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Impacts of Organizational Responses to AI Induced Workforce Transformation on IT Professionals' Attitudes in SMEs

Vrajkumar Patel[1*]
[1]Master of Business Administration in Informatics, Judson University, Elgin, Illinois, USA
Email: vrajpatel5471@gmail.com
ORCID: https://orcid.org/0009-0001-2162-0319

Chirag Suthar[2]
[2]Master of Business Administration, Central Michigan University, Mount Pleasant, Michigan, USA
Email: Sutharchirag111@gmail.com
ORCID: https://orcid.org/0009-0009-5384-1819

Dhruviben Patel[3]
[3]Master of Computer Science, University of Houston-Clear Lake, Houston, Texas, USA
Email: Dhruvipatel2623@gmail.com
ORCID: https://orcid.org/0009-0004-7620-1981
[*]Corresponding author email: vrajpatel5471@gmail.com/vrajkumarpatel1@outlook.com

Abstract

This study is designed to explore the relationship between perceived AI-induced workforce transformation and IT professionals' attitudes towards the use of AI in small and medium-sized enterprises (SMEs) in the United States, with the mediating role of perceived ease of use and AI use anxiety. The research design used was a quantitative, non-experimental, cross-sectional survey with respondents comprising 252 IT professionals from U.S. SMEs impacted by AI-related changes in the workplace. The direct and indirect associations were evaluated by partial least squares structural equation modelling (PLS-SEM) and 5,000 bootstrap replications. The results indicate that perceived workforce transformation due to AI positively influences attitudes toward AI use ($\beta = 0.185$, $p = 0.001$) and perceived ease of use ($\beta = 0.656$, $p < 0.001$). In addition, perceived ease of use is a significant mediator of this relationship ($\beta = 0.254$, $p < 0.001$). The use of AI anxiety also indirectly associates with a significant value of $\beta = 0.195$, $p < 0.001$, but in the opposite direction to the hypothesised negative mediation. The model accounts for 61.5% of the variance in attitudes towards AI. Overall, the results emphasise the need for organisational support, usability, and the reactions of employees to the implementation of AI.

Keywords: *IT professionals; SMEs; AI workforce transformation; Technology Acceptance Model; human AI collaboration; IT reskilling.*

1. Introduction

The study centres on how AI is influencing workforce transformations in SMEs, highlighting IT professionals, including software developers, data analysts, AI experts, cyber security specialists, and IT managers. It states that the adoption of AI in SMEs is shaped by IT professionals' work practices such as system integration, data governance, monitoring of the model, and partnerships with AI in delivery processes. Many organisations and IT jobs have been disrupted by the introduction of AI technologies. The potential of the AI technologies to transform key business processes and the workforce is evident. The World Economic Forum anticipates that by 2030, AI will generate approximately 170 million new jobs and displace 92 million existing roles, hence highlighting a new level of workforce transformation that has not been experienced since the Industrial Revolution (Westover, 2025; Högemann et al., 2025). AI technologies such as machine learning and automation have transformed how SMEs are operating businesses (Adesanmi, 2025). Data and automation, combined with AI, can help these enterprises streamline the processes, cut costs, and deliver improved customer experience. For instance, AI can be used to detect market trends, optimise stock levels, and offer individualised customer interactions, thereby enabling SMEs to innovate and remain competitive (De La

Cruz et al., 2025). The findings indicate the powerful role of IT professionals' perception and attitude in the acceptance, resistance and successful use (AI, 2025) of AI (Khan et al., 2020).

Although there have been earlier studies on the uptake of AI, the impact on the workforce, and adapting the organisation, fewer studies have concentrated on the organisational responses embedded in the implementation of AI, and how these responses are understood by IT professionals in SMEs (Brahmaji, 2024; Zhang, 2024; Henry and Essah, 2025; Sha & Chai, 2025; Söllner et al., 2025; Stoykova & Shakev, 2023). Oldemeyer et al. (2025) asserted that barriers towards the use of AI remain relevant for SMEs and Savolainen et al. (2026) showed that attitudes towards AI affect attitudes of workers. The current study thus investigates the attitudes of IT workers toward the employee attitude toward AI use at work, contingent upon the perceived AI-induced workforce transformation, and looks at the potential mediation of perceived ease of use and AI-use anxiety. The study adds to the literature by identifying the implementation of AI in SMEs as an organisational change problem, by extending TAM, and by adding anxiety about using AI as a threat response pathway.

Previous research has examined the adoption of AI, the disruption of the labor market, and the adaptation of organisations; little research has examined the meaning of organisational adaptation within the context of the AI-related disruption to the labor market or the effects of changes in organisational adaptation on attitudes toward AI at work in U.S. SMEs. It's important to note that while IT professionals use and deploy AI systems, SMEs might not have formal change-management capabilities. The research question used is: Is there evidence of a direct and indirect (mediated by cognitive usability beliefs and affective anxiety) relationship between perceived changes in automation, reskilling, role redesign and employees' attitudes?

This study used a quantitative, non-experimental, cross-sectional design to examine the relationship between the perceived workforce transformation due to the use of artificial intelligence (AI) and IT professionals' attitudes toward the use of AI in U.S. small and medium-sized enterprises (SMEs) through two indirect statistical pathways: perceived ease of use of AI and AI use anxiety. The unit of analysis for the unit used was the IT professional. Given the study's design, there were no causal or mediating relationships tested (only two mediation pathways and one direct association). The study addressed the following research questions:

- RQ1: What is the relationship between the attitudes of IT professionals about using AI in U.S. SMEs and their perception of AI-induced workforce transformation?
- RQ2: Is there a statistical mediation effect between the perceived AI-induced workforce transformation and IT professionals' attitudes toward AI use in U.S. SMEs?
- RQ3: Does the mediating role of anxiety exist between perceived AI-induced workforce transformation and IT professionals' attitudes towards AI use in U.S. SMEs?

2. Literature Review

The model shows four constructs. Perceived workforce transformation due to AI is linked to overall perceived workforce transformation as a result of AI (including the automation of IT tasks, reskilling support, redesign of IT roles to integrate AI, and management communication around the impact of AI on roles and careers). Second, perceived ease of use is a belief in the ease of learning, understanding, controlling and using workplace AI tools. Third, the term AI use anxiety refers to uneasiness, stress, or fear of making errors in the use of AI. Fourth, the attitude towards the use of AI is the respondent's positive disposition toward using AI at work, as measured by intended-use items.

The perceived change in workforce by IT professionals to work tasks, role expectations, skill requirements, and human–AI collaboration due to AI implementation is defined as perceived AI-induced workforce transformation in this study. It is seen as a reflective construct based on perception, with the survey items representing a shared underlying perception of the changes in the labor market posed by AI (Akinlade et al., 2025; Savolainen et al., 2026). This construct is measured by the perception of organisational change signals (OCS) which include communication regarding the impact of roles, clarity of information, job redesign for human-ai collaboration, reskilling support, and automation of IT tasks. Akinlade et al., (2025) and Bobitan et al., (2024) proposed that the restructuring and skills preparation in the workplace due to AI impacts employee perceptions of change.

The use of AI likely will impact employee sentiment on the application of AI in SME environments. Theoretically, it is possible because transformation strategies are seen as signals of organisational intent, and IT professionals apply them to evaluate the type of AI adopted: augmenting or displacing. Akinlade et al. (2025) found that leadership reactions stemming from the restructuring using AI are associated with the perceived risk and perceived support, which is heightened in SMEs where communication is informal and leaders are highly visible. The hypothesis should be treated with suspicion, however, since the effect is different from context to context and the direction and strength of the effect will be related to the way the transformation is designed and communicated. Bobitan et al. (2024) observed that uneven support may have the counterproductive effect of reducing or reversing attitudinal results due to being unprepared for changes in skills with AI.

AI can cause a reduction in job satisfaction and foster negative attitudes when job value is perceived as being lost due to job replacement by AI, which can negatively affect morale and motivation in displacement-oriented strategies (Akinlade et al., 2025; Almaqtari, 2024). The Human–AI interaction, training, and capacity building are the focus of augmentation strategies, which can lead to better attitudes, as IT workers are more likely to use AI as a support tool than a threat (Akinlade et al., 2025; Shoib, 2025). Hybrid approaches are a mix of automation and selective reskilling, and can lead to mixed attitudinal results if organisational signals are ambiguous or benefits are not evenly distributed (Akinlade et al., 2025; Shoib, 2025). The takeaway is that the impact of AI transformation is not a one-off event, and attitudinal effects should be considered in the context of the organisation's strategic profile.

The mediation of perceived ease of use is consistent with TAM, which suggests that beliefs about ease of use and performance value are key to forming attitudes (Ma & Liu, 2011; Reis et al., 2020). These beliefs should be reinforced by organisational practices like training, usability support, and collaborative role redesign; and linked to more positive attitudes (Zeng et al., 2022; Shoib, 2025). The anxiety pathway works differently: In anxiety interactions with AI, the reactions are related to a threat of error, a threat to autonomy, or a threat to job loss. Sadeghi (2024) suggested that uncertainty can be mitigated by positive and learning facilitating leadership, and indecisive signalling can worsen it.

Socio-technical systems theory also suggests that the success of technology implementation depends on the interaction between the technical system and the social system, among others the communication system, role clarity and managerial signalling (Trist & Bamforth, 1951; Orlikowski, 1992). This view is especially relevant in the context of the SME IT, where signals about the introduction of AI within the organisation shape the professionals' view of the technology as augmentative or displacive. Task-based approaches also highlight the differences between routine and non-routine tasks when it comes to automation susceptibility, and may suggest that the attitudinal impact of workforce changes could vary widely by task and by how it is framed as a change within the organisation (Autor et al., 2003).

Perceived ease of use is one of the core beliefs that affect attitudes toward technology as identified by the technology acceptance model (TAM) (Ma & Liu, 2011). According to the present model, ease-of-use beliefs are external organisational antecedents of perceived AI-induced workforce transformation. The ease of use beliefs should further be linked to more positive attitudes towards AI use. At the same time, confidence in being able to learn and control AI tools should be bolstered by reskilling, helpful documentation, technical support, and coherent workflow redesign.

This study emphasises the ease of use aspect as it is assumed that if AI tools are understandable, controllable, easy to use and integrate into the regular work process, the attitude of IT practitioners will be more positive towards AI (Khaouja et al., 2021; Savolainen et al., 2026). There is not necessarily easy to use technology in SME IT. Additionally, it is influenced by the training, technical documentation, workflow redesign, managerial support, and opportunities to evaluate AI tools in actual work settings. However, Ma and Liu (2011) asserted that the PWEU is a key factor in technology acceptance, and Shmatko & Volkova (2020) found that both technological and organisational factors affect the use of AI.

But accepting technology isn't the only driver of how employees react to AI-driven change in their work. Implementing AI can also be seen as a threat to competence, autonomy, job security and professional value. The use of anxiety about AI is thus included as a parallel mediator. It reflects emotional reactions that may arise if IT specialists are unsure about the possibility of making a mistake, are evaluated by AI systems or lose control over their job processes (Ternikov, 2022). This threat response perspective is particularly applicable in SME as roles tend to have less rigid boundaries, there may be less capacity to re-skill, and there may be greater visibility in the way in which leadership signals are given. Sadeghi (2024) suggested that leadership communication is a factor in minimising uncertainty, while Park et al. (2024) revealed that at the workplace, the attitudes of AI involve affective responses.

Threat-Response Pathway

The affective pathway is accounted for by threat-rigidity theory. AI-driven changes can trigger anxiety emotions among employees when perceived as ambiguous, displacement-oriented or a threat to competence, autonomy, job security, and professional identity, which can lead to employees' reluctance to accept the technology (Staw et al., 1981; Sadeghi, 2024). On the other hand, if the communication is clear, roles are protected, and the reskilling is credible, that should lead to a decrease in anxiety. So, the anxiety pathway can be considered to be theoretically separate from the cognitive ease-of-use pathway. Between the two variables in the middle is mediators and not moderators. A mediator is a variable that is related to an antecedent and an outcome, but not directly connected to the outcome in and of itself; a moderator is a variable that interacts with an antecedent and an outcome, and thus is related to the interaction of those two variables. In this study, there is no interaction term and no moderation test of the subgroups. All measures are obtained at the same point in time, and the mediation results should be understood as indirect associations in line with theory rather than as evidence of temporal and/or causal mechanisms.

This model has three hypotheses that can be tested. H1 shows the direct association, H2 and H3 show two different mediation pathways.

- H_1: The relationship between perceived AI-induced workforce metamorphosis and attitudes of IT professionals towards AI use in SMEs in the U.S. is positive.
- H_2: The perceived ease of use had a positive mediating effect between the perceived AI-induced workforce transformation and IT professionals' attitudes toward using AI in U.S. SMEs.
- H_3: The relationship between perceived transformation and IT professionals' attitudes towards AI use in U.S. SMEs is negatively mediated by AI use anxiety.

Figure 1 identifies two direct relationships between perceived AI-induced workforce transformation and attitude toward AI use: (a) perceived AI-induced workforce transformation → attitude toward AI use and (b) perceived AI-induced workforce transformation → AI use anxiety, and attitude toward AI use. The term "mediator" is used because PEU and AU anxiety are variables that lie between the variables and do not simply "moderate" any relationship. There is no interaction term; the group-comparison hypothesis is not tested. Due to the cross-sectional nature of the study, the arrows indicate theoretically sequenced relationships, not necessarily causal relationships. This is in line with the Technology Acceptance Model, which correlates ease of use with positive attitudes towards the technology (Ma and Liu, 2011). The second indirect path is through anxiety of AI usage, which can be due to unclear job impacts, role uncertainty, fear of mistakes, and possible feelings of displacement. Given that, Park et al. (2024) analysed AI attitudes in the workplace as being multidimensional, justifying the use of cognitive and affective attitudes.

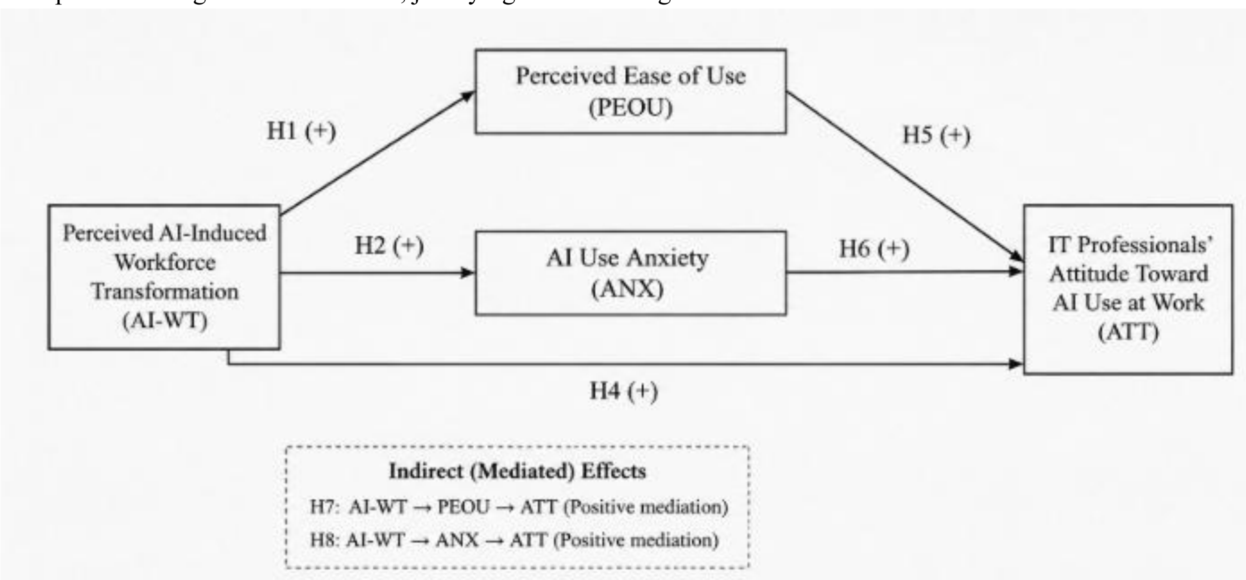

Figure 1 Conceptual Framework

3. Methodology

To assess AI-induced workforce transformation and its association with perceived ease of use, AI use anxiety and attitude toward AI use, a non-experimental, cross-sectional survey design was adopted, which is of a quantitative nature. The unit of analysis was the IT professional. This design would be suitable for testing a theory-based latent-variable model with standardised responses to a survey, but would not allow for a determination of the temporal order or causality of the variables since they were all measured at the same time. Therefore, the results are presented as statistical associations (direct and indirect) and not as causal relationships (Taris et al., 2021).

The focus group consisted of IT professionals working in U.S. SMEs who had implemented changes to their IT workflows that involved AI. To participate, respondents had to be at least 18 years old with an IT job and employed by a U.S. SME where they were directly impacted by changes in work practices related to AI. A non-probability sampling technique called purposive was adopted for the online sampling. The survey was given using SurveyMonkey. Eligibility for SME was judged by 260 returned questionnaires, eight of which were excluded due to being ineligible, incomplete or patterned responding, which resulted in 252 cases available for use. Due to the non-probability nature of the sampling and the use of a self-reported SME status and exposure to AI, the sample should not be considered representative of all U.S. SME IT professionals in general.

There were four items rated on a 5-point Likert scale for each construct, ranging from “strongly disagree to agree strongly. Perceived AI-induced workforce transformation covered the questions regarding IT task automation, organising investment in reskilling/upskilling, redesign of roles for human-AI collaboration, and clarity of management message regarding the impact of AI on jobs and careers. The construct was considered the respondent’s perception of the overall degree and management of the workforce change related to AI.

Perceived ease of use was defined as perceived ease of learning, understanding, controlling and using workplace AI tools. AI use anxiety was assessed as uneasiness, anxiety, fear of making mistakes and stress due to the recurrent use of AI. The attitude toward AI use was measured by four intended use statements that included the willingness to use AI tools, to use AI tools to assist in work, to use AI-generated outputs and to choose a work method that employs AI tools. In Appendix A, all item wording is reported. The employees’ attitude towards the use of AI in the workplace was assessed by the items that tapped the general evaluative disposition of the respondent to the use of AI in employment. Park et al. (2024) argued for the use of the workplace AI attitude dimensions, and Ma and Liu (2011) argued for the use of perceived ease of use in technology acceptance studies.

An anonymous participation, neutral wording of questionnaire items, and separating predictor, mediator, and outcome items into separate sections of the questionnaire were procedural safeguards. However, there was no control for common method variance, with all the focal variables being measured by the same respondent in a single survey. It was also tested statistically in PLS SEM, with full collinearity VIFs for all latent constructs; VIFs below 3.3 indicate low levels of method inflation (Hayes, 2022). A robustness check incorporated a common-methods element; anything that was not substantive was held constant.

Partial least squares structural equation modeling (PLS-SEM) was used to estimate the latent-variable mediation model. The analysis was first divided into two distinctly discerned phases. The reflective measurement model was evaluated based on the indicator loadings, Cronbach’s alpha, composite reliability, and average variance extracted (AVE), along with the heterotrait-monotrait ratio (HTMT). Secondly, the structural model was evaluated using collinearity diagnostics, path coefficients, bootstrapping tests (5,000 replications), specific indirect effects, and R^2 values. One direct and two indirect effects were tested in the analysis, but there was no moderation analysis or interaction term. This is a cross-sectional design, which means that a strong indirect effect is not necessarily a temporal causal relationship but rather a pattern of relationships that is consistent with the suggested theory. The table for the structural model should also include, before submission, the available 95% bootstrap confidence intervals and inner-model VIF values from the output of the analysis.

4. Results

The findings from the PLS-SEM measurement and structural models evaluating the relationships between induced workforce change and AI, and employee attitudes toward AI in SMEs. It initially examines reliability, convergent validity and discriminant validity of the constructs. It then presents path coefficients and indirect effects to test the hypothesized relationships and reports R-squared to assess the model's explanatory power.

Sample characteristics

Table 1 Demographic Profile

		Frequency	Percentage
Gender	Male	82	32.5
	Female	80	31.7
	Other	90	35.7
IT role	Developer	37	14.7
	Data analyst	35	13.9
	IT manager	40	15.9
	IT operations	27	10.7
Organisation's AI Integration Approach	Displacement Oriented	84	33.3
	Augmentation Oriented	81	32.1
	Hybrid	87	34.5
Total		252	100%

Table 1 summarises the sample characteristics for 252 SME IT professionals. The number of respondents was 82 (32.5%) for males, 80 (31.7%) for females, and 90 (35.7%) for other respondents. IT role distribution included developers at 37 (14.7%), data analysts at 35 (13.9%), IT managers at 40 (15.9%), and IT operations staff at 27 (10.7%). In addition, there are three ways of using AI: displacement (84, 33.3%), augmentation (81, 32.1%) and hybrid (87, 34.5%). These values refer to the sample, but are not considered to be moderation or group comparison analysis unless additional analysis is included.

Measurement Model Analysis

Table 2 Measurement Model

Latent variable	Indicator	Factor loading	Cronbach's alpha	Composite reliability	AVE
AI Induced Workforce Transformation	AI-IWT1	0.859	0.881	0.918	0.737
	AI-IWT2	0.876			
	AI-IWT3	0.845			
	AI-IWT4	0.853			
AI Use Anxiety	AIUA1	0.903	0.903	0.933	0.777
	AIUA2	0.912			
	AIUA3	0.919			
	AIUA4	0.784			
Employee Attitude	EA1	0.898	0.915	0.940	0.797
	EA2	0.876			
	EA3	0.912			
	EA4	0.886			
Perceived Ease of Use	PEOU1	0.829	0.875	0.915	0.729
	PEOU2	0.906			
	PEOU3	0.885			
	PEOU4	0.790			

Table 2 presents measurements of the reflective quality of the four latent variables using indicator loadings, internal consistency, and convergent validity. AI-induced workforce transformation has good indicator loadings ranging from 0.845 to 0.876, Cronbach's alpha = 0.881, composite reliability = 0.918, and AVE = 0.737. The anxiety toward the use of AI has high loadings ranging from 0.784 to 0.919, Cronbach's alpha = 0.903, composite reliability = 0.933, and

AVE = 0.777. The loadings of the employee attitude records range from 0.876 to 0.912 with Cronbach's α = 0.915, composite reliability = 0.940 and the AVE = 0.797. Perceived ease of use loadings are between 0.790 and 0.906, and Cronbach's alpha = 0.875, composite reliability = 0.915 and AVE = 0.729. All the loadings are greater than 0.70, and all the AVEs are greater than 0.50, indicating that the constructs have good reliabilities and convergent validities. These are values that meet generally accepted standards for indicator reliability, internal consistency and convergent validity.

Discriminant Validity

Table 3 Discriminant Validity

	AI Induced Workforce Transformation	AI Use Anxiety	Employee Attitude
AI Use Anxiety	0.682		
employee Attitude	0.704	0.754	
Perceived Ease of Use	0.747	0.737	0.801

Table 3 reports the HTMT ratios to evaluate discriminant validity that is whether a construct is empirically unique from the others. The HTMT value for AI-induced workforce transformation & AI use anxiety is 0.682, and the value for AI-induced workforce transformation & employee attitude is 0.704. The correlation of the HTMTs between anxiety, using AI and employee attitude is 0.754. The perceived ease of use has an AI-induced workforce transformation value of 0.747, the AI use anxiety value is 0.737, and the employee attitude value is 0.801. The relationship between all the constructs is lower than the cut-off point of 0.85, suggesting that they are related but empirically distinct.

Path Coefficient Analysis

Table 4 Path Analysis

Path	Path coefficient (β)	T statistic	P value
AI Induced Workforce Transformation → AI Use Anxiety	0.610	10.834	<0.001
AI Induced Workforce Transformation → Employee Attitude	0.185	3.305	0.001
AI Induced Workforce Transformation → Perceived Ease of Use	0.656	13.310	<0.001
AI Use Anxiety → Employee Attitude	0.320	6.202	<0.001
Perceived Ease of Use → Employee Attitude	0.388	7.029	<0.001
Specific indirect effects (bootstrapping results)			
Specific indirect effect	Indirect effect (β)	T statistic	P value
AI-IWT → AI Use Anxiety → Employee Attitude	0.195	5.183	<0.001
AI-IWT → Perceived Ease of Use → Employee Attitude	0.254	6.246	<0.001

Direct and specific indirect effects are given in Table 4. Perceived AI-induced workforce transformation was positively associated with AI use anxiety (β = 0.610, t = 10.834, p < .001), attitude toward AI use (β = 0.185, t = 3.305, p = .001), and perceived ease of use (β = 0.656, t = 13.310, p < .001). This is in line with component paths of H2, as perceived ease of use was positively related to attitude toward AI use (β = 0.388, t = 7.029, p < .001). This supports the component paths of H2, which predicted that the perceived ease of use would be positively related to attitude toward AI use (β = 0.388, t = 7.029, p < .001). The indirect effect was positive and significant (β = 0.254, t = 6.246, p < .001) and this supported H2. AI use anxiety was also positively associated with attitude toward AI use (β = 0.320, t = 6.202, p < .001), and the reported indirect effect through anxiety was positive (β = 0.195, t = 5.183, p < .001). The H3 hypothesis is not supported since it predicted the negative anxiety mechanism. Before any substantive interpretation can be done, the positive signs need to be checked for coding, and the directionality of the attitude score checked.

Model Explanatory Power

Table 5 Model Explanatory Power

Endogenous construct	R^2	Adjusted R^2
AI Use Anxiety	0.372	0.369
Employee Attitude	0.615	0.610
Perceived Ease of Use	0.430	0.428

Table 5 reports the model's explanatory power. The variance in AI use anxiety and perceived ease of use was best explained by perceived workforce transformation due to AI, which explained 37.2% and 43.0% of the variance, respectively. The overall model explained 61.5% of the variance in attitude towards the use of AI. These R^2 values represent an in-sample explanatory power, and a similar R^2 and adjusted R^2 do not indicate a lack of overfitting or predictive validity out of sample.

5. Discussion

H1 is supported, as the present study revealed that there is a significant positive association between perceived AI-induced workforce transformation and IT professionals' attitudes toward the use of AI in SMEs. While this direct link was statistically significant, it was also relatively weak compared to the indirect pathways, indicating that workforce transformation within organisations is not necessarily the complete answer to employees' attitudes towards AI. Rather, the results suggest that the connection is more aptly described by the cognitive and emotional reactions of employees. This interpretation is consistent with socio-technical systems theory, which posits that employees' responses are a function of the interplay between the technological change and organisational processes including communication, role clarity and support, not technology per se (Orlikowski, 1992). Likewise, prior studies have found positive employee perceptions to be linked to supportive organisational AI implementation (Akinlade et al., 2025), and the direct connection found in the present study is relatively weak, which means there are other mechanisms at play.

Perceived ease of use was the most powerful indirect path between perceived AI-induced workforce transformation and employee attitudes, thus supporting H2. The relationship was stronger than that of the anxiety pathway, which could be explained by the study population, as the respondents were IT professionals who are likely to be more technologically familiar and adaptable. In this context, organisational practices like reskilling, workflow redesign, or explicit AI usage could have bolstered the feeling that AI systems are manageable and usable, fostering a stronger connection with attitudes than emotional reactions alone. This result is similar to the Technology Acceptance Model (TAM), which indicates that perceived ease of use is a key factor in the acceptance of technology (Ma & Liu, 2011). Consistent with these results, Savolainen et al. (2026) found that organisational support was associated with increased ease-of-use perceptions at AI implementation.

The results concerning H3 are not to be interpreted as carefully. Though the indirect relationship through the use of AI was statistically significant, the hypothesis was rejected because H3 anticipated a negative indirect relationship while the result was positive. This suggests that the direction of the relationship is not the same as the one suggested in the hypothesis which might be due to the direction of coding of the attitude measure or the direction of respondents' perceptions. However, the anxiety pathway showed a significant indirect relationship, but this was less than that of perceived ease of use. This means that although there are concerns about AI that remain pertinent, they may not be the main mechanism associated with perceived workforce transformation and employee attitudes in this sample. A potential reason for this is that the organisations surveyed had previously made changes related to AI, which meant that, though respondents felt some uncertainty, they all had some experience with AI. This interpretation is generally in line with the threat-rigidity theory (Staw et al., 1981) which suggests that uncertain situations are linked to defensive reactions, but that positive organisational practices can diminish the salience of such reactions. Similarly, Sadeghi (2024) found that increased organisational transparency is related to a decrease in AI-related uncertainty.

A key finding was that there was a stronger cognitive pathway from perceived ease of use than emotional pathway from anxiety. This does not mean that anxiety is not important, but in the current study, perceptions of AI usability were more strongly related to employee attitudes than emotional concerns. Overall, this indicates that organisational efforts that focus on enhancing employee comprehension, usability, and trust in AI might have a stronger connection to positive attitudes compared to those solely addressing anxiety. However, since the study used a cross-sectional approach, the findings should be interpreted as associations and not causal/temporal relationships.

Theoretically, the results contribute to the Technology Acceptance Model by proposing that perceived AI induced workforce transformation is a significant organisational context of employees' ease of use perceptions and therefore related to their attitudes towards AI. Results are also consistent with socio-technical systems theory, showing that attitudes are related to organisational practices that accompany technological change and not only to the implementation of technology. In addition, the substantial anxiety pathway corroborates threat-rigidity theory, suggesting that emotional reactions are still important in the context of organisational change with AI, though the cognitive evaluations showed a somewhat stronger relationship in the current sample. Taken together, the results help to enrich the literature by combining the cognitive and affective mechanisms in a single model of AI workforce transformation in SMEs.

However, the reported findings should be interpreted as sample-specific associations that warrant further examination using longitudinal designs and probability-based sampling approaches.

6. Conclusion

The findings of this study confirm that there is a significant direct and indirect relationship between the perception of the workforce transformation caused by AI and attitude toward using AI in SMEs through perceived ease of use and AI use anxiety. The results highlight the role of cognitive and affective reactions in clarifying employees' attitudes within the framework of organisational change that involves AI technology. The study also contributes to the technology acceptance research field and provides a comprehensive analysis of the cognitive and affective processes that mediate the impact of signals of organisational AI change on IT professionals' AI orientations in the context of workplace change caused by AI.

The results show that implementing AI in SMEs' IT environments is not merely about technology, but also about organising practices that facilitate employees' interactions with AI. Considering the importance of perceived ease of use in the proposed model, the strategy for integrating AI should involve guidance and training for IT workers to ensure that they feel confident in using AI in their technical processes. Additionally, the role of AI as an augmentative technology is important to communicate clearly to minimise uncertainty in the workforce transition. The findings also indicate that a strategy for the implementation of AI in SMEs should take into account both cognitive and affective aspects of technology acceptance: enhancing perceptions of ease of use while also raising awareness of AI-related concerns. This can foster a more positive mindset within IT teams transitioning to AI in their organisations.

The results in this study have certain limitations in their interpretive scope. First of all, it is important to note that this cross-sectional design does not allow causal inferences, even though the mediation relationships are theoretically sound and statistically significant, the direction of the associations can only be determined in longitudinal designs (Taris et al., 2021). Second, the data used in these surveys is self-reported, which may lead to common method bias and social desirability effects, however overall, there was a low incidence of common method bias and social desirability effects with VIF values of 1 (full collinearity) or lower being observed across all variables (Koller et al., 2023). Third, the non-probability sampling method restricts the generalisation of the findings to the larger population of U.S. SME IT professionals, and industry-specific dynamics were not explored; the processes of AI adoption in technology-focused SMEs may vary significantly from those in other industries (Hızarcı et al., 2024). Fourth, the perceived workforce transformation due to AI was reflected as a construct, and future studies could benefit from formative specification to more fully capture the theoretically different aspects of this construct. Lastly, no attempt was made to model job insecurity and behavioral intention to use AI, though this could be an important pathway that co-occurs. Future research is needed to include multi-wave longitudinal designs, objective organisational indicators, multi-source data to reduce the same-source bias, and moderation analysis to explore the moderating influence between organisational culture, LMX, and the transformation–attitude relationship.

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9. Conflict of Interest Statement

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