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The Impact of Inclusive Leadership on AI Use Intent: The Mediating Role of Psychological Safety, Emotional Regulation, and Trust *

Kapsayıcı Liderliğin Yapay Zekâ Kullanım Niyeti Üzerindeki Etkisi: Psikolojik Güvenlik, Duygusal Düzenleme ve Güvenin Aracı Rolü

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ÖZ

Bu çalışma, kapsayıcı liderliğin çalışanların yapay zekâ (YZ) kullanma niyetine etkisini incelemeyi ve bu ilişkide psikolojik güvenlik, duygusal düzenleme ve YZ'ye duyulan güvenin aracı rollerini test etmeyi amaçlamıştır. Modele göre, kapsayıcı liderlik bağımsız değişken, YZ kullanma niyeti bağımlı değişken, psikolojik güvenlik ve duygusal düzenleme aracı değişkenler ve YZ'ye duyulan güven hem aracı hem de doğrudan etkileyen değişken olarak belirlenmiştir. Çalışma, modelin güvenilirlik ve geçerlilik kriterlerini karşıladığını (CR > 0,70; AVE> 0,50; HTMT <0,90), yapısal modelin kabul edilebilir bir uyum gösterdiğini (SRMR = 0,079) ve açıklayıcı gücünün orta-yüksek düzeyde olduğunu (R^2 ortalama = 0,443; YZ kullanım niyeti R^2 = 0,619) belirlemiştir. Sonuç olarak, çalışma, YZ benimseme sürecinde bireysel duygusal öz düzenleme kapasitesinin ve güven mekanizmalarının merkezi rolünü ortaya koymuş ve YZ kabulünün yalnızca bilişsel değil, aynı zamanda duygusal ve örgütsel dinamikler tarafından da şekillendirildiğini göstermiştir.

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A B S T R A C T

The present study aimed to examine the impact of inclusive leadership on employees' intention to use artificial intelligence (AI) and to test the mediating roles of psychological safety, emotional regulation, and trust in AI in this relationship. According to the model, inclusive leadership was identified as the independent variable, intention to use AI as the dependent variable, psychological safety and emotional regulation as mediating variables, and trust in AI as both a mediating and direct influencing variable. The study determined that the model met the reliability and validity criteria (CR > 0.70; AVE > 0.50; HTMT < 0.90), the structural model showed acceptable fit (SRMR = 0.079), and the explanatory power was at a moderate-high level (R^2 mean = 0.443; AI use intention R^2 = 0.619). In conclusion, the study revealed the central role of individual emotional self-regulation capacity and trust mechanisms in the AI adoption process, and demonstrated that AI acceptance is shaped not only by cognitive but also by emotional and organizational dynamics.

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1. Introduction

In recent years, artificial intelligence (AI)-based systems have become central to core organizational areas such as decision-making, data analysis, process automation, and customer management. In this context, the contribution of AI technologies to organizational performance depends not only on technical infrastructure but also on employees' adoption and intention to use these systems. Academic studies on human-automation interaction reveal that trust in technology is one of the fundamental determinants of usage behavior (Lee & See, 2004). Especially in learning, autonomous, and sometimes opaque systems like AI, trust becomes a critical precursor to the intention to use (Glikson & Woolley, 2020).

However, a significant portion of studies on AI adoption focuses on cognitively based variables such as perceived benefit, ease of use, and performance expectations. Yet, social relationships within the organization, leadership behaviors, and the psychological climate can significantly shape employees' attitudes towards technology and their trust assessments. At this point, inclusive leadership stands out as an accessible and supportive leadership approach that encourages employee contributions (Nembhard & Edmondson, 2006). Inclusive leaders strengthen psychological safety by creating an environment where employees can express their ideas and learn without fear of making mistakes (Edmondson, 1999).

Psychological safety refers to a work climate where individuals can exhibit interpersonal risk-taking behaviors without fear of punishment (Edmondson, 1999). This type of safe environment is associated not only with team performance and organizational learning, but also with the adoption of new and complex technologies. Employees who are engaged in trying and learning new systems tend to be more willing and courageous in environments where the fear of making mistakes is low. Accordingly, psychological safety is a critical socio-psychological mechanism in building trust in AI within organizational structures.

Emotional regulation, within the scope of self-regulation processes, is a crucial phenomenon that determines how and when an individual experience and manages their own emotional states (Gross, 1998). In organizational settings, the capacity for emotional regulation at the individual level closely influences decisions regarding the use of AI. Although uncertainty and the perception of loss of control are intense in technological environments, employees can develop trust towards technology thanks to emotional regulation strategies (Verburg et al., 2018). According to Social Cognitive Theory (SCT), individual behaviors develop through the interaction of environmental factors with cognitive and emotional processes (Bandura, 2001). In this context, in a social environment created with an inclusive leadership approach, individuals' intention to use AI can develop thanks to their emotional regulation capacities and trust assessments.

The present study aims to examine the impact of inclusive leadership in organizations on employees' intention to use AI and to identify the mediating roles of psychological safety, emotional regulation, and trust in AI in this interaction. In this paper model, which integrates leadership with technology acceptance intention, it is predicted that inclusive leadership creates a psychologically safe work environment, that this environment supports individuals' emotional regulation processes, and that trust in AI and intention to use it are strengthened through these psychological mechanisms.

This paper makes three key contributions to the literature. First, it offers a leadership-based approach to the AI adoption literature. Most existing studies in the literature explain AI use through technical features or individual attitudes; however, this paper emphasizes that the leadership approach is decisive in shaping trust in and intention to use AI. Second, by evaluating the concept of psychological safety within the context of AI, this paper demonstrates that this variable plays a significant role in the adoption of advanced technologies. Third, by including emotional processes in the technology acceptance model, it reveals that AI use decisions are shaped by emotional self-regulation mechanisms along with rational evaluations.

This paper develops a holistic and multi-layered approach to the AI adoption process by evaluating it from organizational (inclusive leadership), social (psychological safety), cognitive (trust in AI), and intrapersonal emotional (emotional regulation) dimensions. Specifically, this approach provides an examination of how organizational and psychological processes influence AI use behavior.

2. Conceptual Framework and Hypothesis Development

This paper is grounded in Social Exchange Theory (SET) (Blau, 1964) and Social Cognitive Theory (SCT) to explain the impact of inclusive leadership on employees' intention to use AI (Bandura, 2001). According to SET, employees tend to respond with positive attitudes and behaviors when they perceive that they are valued, supported, and treated fairly within the organization. SCT, on the other hand, emphasizes that behavior is shaped by the interaction of environmental cues, cognitive evaluations, and self-regulation processes. In the adoption of technologies that involve uncertainty and require fault tolerance, such as AI, these two theoretical lines together allow for an explanation of how leadership shapes the social climate and how individuals approach technology through emotional-cognitive mechanisms.

Inclusive leadership refers to accessible and supportive leadership behaviors that invite employee contributions. This approach can strengthen psychological safety in the organization by facilitating employees' sharing of thoughts and taking interpersonal risks (Nembhard & Edmondson, 2006). Psychological safety refers to a climate in which individuals can exhibit behaviors such as making mistakes, asking questions, or expressing different opinions without fear of punishment, and is seen as a fundamental mechanism supporting learning behaviors (Edmondson, 1999). Findings that inclusive leadership, in particular, strengthens employee participation and creative contributions through psychological safety also support this relationship (Carmeli et al., 2010). Accordingly:

H1: Inclusive leadership positively affects psychological safety.

Trust in AI, on the other hand, is shaped by employees' evaluations of the system's predictability, accuracy, and proper functioning. The human-automation interaction literature indicates that trust is a critical variable determining the behavior of "using technology appropriately"; it is emphasized that low trust can lead to disuse, while excessive trust can lead to misuse (Lee & See, 2004). In environments with high psychological safety, employees' anxiety about making mistakes and defensive attitudes will weaken, and their behavior of trying and learning new technologies may strengthen (Edmondson, 1999). This finding can also positively affect trust assessments regarding the use of AI within organizations. Therefore:

H2: Psychological safety positively influences trust in artificial intelligence.

Trust plays a direct determining role in the formation of AI use intention. As the level of trust increases, individuals may show a greater tendency to rely on technological systems and integrate them into business processes (Lee & See, 2004). Furthermore, AI-specific trust discussions indicate that the learning and sometimes opaque functioning of AI systems makes trust formation even more critical; therefore, trust should be considered a central concept in AI adoption processes (Glikson & Woolley, 2020). For this reason:

H3: Trust in artificial intelligence positively influences the intention to use AI.

In the context of AI, explaining adoption behavior solely through cognitive evaluations may be limited; because AI applications can generate emotional responses such as uncertainty, performance pressure, and a perception of loss of control. Emotional regulation is a fundamental self-regulation process that determines how an individual experience and manages their emotions (Gross, 1998). Strategies such as cognitive re-evaluation, in particular, can produce more functional results in conditions of uncertainty and stress, while strategies such as suppression can be associated with negative outcomes (Cutuli, 2014). In this framework, employees with high emotional regulation capacity can be expected to evaluate AI more balancedly and develop trust. Accordingly:

H4: Emotional regulation positively influences trust in artificial intelligence.

Emotional regulation can affect not only trust but also behavioral intention directly. Social Cognitive Theory emphasizes that individuals can develop more adaptive behaviors in uncertain situations through their self-regulation capacities (Bandura, 1986). Given the nature of AI use, which requires learning and trial and error, it is theoretically consistent that emotional regulation skills play a direct role in approach to and intention to use technology. Accordingly:

H5: Emotional regulation positively influences the intention to use artificial intelligence.

In addition to the direct relationships, the present study proposes indirect mechanisms through which organizational and psychological factors may influence trust in AI and AI use intention. Inclusive leadership may contribute to employees' trust in AI by fostering a psychologically safe environment in which employees feel more comfortable experimenting with, learning about, and evaluating AI-based systems. Therefore, psychological safety may transmit the effect of inclusive leadership to trust in AI. Accordingly:

H6: Psychological safety mediates the relationship between inclusive leadership and trust in artificial intelligence.

Trust in AI may also function as a mechanism through which psychological safety influences employees' intention to use AI. Employees who feel psychologically safe may be more willing to interact with unfamiliar technologies, and these experiences may contribute to stronger trust assessments and, consequently, greater use intention. Accordingly:

H7: Trust in artificial intelligence mediates the relationship between psychological safety and intention to use artificial intelligence.

Finally, the model proposes a sequential mediation mechanism in which inclusive leadership strengthens psychological safety, psychological safety contributes to trust in AI, and trust in AI subsequently increases the intention to use AI. This sequential mechanism integrates organizational, social, and cognitive processes within the AI adoption framework. Accordingly:

H8: Psychological safety and trust in artificial intelligence sequentially mediate the relationship between inclusive leadership and intention to use artificial intelligence.

3. Research Model and Methodology

In this paper, the effect of inclusive leadership on employees' intention to use artificial intelligence (AI) was tested through the variables of psychological safety, emotional regulation, and trust in AI. In the developed model, inclusive leadership was positioned as the independent variable; psychological safety and emotional regulation as mediating variables; trust in AI as a variable that both mediates and directly affects the intention to use; and the intention to use AI as the ultimate dependent variable. Within the framework of Social Exchange Theory and Social Cognitive Theory, the model is based on the assumption that leadership behaviors shape the organizational climate, transforming into behavioral intentions through individual cognitive and emotional processes. The research model is shown in Figure 1.

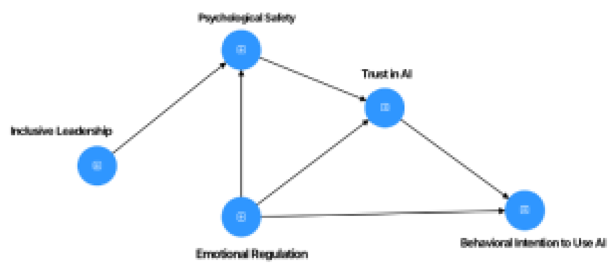

Figure 1. Research Model and Assumed Relationships

In the present study, which utilized a quantitative research method, data were obtained through a survey technique. Causal relationships between variables were determined using the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis method. PLS-SEM, which allows testing multiple mediation relationships in complex structural models, is less sensitive to distribution assumptions and derives reliable results in medium-sized samples. Therefore, this analytical method was used in this paper (Hair et al., 2017). In particular, since the aim was to test both direct and indirect effects within the same model, the PLS-SEM method provides a suitable analytical framework for the research objective.

Before starting the analysis process, the dataset was examined for missing data and outliers, and necessary data cleaning procedures were performed. Then, the measurement model was evaluated. The internal consistency reliability of the measurement model was tested using Cronbach's Alpha and Composite Reliability (CR) coefficients. Cronbach's Alpha and CR values above 0.70 were considered sufficient confidence levels. Convergent validity was assessed using Average Variance Extracted (AVE) values, with AVE values expected to be above 0.50. Discriminant validity was examined using the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait-Monotrait (HTMT) ratio. HTMT values below the recommended threshold indicate sufficient separation between constructs.

After determining that the measurement model was at an acceptable level, structural model analysis was performed. Within the structural model, path coefficients (β), t-values, and p-values were reported; the significance of the hypotheses was tested using the bootstrap resampling method. The explanatory power of the model was evaluated using the coefficient of determination (R^2); effect sizes (f^2) and predictive power (Q^2) values were also examined. The overall fit of the model was interpreted by considering the Standardized Root Mean Residual (SRMR) value. The SRMR value is within acceptable limits, which proves that the model is consistent with the data.

A research model was developed by examining existing hypotheses and measurement tools in the literature. In this context, scales related to inclusive leadership, psychological safety, emotional regulation, trust in AI, and intention to use AI were developed using scales previously proven to be valid and reliable in the literature. Scale items were measured using a 5-point Likert scale.

Universe and Sample

Istanbul was chosen as the population due to its status as Turkey's technology and economic center and the intensive use of artificial intelligence applications in technoparks. Within this scope, the population consists of private sector employees working in businesses located within technoparks in Istanbul that interact with AI-based applications in their business processes, as well as those working in e-commerce, finance, telecommunications, information technology, logistics, service, and manufacturing sectors. The sample was determined using a purposive sampling method from a population of experienced participants to accurately measure variables such as trust in AI and intention to use AI. According to the partial least squares structural equation modeling (PLS-SEM), samples of 200 or more produce reliable and stable results; therefore, the sample size for this paper was accepted as 384 (Hair et al., 2017).

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4. Data Collection Tool

In the present study, data were obtained using a structured questionnaire. The questionnaire, consisting of two parts, included questions in the first part aimed at determining the demographic characteristics of the participants, and in the second part, scales with previously proven validity and reliability were used to measure the variables included in the research model. The inclusive leadership variable was measured using the Inclusive Leadership Scale developed by Carmeli et al., (2010). This scale consists of statements that evaluate the leader's levels of openness, accessibility, and support towards employees, and was developed particularly in the context of its relationship with employee participation and psychological safety. The scale is widely used in the organizational behavior literature for measuring inclusive leadership. The Turkish adaptation and validity-reliability study of the scale were carried out by Çelik and Polat (2023), and the Turkish form of the scale was used in the present study (Carmeli et al., 2010; Çelik & Polat, 2023).

The psychological safety variable was measured using the Psychological Safety Scale developed by Edmondson (1999). The scale assesses employees' perceptions of their ability to act without fear of negative consequences when expressing their opinions, making mistakes, or taking interpersonal risks. The Turkish adaptation and validity-reliability study of the scale was conducted by Yener (2015). As a result of the analyses conducted by Yener (2015), it was determined that the Turkish form of the scale is a valid and reliable measurement tool. The Turkish form of the scale was used in the present study (Edmondson, 1999; Yener, 2015).

Emotional regulation was measured using selected items from the Difficulties in Emotion Regulation Scale–16 (DERS-16), developed by Bjureberg et al. (2016) as a brief form of the original Difficulties in Emotion Regulation Scale developed by Gratz and Roemer (2004). The Turkish adaptation and psychometric evaluation of the DERS-16 were conducted by Yiğit and Guzey Yiğit (2019). The original DERS-16 assesses difficulties in understanding, accepting, and regulating emotions. In the present study, the item scores were reverse-coded prior to the structural model analysis; therefore, higher scores indicate stronger emotional regulation capacity and lower levels of difficulty in emotion regulation. This scoring procedure ensured consistency between the operational definition of the construct, the proposed hypotheses, and the interpretation of the structural coefficients (Bjureberg et al., 2016; Gratz & Roemer, 2004; Yiğit & Guzey Yiğit, 2019).

Trust in artificial intelligence was measured using the trust-related items of the Artificial Intelligence Adaptation Scale developed by Kanoğlu and Durak (2025). These items assess individuals' perceptions of the reliability, consistency, predictability, and trustworthiness of artificial intelligence applications. The conceptual definition of trust was also informed by the Trust in Automation Scale developed by Jian, Bisantz, and Drury (2000). Thus, Kanoğlu and Durak's (2025) scale constituted the primary measurement instrument, whereas Jian et al. (2000) provided the theoretical foundation for conceptualizing trust in automated and artificial intelligence–based systems. The psychometric adequacy of the construct was subsequently evaluated within the measurement model of the present study (Jian et al., 2000; Kanoğlu & Durak, 2025).

Table 1. Measurement Items Used in the Study

Variable	Source
Inclusive Leadership	
My manager is open to employees expressing their opinions.	
My manager is accessible when I need to be.	(Carmeli et al., 2010; Çelik & Polat, 2023)
My manager encourages me to voice my concerns.	
My manager values employee contributions.	
My manager creates a suitable environment for sharing new ideas.	
Psychological Safety	(Edmondson, 1999; Yener, 2015)
I feel that when I make a mistake in this workplace, it won't be used against me.	
I can easily express my work-related problems.	
I feel safe expressing my different opinions.	
My colleagues listen to me without judging me.	
I'm not afraid to take risks in this team.	
Emotional Regulation	(Bjureberg et al., 2016; Yiğit & Guzey Yiğit, 2019)
I find it difficult to make sense of my feelings.	
I find it difficult to control my behavior when I feel bad.	
When I feel bad, I believe I will stay that way for a long time.	
When I feel bad, I find it difficult to focus on other things.	
When I feel bad, my emotions become unbearable.	
Trust in AI	(Jian et al., 2000; Kanoğlu & Durak, 2025)
I trust the outputs of artificial intelligence systems.	
I think artificial intelligence systems work consistently.	
I believe artificial intelligence systems make correct decisions.	
I think artificial intelligence systems are reliable.	
I can make decisions based on artificial intelligence systems.	
Intention to Use Artificial Intelligence	(Batuk et al., 2025; Flavián et al., 2022)
I would like to use AI tools in my work.	
I enjoy using AI applications.	
I plan to use AI-based systems more in the future.	
Working with AI makes my job easier.	
I prefer to actively use AI technologies.	

Note. Emotional regulation items were reverse-coded before the analysis; thus, higher scores indicate stronger emotional regulation capacity.

In this context, the scale proposals were developed based on the study by Flavián, Pérez Rueda Belanche, and Casaló, (2022), which examines the relationship between the intention to use AI and their awareness and readiness levels regarding technology. Additionally, the AI Acceptance Scale Short Form developed by Batuk, Aktu, and Türk (2025) regarding the intention to use AI was also utilized in the scale proposals. The scale evaluates individuals' tendency to use artificial intelligence applications, their behavioral intentions towards these technologies, and their level of willingness regarding their use. The validity and reliability of the scale have been supported in related studies, and the psychometric adequacy of the measurement model has been confirmed in this paper (Batuk et al., 2025; Flavián et al., 2022).

5. Findings

A total of 384 private sector employees participated in the study. 69.8% of the participants were male, and the majority of the sample was in the 31-40 age range (39.3%). 94.0% of the participants had a bachelor's degree or higher. The highest rate in terms of work experience was in the 11–20-year range (40.6%).

Table 2. Demographic and Professional Characteristics

Gender	n	%
Male	268	69.8
Female	116	30.2
Age		
25–30	86	22.4
31–40	151	39.3
41–50	106	27.6
51 and over	41	10.7
Education Level		
Bachelor's Degree	192	50.0
Master's Degree	169	44.0
Doctorate	23	6.0
Work Experience (Years)		
0–5	77	20.1
6–10	59	15.4
11–20	156	40.6
21 and over	92	23.9
Sector		
Information Technology / Software / Artificial Intelligence	112	29.2
Finance / Banking / Fintech	68	17.7
E-commerce and Digital Platforms	54	14.1
Telecommunications	38	9.9
Logistics and Supply Chain	46	12.0
Manufacturing and Industry (Digitalized)	36	9.4
Service Sector (Consulting, Healthcare, Education, etc.)	30	7.7

In terms of sectoral distribution, Information Technology/Software/Artificial Intelligence (29.2%) ranks first; followed by finance/fintech (17.7%) and e-commerce (14.1%). This structure points to a sample of experienced and highly educated individuals operating in technoparks and digitally intensive sectors.

5.1. Evaluation of the Measurement Model

The PLS-SEM approach was used to evaluate the measurement model, and the analyses were performed using SmartPLS 4.0 software. Factor loadings, indicator reliability, Cronbach's Alpha, rho_A coefficient, composite reliability (CR), and mean explained variance (AVE) values were used to test the measurement model.

In the initial analysis, it was determined that some items had factor loadings below the 0.70 threshold, and these items were removed from the dataset and the model was re-analyzed. The re-analysis showed that all indicators had factor loadings within acceptable limits. Factor loadings above 0.70 indicate that the indicators adequately represent the relevant construct.

In terms of internal consistency, Cronbach's Alpha and rho_A coefficients above 0.70; composite reliability (CR) values exceeding 0.70; and AVE values above 0.50 indicate that the model meets the reliability and convergent validity criteria. The findings reveal that all dimensions included in the research model have sufficient internal consistency, construct reliability, and convergent validity (Table 3).

In conclusion, the measurement model satisfies the essential reliability and validity requirements necessary for transitioning to structural model analysis (Figure 2).

According to the Fornell–Larcker criterion, the root mean square of the explained variance (AVE) of each latent construct is higher than the correlation coefficients of that construct with other constructs (Emotional Regulation = 0.796; Inclusive Leadership = 0.845; Intention to Use AI = 0.886; Psychological Safety = 0.771; Trust in AI = 0.800). This result indicates that all constructs included in the measurement model satisfy the discriminant validity requirement (Fornell & Larcker, 1981).

Furthermore, when the Heterotrait–Monotrait Ratios (HTMT) are examined, it is seen that all pairwise comparisons remain below the recommended threshold of 0.90 (highest value: ER–UI = 0.875). The HTMT approach proposed by Henseler, Ringle, and Sarstedt (2016) is considered a more sensitive discriminant validity test compared to the Fornell–Larcker criterion. In this context, the findings reveal that there is no excessive conceptual overlap between the constructs and that discriminant validity is ensured even with the stricter HTMT criterion (Henseler et al., 2016). The measurement model exhibits strong discriminant validity within the framework of both the traditional Fornell–Larcker criterion and the modern HTMT approach, providing a sufficient methodological basis for transitioning to structural model analysis (see Table 4).

5.2. Evaluation of the Structural Model

The suitability and explanatory power of the structural model were evaluated within the framework of PLS-SEM. First, the model fit indices were examined. In the PLS-SEM literature, the SRMR (Standardized Root Mean Square Residual) value is accepted as one of the basic fit measures, and values below 0.10 indicate acceptable fit (Henseler et al., 2016). The SRMR value obtained in the study was calculated as 0.079, which is below the commonly recommended threshold of 0.08. This result indicates an acceptable level of model fit (Hair et al., 2017; Henseler et al., 2016). In complex structural models and analyses involving multiple latent variables, it is methodologically considered normal for the SRMR value to produce results close to the boundary value.

Table 3. Measurement Model Results.

Variables	Items	Factor Loads	Cronbach's alpha	rho_A	CR	AVE	R^2
Inclusive Leadership	IL1	0.890	0.899	0.905	0.926	0.714	
	IL2	0.874					
	IL3	0.835					
	IL4	0.832					
	IL5	0.788					
Psychological Safety	PS1	0.768	0.831	0.838	0.880	0.595	**0.317**
	PS2	0.727					
	PS3	0.790					
	PS4	0.795					
	PS5	0.804					
Emotional Regulation	ER1	0.732	0.807	0.825	0.873	0.634	
	ER3	0.893					
	ER4	0.774					
	ER5	0.778					
Trust in AI	TAI2	0.842	0.816	0.852	0.876	0.640	0.393
	TAI3	0.859					
	TAI4	0.733					
	TAI5	0.758					
Intention to Use Artificial Intelligence	UI1	0.785	0.859	0.865	0.916	0.785	0.619
	UI4	0.902					
	UI5	0.962					

Table 4. Discriminant Validity and Correlation Results

	Correlations					Fornell-Larcker Criterion					HTMT Rates				
Scale	**ER**	**IL**	**UI**	**PS**	**TAI**	**ER**	**IL**	**UI**	**PS**	**TAI**	**ER**	**IL**	**UI**	**PS**	**TAI**
ER	1.000					**0.796**					—				
IL	0.553	1.000				0.553	**0.845**				0.627	—			
UI	0.735	0.597	1.000			0.735	0.597	**0.886**			0.875	0.682	—		
PS	0.517	0.472	0.443	1.000		0.517	0.472	0.443	**0.771**		0.626	0.535	0.513	—	
TAI	0.611	0.645	0.672	0.437	1.000	0.611	0.645	0.672	0.437	**0.800**	0.702	0.747	0.771	0.497	—

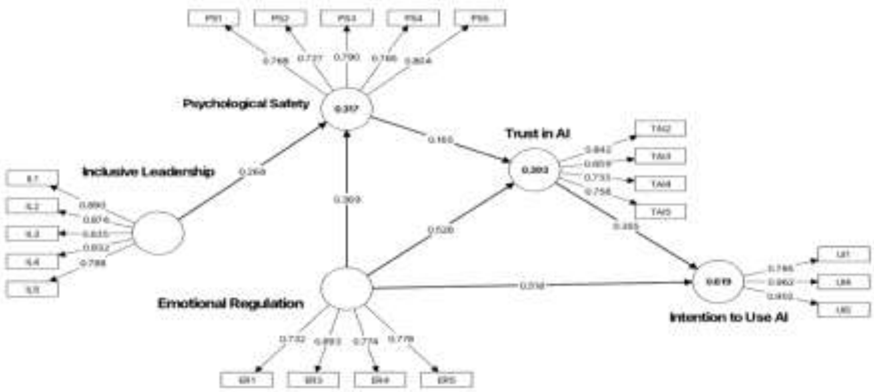

Figure 2. Measurement Model (PLS-SEM Results)

Furthermore, it is known that the primary aim of the PLS-SEM approach is not to maximize global fit, as in covariance-based SEM, but rather to increase explanatory power and predictive power (Hair et al., 2017).

To evaluate the explanatory power of the model, the R^2 coefficients of the dependent variables were examined. For intention to use artificial intelligence, $R^2 = 0.619$, indicating that 61.9% of the variance in this variable is explained by the model. For the psychological safety variable, $R^2 = 0.317$, and for the trust in artificial intelligence variable, $R^2 = 0.393$. According to Hair et al.'s (2017) classification, these values indicate a moderate level of explanatory power. The average R^2 value of the model is 0.443, indicating that the structural model generally has a satisfactory level of explanatory power.

When these findings are considered together, it can be said that the model exhibits a structure that is consistent with the theoretical framework in terms of both fit and explanatory power, and is statistically acceptable (see Table 5). The structural model results estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM) are presented in Figure 3.

Accordingly, the standardized path coefficients and their significance values between latent variables, as well as the explained variance (R^2) values for endogenous variables, are indicated. The standardized factor loadings for the measurement model are also shown in the figure. The figure provides a comprehensive visualization of the proposed relationships and the overall explanatory power of the model.

5.3. Testing Hypotheses in the Structural Model

Using the PLS-SEM method, the hypotheses proposed in the structural model were tested considering direct effects between latent variables, standardized path coefficients (β), t-statistics, and p-values, with a significance level of 5% ($p < 0.05$).

Data related to this analysis are presented in Table 6. The statistical significance of the path coefficients in the structural model was tested using a non-parametric bootstrapping method, employing a two-tailed test approach with 5,000 subsamples. The significance level was set at 5% ($\alpha = 0.05$), confidence intervals were calculated using the percentile bootstrap method, and fixed random seed was used to ensure the reproducibility of the results. This approach is consistent with the practices recommended in the PLS-SEM literature and ensures reliable evaluation of path coefficients.

Table 6 presents the coefficient magnitudes and statistical significance levels of the direct, indirect, and total effects in the model. When examining direct effects, the highest coefficient is observed in the path from emotional regulation → trust in artificial intelligence ($\beta = 0.526$, $p < 0.001$). The direct effect of emotional regulation on intention to use artificial intelligence is also high ($\beta = 0.518$, $p < 0.001$). The effect of trust on intention to use is moderate-high and statistically significant ($\beta = 0.355$, $p < 0.001$). The effect of inclusive leadership on psychological safety is significant ($\beta = 0.268$, $p = 0.001$). In contrast, the effect of psychological safety on trust remains low and is not statistically significant ($\beta = 0.165$, $p = 0.075$).

Table 5. Structural Model Fit and Explanatory Power

Scale	Criteria	Value	Result
SRMR	< 0.08	0.079	Acceptable fit

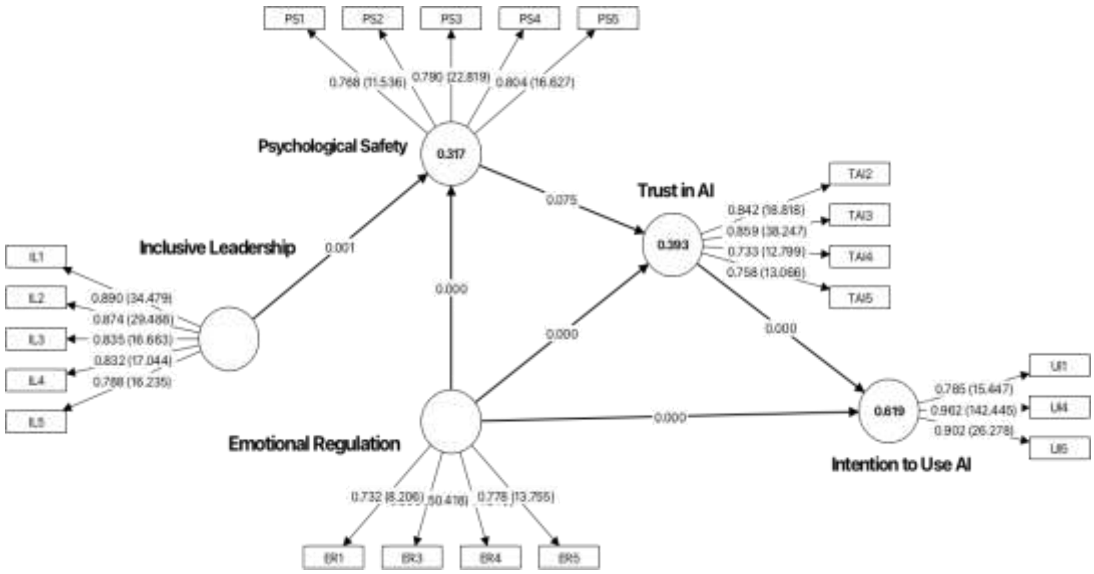

Figure 3. Structural Model Results Obtained via PLS-SEM

Table 6. Structural Model Results: Direct, Indirect, and Total Effects

	Path	Direct β	Direct p	Indirect β	Indirect p	Total Effect	Result
H1	Inclusive Leadership → Psychological Safety	0.268	0.001	–	–	0.268	Supported
H2	Psychological Safety → Trust in AI	0.165	0.075	–	–	0.165	Not supported
H3	Trust in AI → Intention to Use AI	0.355	0.000	–	–	0.355	Supported
H4	Emotional Regulation → Trust in AI	0.526	0.000	0.061	0.115	0.587	Supported
H5	Emotional Regulation → Intention to Use AI	0.518	0.000	0.208	0.000	0.726	Supported
H6	Inclusive Leadership → Trust in AI (via PS)	–	–	0.044	0.192	0.044	Not supported
H7	Psychological Safety → Intention (via Trust)	–	–	0.058	0.090	0.058	Not supported
H8	Inclusive Leadership → Intention (serial mediation)	–	–	0.016	0.204	0.016	Not supported

In terms of indirect effects, the highest indirect coefficient occurred in the emotional regulation → intention to use pathway ($\beta = 0.208$, $p < 0.001$). The indirect effect in the emotional regulation → trust pathway was low and not statistically significant ($\beta = 0.061$, $p = 0.115$). The indirect effects of inclusive leadership on trust and intention to use had low coefficient values ($\beta = 0.044$ and $\beta = 0.016$; $p > 0.05$). Similarly, the indirect effect of psychological safety on intention to use also remained low and was not found to be significant ($\beta = 0.058$, $p = 0.090$).

When comparing total effects, the highest total effect was observed in the emotional regulation → intention to use pathway ($\beta T = 0.726$). This was followed by the emotional regulation → trust pathway ($\beta T = 0.587$) and the trust →

intention to use pathway (βT = 0.355). The overall effects of inclusive leadership on trust and intention to use remained low (βT = 0.044 and β = 0.016).

These findings reveal the relative effect sizes of the relationships in the model at the direct, indirect, and total effect levels.

6. Discussion

The present study examines the relationships between inclusive leadership, psychological safety, emotional regulation, trust in artificial intelligence (AI), and intention to use AI within a holistic structural model framework. The findings show that individual-level self-regulation capacity and trust mechanisms play a central role in the AI adoption process, while the indirect effects of organizational climate-based variables remain limited. This result goes beyond approaches that predominantly focus on cognitive evaluations in the technology adoption literature (Davis, 1989), revealing the explanatory power of emotional processes in the context of AI. The findings demonstrated that emotional regulation produces strong and significant effects on both trust in AI and intention to use AI. This finding is consistent with self-regulation theory, which posits that emotional regulation capacity supports adaptive behavior in conditions of uncertainty and stress (Gross, 1998). Given the potential of AI applications to generate algorithmic uncertainty, performance evaluation pressure, and a perception of loss of control, it can be expected that individuals with high emotional regulation capacity will evaluate these systems more balancedly and use them more willingly. Furthermore, Social Cognitive Theory suggests that individuals can develop more adaptive behaviors in uncertain situations through their self-regulation capacity (Bandura, 2001). In this context, the findings show that the AI adoption process is shaped not only by cognitive variables such as perceived benefit and ease of use, but also by the individual's emotional processing capacity. The significant impact of trust in AI on intention to use aligns with studies in the human-automation interaction literature that emphasize trust as one of the key determinants of technology use behavior (Lee & See, 2004). Furthermore, it is stated that in the context of AI, trust is formed through assessments of the system's predictability, adequacy, and intentionality, and plays a central role in the adoption process (Glikson & Woolley, 2020). The study determined that the trust variable influences the intention to use the AI through both direct and indirect effects, proving that trust functions as a fundamental transmission mechanism in the AI adoption process.

Research findings in the literature are consistent with the findings regarding the positive and significant effect of inclusive leadership on psychological safety (Carmeli et al., 2010; Nembhard & Edmondson, 2006). Psychological safety is a fundamental mechanism that supports a work environment and learning behaviors where individuals can act comfortably without fear of punishment for making mistakes and expressing different opinions (Edmondson, 1999). Furthermore, the fact that the effect of psychological safety on trust in AI was not found to be statistically significant suggests that AI trust may be based on more technical and cognitive evaluations outside of organizational climate. Perceptions of trust in AI systems may depend on factors such as algorithmic accuracy, transparency, and performance reliability. This indicates a distinction between interpersonal trust climate and epistemological trust in technology. The lack of support for sequential mediation hypotheses is also noteworthy in this context. The low level of indirect effects established through psychological safety suggests that leadership and organizational climate variables may play a more distal (indirect and weakening) role in the AI adoption process. This finding suggests that trust formation in the context of AI occurs more directly through individual psychological mechanisms and assessments of system characteristics. In particular, strong direct effects of emotional regulation may have statistically weakened the mediation chain. This indicates that the individual and emotional dimensions of the AI adoption process may be more critical than suggested in the literature.

Overall, the present study offers two significant contributions to AI adoption models. First, by integrating the emotional regulation variable into the technology adoption framework, it reveals the strong explanatory role of individual self-regulation capacity in the context of AI. Second, by demonstrating that organizational leadership and psychological safety variables have a limited effect on the chain leading to AI use intention, it empirically shows that AI trust is shaped more through individual and cognitive-emotional mechanisms. In this respect, the study contributes to a reassessment of the relative weight of organizational and individual-level mechanisms in the AI adoption literature.

7. Conclusion

The present study aims to contribute to the AI adoption literature by examining the relationships between inclusive leadership, psychological safety, emotional regulation, trust in artificial intelligence, and intention to use AI within a holistic structural model framework. Research findings indicate that emotional self-regulation capacity and trust mechanisms, particularly at the individual level, are decisive in the formation of the intention to use AI.

According to the research results, emotional regulation strongly influences the intention to use, both directly and indirectly through trust. In this context, the AI adoption process is shaped not only by cognitive evaluations but also by the individual's emotional processing capacity. While the trust variable has a significant effect on the intention to use, it is not supported by sequential mediation structures established through organizational climate-based variables. This suggests that AI trust may be formed more through individual and system-oriented evaluations.

The study found a significant effect of the inclusive leadership approach on psychological safety. This result demonstrates that leadership behaviors are effective in shaping the organizational climate. However, this effect remains weak on trust in AI and intention to use, suggesting that individual psychological factors may be more influential in technology adoption processes. In this context, the research allows for the evaluation of the impact of organizational and individual-level variables between the leadership literature and the technology acceptance literature.

When the research results are evaluated generally, it is concluded that the AI adoption process has a multi-layered structure, and that individual self-regulation capacity is particularly central to this process. In this context, the research provides a theoretical contribution to the literature by integrating the emotional regulation variable into AI adoption models. It also guides detailed research into the factors contributing to the formation of AI trust. The research reveals that in today's world, where the impact of digital transformation processes is felt in every field, the effective and sustainable adoption of AI technologies is closely related not only to technical infrastructure studies but also to individuals' psychological adjustment capacity and trust formation processes.

In conclusion, this paper highlights the central role of individual emotional mechanisms and trust structures in the AI adoption literature, offering a theoretical and empirical framework for future research.

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