terms indicate that the two relationships become

stronger as the level of Digital Transformational Leadership increases.

The findings indicate a substantial mediating effect of the smart work environment on the connection between organizational AI absorptive capacity and Digital Innovative Behavior (indirect effect β = 0.506, t = 8.732, p < 0.001; H6). The indirect effect equals the product of the two component paths (0.742 × 0.681 ≈ 0.505), and its bootstrap confidence interval [0.412, 0.598] does not include zero. Because the direct effect of AIAC on DIB (β = 0.389) is also positive, the mediation is partial (complementary) in the sense of Zhao et al. [23]: the total effect of AIAC on DIB is 0.895 (0.389 + 0.506), and the indirect path accounts for approximately 56.5% of it (variance accounted for, VAF = 0.506 / 0.895). In other words, the effect of artificial intelligence on innovation is partly direct, and partly the result of the process through which the work environment is transformed. This transformation plays an intermediary role, acting as a medium of the influence of the organizational resources and their transmission to the employee's behavior.

Table 4. Results of hypothesis testing

Hyp.	Path	β	t-value	p-value	Decision
H1	SWEP → DIB	0.681	10.842	0.000	Supported
H2	AIAC → SWEP	0.742	12.315	0.000	Supported
H3	DTL × AIAC → SWEP	0.276	4.983	0.000	Supported
H4	DTL × SWEP → DIB	0.241	4.417	0.000	Supported
H5	AIAC → DIB (direct)	0.389	6.214	0.000	Supported
H6	AIAC → SWEP → DIB (indirect)	0.506	8.732	0.000	Supported (partial)

Source: created by the authors.

Note: β = standardized path coefficient; t- and p-values obtained by bootstrapping (5,000 subsamples, two-tailed); × denotes an interaction (moderating) term.

Table 4. summarizes the hypothesis tests. The two direct paths of the mediation chain are the strongest relationships in the model: AIAC → SWEP (β = 0.742) and SWEP → DIB (β = 0.681), both with t-values above 10. The direct effect of AIAC on DIB (β = 0.389) is about half the size of the AIAC → SWEP path, which is consistent with partial mediation. The two moderating effects are smaller (β = 0.276 and 0.241), as is usual for interaction terms, but the first is highly significant (t = 4.983). The indirect effect (β = 0.506) is significant and close to the product of its two component paths, as expected for a mediated path

Table 5. Confidence intervals, effect sizes, and collinearity diagnostics

Path	95% CI	f²	VIF
AIAC → SWEP	[0.654, 0.812]	0.963	1.842
SWEP → DIB	[0.598, 0.752]	0.874	2.316
AIAC → DIB	[0.271, 0.498]	0.162	2.108
DTL × AIAC → SWEP	[0.171, 0.376]	0.038	1.927
DTL × SWEP → DIB	[0.139, 0.338]	0.032	2.451
AIAC → SWEP → DIB	[0.412, 0.598]	–	–

Source: created by the authors.

Note: CI = percentile bootstrap confidence interval; f² = Cohen's effect size (0.02 small, 0.15 medium, 0.35 large); VIF = inner-model variance inflation factor.

Table 5. complements Table 4 with the bootstrap confidence intervals, the effect sizes, and the collinearity diagnostics of each path. A path is considered significant when its 95% confidence interval does not include zero. The effect size f² indicates how much R² of the endogenous construct decreases when the predictor is removed from the model. For interaction terms, f² values of 0.005, 0.01, and 0.025 are regarded as small, medium, and large effects, respectively [18]

Figure 2. Displays the estimated structural model with the standardized path coefficients and the R² values of the endogenous constructs, so that each hypothesis in Figure 1 can be compared directly with its estimated effect

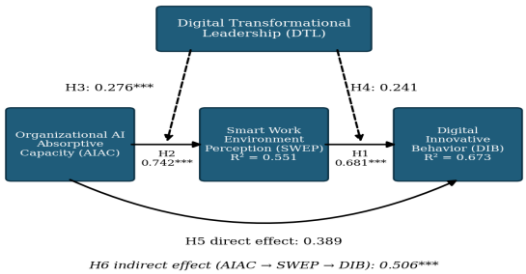


Fig. 2: Estimated structural model (standardized coefficients; *** p < 0.001)

Source: created by the authors.

5 Discussion

The findings from the study have clearly demonstrated that organizational AI absorptive capacity is significant when developing a smart work environment in the telecommunication industry (H2).

This observation can be attributed to the fast pace at which the industry is changing. Adaptation to AI technology is currently not just about technology but rather the organizational ability to do so. It is important for organizations to have the necessary capabilities to be able to acquire technical knowledge and utilize it in their business processes. Organizations that are capable in this respect are more likely to adapt to smart technology through a restructured work environment.

The findings further indicated that the smart working environment had a profound effect on the Digital Innovative Behavior of employees (H1). This may be due to the characteristics of the smart working environment that are automated, provide instant feedback, and improve knowledge management systems. The smart environment is not just efficient but also an environment that promotes innovation and helps employees engage in innovation by allowing them to explore different ideas, use the digital medium in novel ways, and find solutions to business problems in a creative manner.

The findings have further corroborated the mediating effect of the smart work environment on the relationship between organizational AI absorptive capacity and Digital Innovative Behavior (H6), indicating that this smart work environment acts as an intermediary factor through which the effects of the former variable are channeled to the latter. Because AIAC also has a direct effect on DIB (H5), the mediation is partial: AIAC influences DIB both directly ($\beta = 0.389$) and indirectly through SWEP ($\beta = 0.506$), with the indirect path accounting for about 56.5% of the total effect. The effects therefore depend to a large extent on how the organizational context is changed to affect the employees' actions. Consequently, the smart environment becomes an important explanation of how AI affects the individuals via the organization.

With respect to the effect of Digital Transformational Leadership as a moderator, the findings indicated that Digital Transformational Leadership positively moderates the relationship between AIAC and SWEP (H3, $\beta = 0.276$) and the relationship between SWEP and DIB (H4, $\beta = 0.241$). The rationale behind this phenomenon lies in the fact that Digital Transformational Leadership is not only about giving instructions from the managerial position but includes such important elements as building a common vision regarding digital transformation, motivating employees to work with technology, overcoming employee resistance to new technologies, and fostering experimentation and innovation.

Thus, Digital Transformational Leadership helps increase organizational trust and create the proper conditions for implementing digital transformation, contributing to the effectiveness of organizational absorptive capacity and of the smart environment concerning innovative behavior. In summary, the research indicates that digital innovation in telecommunication organizations results from the interaction of different factors. Specifically, organizational capacities (absorptive capacity), technological infrastructure (smart environment), human resources (employees), and management (Digital Transformational Leadership) operate together, resulting in digital innovation.

These findings are also influenced by the level of advancement associated with the telecommunications industry as one of the industries with the highest levels of advancements in the process of digitalization, which allows the utilization of digital infrastructure to support artificial intelligence, and this makes the contribution of the studied factors even more clear and tangible.

6 Contributions of the Study

6.1 Theoretical Contributions

This research makes an important theoretical contribution to the field of digital transformation and artificial intelligence by incorporating Absorptive Capacity Theory and Socio-Technical Systems Theory within a holistic framework. It is shown that absorptive capacity in organizations is able not only to explain technology adoption but also to show how technical knowledge is turned into an intelligent working environment, thereby impacting worker behavior. In addition, Socio-Technical Systems Theory is extended in terms of the significance of the intelligent environment as the mediator between technology and worker behavior. Moreover, one important feature of this study is the introduction of Digital Transformational Leadership as a moderator. This shows that apart from having a direct effect, leadership can have an interactive effect on the effectiveness of organizational and technological capabilities in an organization.

6.2 Practical Implications

The paper provides a number of practical implications that can be used by telecommunications firms. The need to increase organizational absorptive capacity in artificial intelligence is pointed out with respect to the need to invest in training, digitalization, and the creation of technological

infrastructure. The design of smart work environments through combining digital technologies and personnel is also emphasized. The results also underscore the need for Digital Transformational Leadership practices in telecommunications firms by stimulating innovation among employees and reducing resistance to change, which fosters digital work culture.

7 Conclusion, Limitations, and Future Research

This study examined how organizational AI absorptive capacity shapes employees' Smart Work Environment Perception and Digital Innovative Behavior in Jordanian telecommunications organizations, and how Digital Transformational Leadership conditions these relationships. Based on 279 responses analyzed with PLS-SEM, AI absorptive capacity strongly improved perceptions of the smart work environment, which in turn promoted Digital Innovative Behavior; the smart work environment partially mediated the effect of AI absorptive capacity on Digital Innovative Behavior, and Digital Transformational Leadership strengthened both the AIAC–SWEP and SWEP–DIB relationships.

The study has several limitations. First, its cross-sectional design limits causal inference, and longitudinal designs are recommended. Second, all constructs were measured through self-reported data from a single source, which may introduce common method bias; future studies could combine employee responses with supervisor ratings or objective innovation indicators. Third, the sample was drawn from a single industry in one country, which limits generalizability; replication in other sectors and countries is therefore encouraged. Finally, future research could examine additional mediators and moderators, such as employees' digital skills or organizational learning culture.

Acknowledgement:
This research is funded fully by Zarqa University, Jordan.

Originality and Data Statement:
The authors confirm that the dataset, questionnaire, figures, tables, statistical outputs, and text of this article have not been published previously and are not under consideration for publication elsewhere. Although several of the authors have co-authored earlier studies [14]–[16], those studies addressed different research questions (electronic-commerce adoption in SMEs, the integration of AI and business intelligence, and business intelligence in supply-chain optimization) and were based on different data. The data of the present study were collected independently and specifically for this research, and no material from earlier publications has been reused or adapted.

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.

References:

[1] Omol, E. J., Organizational digital transformation: from evolution to future trends, Digital Transformation and Society, Vol.3, No.3, 2024, pp. 240-256.

[2] Hashem, G., Adopting Industry 4.0 through absorptive capacity and innovation ambidexterity with the moderation of learning capability, Business Process Management Journal, Vol.30, No.6, 2024, pp. 1995-2024.

[3] Corvello, V., De Carolis, M., Verteramo, S., Steiber, A., The digital transformation of entrepreneurial work, International Journal of Entrepreneurial Behavior & Research, Vol.28, No.5, 2022, pp. 1167-1183.

[4] Odugbesan, J. A., Aghazadeh, S., Al Qaralleh, R. E., Sogeke, O. S., Green talent management and employees' innovative work behavior: the roles of artificial intelligence and transformational leadership, Journal of Knowledge Management, Vol.27, No.3, 2023, pp. 696-716.

[5] Aljedaiah, M. N., Alali, H. A. F., The impact of artificial intelligence tools on service quality in the telecom sector, Discover Sustainability, 2026. https://doi.org/10.1007/s43621-026-03496-z

[6] Radović, N., Vujko, A., Stanišić, N., Ljubisavljević, T., Lunić, D., Digital hospitality as a socio-technical system: aligning technology and HR to drive guest perceptions and workforce dynamics, World, Vol.6, No.4, 2025, Article 134.

[7] Bednar, P. M., Welch, C., Socio-technical perspectives on smart working: creating meaningful and sustainable systems, Information Systems Frontiers, Vol.22, No.2, 2020, pp. 281-298.

[8] Seema, S., Saini, G., The key to organizational success in the information age: a socio-technical systems perspective on innovative work behaviour in the Indian IT sector, Journal of Enterprise Information Management, Vol.39, No.3, 2026, pp. 1139-1165.

[9] Iaia, L., Nespoli, C., Vicentini, F., Pironti, M., Genovino, C., Supporting the implementation of AI in business communication: the role of knowledge management, Journal of Knowledge Management, Vol.28, No.1, 2024, pp. 85-95.

[10] Nguyen, T. H., Dinh, V. H., Nguyen, H. M., Do, H. M. H., Luong, M. D., Nguyen, H. H. A., AI-analytics capabilities and knowledge assimilation: driving innovation in SMEs, International Journal of Innovation Science, 2026, pp. 1-25.

[11] Martínez Falcó, J., Sánchez-García, E., Marco-Lajara, B., Akram, U., Digital transformation and green innovation performance: unraveling the role of green knowledge sharing and top management environmental awareness, Internet Research, Vol.35, No.4, 2025, pp. 1621-1656.

[12] Odai, L. A., Xiao, Y., Korankye, B., Ahakwa, I., Navigating digital transformation: the critical role of knowledge sharing and digital transformational leadership in boosting innovation capability in Sub-Saharan Africa, Business Process Management Journal, Vol.32, No.2, 2026, pp. 653-678.

[13] Al Dari, T., Jabeen, F., Hussain, M., Al Khawaja, D., How types of organizational culture and technological capabilities contribute to organizational learning, Management Research Review, Vol.44, No.3, 2021, pp. 437-459.

[14] Alnassar, B., Sabri, M. O., Momani, M., Ismail, A., Awadallah, A., Abudarwish, N., Nassoura, M., Factors that affecting the adoption of electronic commerce in small and medium enterprises (SMEs) in Jordan, Salud, Ciencia y Tecnología, Vol.5, 2025, Article 1354.

[15] Al-Momani, M. M., Alqudah, T. A., Al Swiety, I. A., Mahrakani, N., Abdulraheem Nassoura, M. B., Al Attar, M. K., Integrating artificial intelligence (AI) and business intelligence (BI): a framework for improving enterprise performance, TEM Journal, Vol.14, No.3, 2025.

[16] Al-Momani, M. M., Awadallah, A., Alnassar, B., Ismail, A., Nassoura, M., Abudarwish, N., The role of business intelligence in supply chain optimization: a case study of the Carrefour Market in Jordan, Data and Metadata, Vol.4, 2025, Article 747.

[17] Cohen, W. M., Levinthal, D. A., Absorptive capacity: a new perspective on learning and innovation, Administrative Science Quarterly, Vol.35, No.1, 1990, pp. 128-152.

[18] Hair, J. F., Risher, J. J., Sarstedt, M., Ringle, C. M., When to use and how to report the results of PLS-SEM, European Business Review, Vol.31, No.1, 2019, pp. 2-24.

[19] Fornell, C., Larcker, D. F., Evaluating structural equation models with unobservable variables and measurement error, Journal of Marketing Research, Vol.18, No.1, 1981, pp. 39-50.

[20] Kock, N., Hadaya, P., Minimum sample size estimation in PLS-SEM: the inverse square root and gamma-exponential methods, Information Systems Journal, Vol.28, No.1, 2018, pp. 227-261.

[21] Cohen, J., Statistical Power Analysis for the Behavioral Sciences, 2nd ed., Lawrence Erlbaum Associates, 1988. ISBN: 9780203771587.

[22] Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., Ringle, C. M., Predictive model assessment in PLS-SEM: guidelines for using PLSpredict, European Journal of Marketing, Vol.53, No.11, 2019, pp. 2322-2347.

[23] Zhao, X., Lynch, J. G., Chen, Q., Reconsidering Baron and Kenny: myths and truths about mediation analysis, Journal of Consumer Research, Vol.37, No.2, 2010, pp. 197-206.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

This research is funded fully by Zarqa University, Jordan.

Conflict of Interest

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

Creative Commons Attribution License 4.0 (Attribution 4.0 International, CC BY 4.0)

This article is published under the terms of the Creative Commons Attribution License 4.0
https://creativecommons.org/licenses/by/4.0/deed.en_US