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The Sky is the Limit: Maximize the Intention to Accept Artificial Intelligence-Enabled Transformations in the Airline Industry

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Abstract

This study examines the crucial role of leadership, organizational culture, and peer influence in enhancing employee acceptance of artificial intelligence (AI)- enabled transformation within the airline industry. Acceptance of AI is vital for airlines seeking to leverage technological advancements to improve operational efficiency and customer satisfaction. The study explores how transformational leadership, with a supportive organizational culture and effective peer influence, affects employees' intention to embrace AI transformations mediated by self-efficacy. Data was collected through survey questionnaires distributed to employees of Malaysian airline companies, resulting in 399 valid responses for analysis. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed for data analysis, using 5,000 sub-samples to test the significance of the hypothesized relationships. The results indicate that leadership style, organizational culture, and peer influence all positively impact self-efficacy, which in turn enhances the intention to accept AI transformations. Self-efficacy emerged as a significant mediator, emphasizing the need for strategies to boost employee confidence in handling AI technologies. Based on the findings, the study suggests that future research should focus on longitudinal analyses to observe the long-term effects of leadership and cultural practices on AI adoption. Additionally, exploring these dynamics in different geographical regions and sectors could provide broader insights into the factors influencing technology acceptance. The implications of this study are multifaceted, offering valuable guidance for airline companies aiming to implement AI technologies successfully. By fostering transformational leadership and a culture supportive of innovation, companies can enhance self-efficacy among employees, leading to greater acceptance and smoother integration of AI systems. These findings contribute significantly to the literature on technology acceptance in the airline industry and provide practical frameworks for companies to optimize their workforce's readiness for AI advancements. Ultimately, this approach can drive innovation and maintain competitiveness in a rapidly evolving sector.

Keywords: Peer Influence, Organisational Culture, Leadership Styles, Self-Efficacy, Intention to Accept

Introduction

Artificial intelligence (AI) continues revolutionizing the airline industry by enhancing various operational and customer service aspects. AI's integration into the airline sector is crucial because it can optimize processes, improve efficiency, and elevate the passenger experience. For instance, AI-driven predictive maintenance systems enable airlines to anticipate technical issues and perform timely interventions, reducing downtime and improving safety (Halawi et al., 2024). Additionally, AI helps personalize customer experiences through chatbots and recommendation systems, offering tailored services that enhance customer satisfaction (Cheriyan et al., 2022; Meyer-Waarden et al., 2020). Furthermore, AI's role in revenue management and pricing strategies is becoming increasingly significant (Kebah et al., 2019). By analyzing large datasets on passenger behavior, market conditions, and past pricing strategies, AI can assist airlines in dynamic pricing models to optimize ticket sales and maximize revenue (Ivanov et al., 2021). AI also contributes to air traffic management by improving flight scheduling, reducing delays, and optimizing fuel consumption, collectively contributing to more sustainable operations (Halawi et al., 2024). AI in the airline industry faces challenges and trends, including data privacy concerns, the need for large datasets to train complex algorithms, and the continuous evolution of technology demanding frequent updates and skill enhancements (Jain et al., 2024). The COVID-19 pandemic has accelerated the implementation of AI technologies, particularly in-service robots and contactless interactions, to mitigate health risks (Meidute-Kavaliauskiene et al., 2021). However, as AI adoption grows, there is increasing scrutiny over its ethical implications and regulatory frameworks (Kebah et al., 2019). AI's capacity to replace human jobs also raises societal and ethical concerns that need addressing (Kaur & Kaur, 2024). Despite advancements, research gaps persist in AI's comprehensive integration within the airline industry. Studies must focus on stakeholder perceptions, particularly employees, towards AI technology acceptance to ensure seamless transitions (Chi et al., 2022). Additionally, research exploring AI's long-term impact on workforce dynamics and job satisfaction remains limited. Geske et al. (2024) highlight that while AI can drive efficiency, assessing its economic impact on airline profitability and sustainability is still underexplored. The significance of researching AI in the airline industry extends to policymakers, airline companies, and academicians. Policymakers can leverage findings to develop robust frameworks that ensure ethical AI practices while promoting innovation (Jain et al., 2024). Airlines can utilize insights to strategically implement AI solutions that enhance operational efficiency and customer experience, thus gaining competitive advantages (Abd El Kafy et al., 2022). For academicians, identifying and addressing research gaps could foster new theories and applications of AI in aviation, providing insights into effective technology management and operational strategies (Ivanov et al., 2021). This study assesses the direct and indirect relationships between peer influence, organisational culture, leadership style, and the intention to accept artificial intelligence-enabled transformation among airline employees with self-efficacy as a mediator.

Literature Review

Underpinning Theory

Transformational Leadership Theory is a pivotal framework for understanding how leadership styles influence the acceptance of artificial intelligence (AI) transformations among airline employees. This theory posits that transformational leaders inspire and motivate their followers to exceed their self-interests for the sake of the organisation, often leading to a heightened commitment to change (Bass & Riggio, 2006). By fostering a supportive and empowering environment, transformational leaders can significantly enhance employees' self-efficacy, which is crucial for adopting new technologies, including AI solutions (Eisenbeiss et al., 2008). Furthermore, transformational leaders emphasise the importance of vision and innovation, creating a culture where employees feel valued and engaged. This cultural aspect is particularly vital as organisations face the challenges of technological advancements, such as AI integration (Northouse, 2018). Transformational leadership encourages employees to embrace new technologies and facilitates a collaborative atmosphere where peer influence can enhance acceptance. Employees who observe their leaders actively supporting AI initiatives are likelier to develop a positive attitude toward such changes. Transformational Leadership Theory provides a comprehensive lens to examine the dynamics between leadership, self-efficacy, organisational culture, and technology acceptance, making it a suitable underpinning theory for studying the impact of leadership on airline employees' intentions to accept AI transformations.

Relationship between Leadership Style, Self-Efficacy, & Intention to Accept
The relationship between leadership style and the intention to accept technology transformation is significantly influenced by self-efficacy, a crucial mediating factor. Transformational leadership, in particular, enhances employees' self-efficacy by fostering a supportive environment that encourages innovative thinking and adaptability (Bayraktar & Jiménez, 2020). Leaders who exhibit digital transformational traits can enhance their team's creative self-efficacy, ultimately motivating employees to embrace technological changes (Susanti & Ardi, 2022). Moreover, a positive leadership approach, such as e-leadership, enhances employees' technological self-efficacy and influences their attitudes toward using new technologies (Purnomo et al., 2023). This acceptance is further amplified when leaders model supportive behaviours that promote a culture of innovation, as seen in servant and authentic leadership styles, which drive employees' innovative work behaviour (Gelaidan et al., 2024). Additionally, adaptive leadership facilitates a learning organisational environment that bolsters change self-efficacy, empowering employees to navigate and accept necessary transformations effectively (Chughtai et al., 2023). Thus, effective leadership styles enhance self-efficacy, enabling employees to engage positively with technology transformations and significantly impact their intention to accept new technological initiatives (Li et al., 2020). Therefore, the following hypotheses were proposed for this study:

H1: There is a relationship between leadership style and the intention to accept artificial intelligence among airline employees.
H2: There is a relationship between leadership style and self-efficacy among airline employees.
H3: There is a mediating effect of self-efficacy on the relationship between leadership style and the intention to accept artificial intelligence among airline employees.

Relationship between Organizational Culture, Self-Efficacy, & Intention to Accept
Organisational culture plays a critical role in shaping employees' intention to accept technology transformation, with self-efficacy as a vital mediator in this relationship. A robust and innovation-oriented culture fosters an environment where employees feel supported and encouraged to engage with new technologies, enhancing their self-efficacy (Le et al., 2023). When employees perceive an organisational culture that values technological advancement and learning opportunities, their entrepreneurial self-efficacy is bolstered, motivating them

to embrace change and pursue innovative behaviours (Duong, 2023). Furthermore, integrating cultural capital and ICT skills within an organisation further amplifies this effect, as individuals with higher self-efficacy are more likely to develop positive attitudes toward technology use (Sreejith & Sreejith, 2023). Research has shown that teachers' technological pedagogical content knowledge (TPACK) influences their behavioural intention to utilise technology, highlighting the importance of self-efficacy and attitudes in facilitating acceptance (Bai et al., 2024). Additionally, proactive organisational cultures promote initiative and can link self-efficacy with entrepreneurial intentions, reinforcing that a supportive culture is essential for successful technology transformation initiatives (Naz et al., 2020). A positive organisational culture enhances self-efficacy, significantly influencing employees' willingness to accept and engage with technological innovations (Osman et al., 2018). Thus, the following hypotheses were proposed for this study:

H4: There is a relationship between organisational culture and the intention to accept artificial intelligence among airline employees.
H5: There is a relationship between organisational culture and self-efficacy among airline employees.
H6: There is a mediating effect of self-efficacy on the relationship between organisational culture and the intention to accept artificial intelligence among airline employees.

Relationship between Peer Influence, Self-Efficacy, & Intention to Accept
The relationship between peer influence and the intention to accept new behaviours or technologies is significantly mediated by self-efficacy. Peer influence can be pivotal in shaping an individual's intentions by providing social support and modelling behaviours that facilitate adoption (Trivedi et al., 2022). For instance, when individuals observe their peers successfully adopting new technologies, their confidence in their ability to do the same, known as self-efficacy, is often enhanced (Intaratat et al., 2024). Self-efficacy serves as a mediator by fostering a belief in one's capability to perform a task or embrace a new practice, thereby strengthening the intention to accept (Zou et al., 2023). The supportive nature of peer interactions can provide reassurance and motivation, reducing apprehension and encouraging individuals to engage with novel experiences (Martínez et al., 2024). This dynamic is illustrated in educational settings, where the influence of peer groups combined with increased self-efficacy can significantly impact students' intentions to pursue entrepreneurial ventures (Nurjanah & Harsono, 2024). Furthermore, self-efficacy can help individuals evaluate the costs and benefits of adopting new behaviours, as seen in health-related practices like adolescent e-cigarette use (Durkin et al., 2021). When individuals perceive high self-efficacy, they are more likely to persist in facing challenges, enhancing their likelihood of following through with intentions formed under peer influence. Hence, the following hypotheses were proposed for this study:

H7: There is a relationship between peer influence and the intention to accept artificial intelligence among airline employees.
H8: There is a relationship between peer influence and self-efficacy among airline employees.
H9: There is a relationship between self-efficacy and the intention to accept artificial intelligence among airline employees.
H10: There is a mediating effect of self-efficacy on the relationship between

peer influence and the intention to accept artificial intelligence among airline employees.

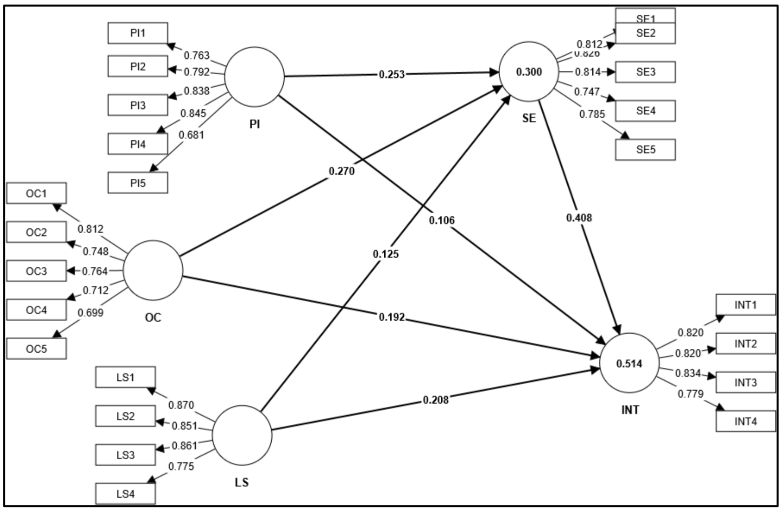

Figure 1: Research Model
Notes: PI=Peer Influence OC=Organizational Culture LS=Leadership Style SE=Self-Efficacy INT=Intention to Accept

Methodology

The methodology of this study focused on employees from Malaysian airline companies. A causal-effect relationship study design was adopted, with airline employees serving as the unit of analysis. Data was collected using a survey questionnaire that included several measurement items: peer influence (5 items) from Stewart et al. (2007), organisational culture (5 items) from J. Andersson et al. (2011), and leadership style (4 items) from Madlock (2008). Self-efficacy, the mediating variable, was measured with five items from Kang et al. (2019), and the dependent variable, intention to accept, was assessed with four items from De Cannière et al. (2009). The study relied on primary data obtained through a non-probability purposive sampling method. Of 561 distributed questionnaires, 421 were returned, achieving a response rate of 75.1%. After ensuring the completeness and quality of the responses, 399 were deemed suitable for further analysis. Structural Equation Modeling (SEM) was employed as the analytical method, utilising the Smartpls4 software. Smartpls4 was chosen for its capability to handle complex SEM models, as highlighted by (Ringle et al. 2022).

Data Analysis

Respondents Profile

The analysis of the respondents' profiles revealed a balanced gender distribution among the airline employees surveyed, with males representing 48.9% (195 respondents) and females slightly more at 51.1% (204 respondents). The age demographics show that most respondents fall within the 41 to 50-year age bracket, comprising 38.3% (153 respondents) of the sample. This is followed by 29.3% (117 respondents) aged between 51 and 60. Younger participants, those under 30 years, account for 27.1% (108 respondents), while those over 60 are the least represented at 5.3% (21 respondents). Regarding educational attainment, a significant portion of the respondents have completed undergraduate studies, accounting for 79.2% (316 respondents), indicating a highly educated workforce. Those with postgraduate qualifications form 9.0% (36 respondents), while those with only secondary and primary education represent 7.3% (29 respondents) and 4.5% (18 respondents), respectively. Income levels reflect a concentration in the middle-income bracket, with 57.4% (229 respondents) earning between RM4,851 and RM10,970, while 29.3% (117 respondents) of respondents earn below RM4,850, and 13.3% (53 respondents) earn above RM10,971. Lastly, a substantial proportion of respondents, 92.5% (369 respondents), are inclined to recommend artificial intelligence to their peers. In contrast, only 7.5% (30 respondents) would not make such a recommendation.

Common Method Bias

The full collinearity test conducted as per Kock (2015) and Kock & Lynn (2012) indicates the assessment of common method bias, where the variance inflation factors (VIFs) are examined for each latent variable: Intention (INT), Peer Influence (PI), Organizational Culture (OC), Leadership Style (LS), and Self-Efficacy (SE). All VIF values are below the threshold of 3.3, suggesting that the model does not suffer from significant standard method bias. Specifically, VIF values range from 1.283 to 2.034, demonstrating satisfactory levels of collinearity, which indicates that common method bias is unlikely to confound the study results.

Table 1
Full Collinearity Test

	INT	PI	OC	LS	SE
INT		2.007	1.953	1.895	1.628
PI	1.965		1.500	1.948	1.942
OC	1.986	1.558		2.033	2.034
LS	1.283	1.347	1.354		1.372
SE	1.410	1.719	1.733	1.755	

Measurement Model

In this study, we followed the methodology suggested by Hair et al. (2017) to assess measurements at both the first and second-order levels. This approach allowed us to pinpoint items with loadings below the 0.7 threshold. Our analysis of construct reliability and validity showed that the Average Variance Extracted (AVE) for all constructs was between 0.560 and 0.705, exceeding the 0.5 benchmark and indicating strong convergent validity (Hair et al., 2017) (see Table 2). Furthermore, composite reliability values for all constructs were above 0.7, ranging from 0.805 to 0.864. Cronbach's alpha values were also above 0.7, from 0.803 to 0.860 (Table 2). To verify discriminant validity, we initially examined cross-loadings to ensure the constructs were accurately measured and represented (detailed in Table 2). Following this, the Heterotrait-Monotrait (HTMT) ratio was used for further validation, adhering to the recommended criteria for discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) as proposed by Henseler et al. (2015). Table 3 included the HTMT ratios, original sample, and 95% confidence intervals, confirming compliance with the HTMT threshold of 0.85.

Table 2
Construct Reliability and Validity & Item Loadings

Constructs	Indicators	Loadings	CA	CR	AVE
Intention	INT1	0.820	0.830	0.834	0.662
	INT2	0.820			
	INT3	0.834			
	INT4	0.779			
Leadership Style	LS1	0.870	0.860	0.861	0.705
	LS2	0.851			
	LS3	0.861			
	LS4	0.775			
Organisational Culture	OC1	0.812	0.803	0.805	0.560
	OC2	0.748			
	OC3	0.764			
	OC4	0.712			
	OC5	0.699			
Peer Influence	PI1	0.763	0.845	0.864	0.618
	PI2	0.792			
	PI3	0.838			
	PI4	0.845			
	PI5	0.681			
Self-Efficacy	SE1	0.812	0.857	0.860	0.636
	SE2	0.826			
	SE3	0.814			
	SE4	0.747			
	SE5	0.785			

Notes: CA=Cronbach Alpha CR=Composite Reliability AVE=Average Variance Extracted

Table 3
Hetrotrait-Monotrait (HTMT) Ratios

	INT	LS	OC	PI
LS	0.554			
OC	0.662	0.498		
PI	0.604	0.482	0.806	
SE	0.736	0.398	0.586	0.562

Structural Model

The evaluation of the structural model adhered to the framework proposed by Hair et al. (2017), involving a detailed examination of pathway coefficients (β) and coefficients of determination (R^2). We employed the Partial Least Squares (PLS) technique using 5000 sub-samples to evaluate the significance of the path coefficients. The results of the hypothesis testing, including confidence intervals, beta coefficients, t-statistics, and p-values, are thoroughly presented in Table 4. This comprehensive analysis provides critical insights into the significance and robustness of the relationships between variables in the structural model. The detailed display of hypothesis testing results in Table 4 offers an in-depth analysis of each hypothesis, presenting beta coefficients, T-statistics, P-values, and final decisions on hypothesis support. This method significantly enhances the clarity and depth of the study's findings, offering a more profound understanding of the interactions among the variables under investigation. The analysis of the ten hypotheses provides a comprehensive understanding of the relationships among leadership style, organisational culture, peer influence, self-efficacy, and the intention to accept changes. *Hypothesis 1*, which examines the direct effect of leadership style on the intention to accept, is accepted with a beta of 0.208, a t-statistic of 4.434, and a p-value of 0.000, indicating a significant favourable influence. Similarly, *Hypothesis 2* is accepted, demonstrating that leadership style positively impacts self-efficacy, with a beta of 0.125, a t-statistic of 2.601, and a p-value of 0.009. Building on this, *Hypothesis 3* shows that leadership style influences intention to accept through self-efficacy, supported by a beta of 0.051, t-statistic of 2.478, and a p-value of 0.013, thus also being accepted. *Hypothesis 4*, which explores the direct impact of organisational culture on intention to accept, is accepted with a beta of 0.192, t-statistic of 3.272, and p-value of 0.001. Meanwhile, *Hypothesis 5* confirms that organisational culture significantly affects self-efficacy, with a beta of 0.270, a t-statistic of 4.544, and a p-value of 0.000.

Hypothesis 6 further supports the mediating role of self-efficacy, showing that organisational culture influences intention to accept indirectly through self-efficacy, as indicated by a beta of 0.110, t-statistic of 4.097, and p-value of 0.000, resulting in acceptance. In contrast, *Hypothesis 7*, which posits that peer influence directly affects the intention to accept, is rejected due to a beta of 0.106, a t-statistic of 1.837, and a p-value of 0.066. However, *Hypothesis 8* is accepted, showing peer influence significantly impacts self-efficacy, with a beta of 0.253, a t-statistic of 4.050, and a p-value of 0.000. Moving to *Hypothesis 9*, the strong relationship between self-efficacy and intention to accept is confirmed with a beta of 0.408, t-statistic of 8.939, and p-value of 0.000, leading to its acceptance. Finally, *Hypothesis 10*, which tests the indirect effect of peer influence on intention to accept through self-efficacy, is also accepted with a beta of 0.103, t-statistic of 3.597, and p-value of 0.000. This comprehensive analysis highlights the significant roles of leadership style, organisational culture, and self-efficacy in shaping the intention to accept while also recognising the vital mediating role of self-efficacy in the influence of peer factors.

Table 4
Hypotheses Testing Results

Hypotheses	Beta	T-statistics	P-values	2.50%	97.50%	Decision
H1: LS -> INT	0.208	4.434	0.000	0.110	0.292	*Accepted*
H2: LS -> SE	0.125	2.601	0.009	0.027	0.219	*Accepted*
H3: LS -> SE -> INT	0.051	2.478	0.013	0.012	0.094	*Accepted*
H4: OC -> INT	0.192	3.272	0.001	0.079	0.309	*Accepted*
H5: OC -> SE	0.270	4.544	0.000	0.152	0.383	*Accepted*
H6: OC -> SE -> INT	0.110	4.097	0.000	0.060	0.166	*Accepted*
H7: PI -> INT	0.106	1.837	0.066	-0.008	0.218	*Rejected*
H8: PI -> SE	0.253	4.050	0.000	0.128	0.371	*Accepted*
H9: SE -> INT	0.408	8.939	0.000	0.316	0.495	*Accepted*
H10: PI -> SE -> INT	0.103	3.597	0.000	0.050	0.165	*Accepted*

Effect Sizes (f^2) & Variance Inflation Factor (VIF)

Table 5 summarises the effect sizes (f^2) based on Cohen's (1992) guidelines, categorising them as minor (0.020 to 0.150), medium (0.150 to 0.350), and large (0.350 and above). The effect sizes in this study range from small (0.012) to large (0.240), indicating varying impacts of the analysed variables. Additionally, the Variance Inflation Factor (VIF) values shown in Table 6 are consistently below the lenient threshold of 5, with the highest being 2.016, suggesting minimal collinearity. This reliability supports comparing effect sizes and interpreting the structural model coefficients. The model exhibits substantial explained variance for the endogenous construct, with an R^2 value of 0.514 (Figure 1). For the mediator, the model accounts for about 30% of the variance, indicated by an R^2 value of 0.300, demonstrating the model's effectiveness in accurately capturing mediation dynamics and representing the underlying processes.

Table 5
Effect Sizes (f^2) & Variance Inflation Factor (VIF)

	f2		VIF	
	INT	SE	INT	SE
LS	0.069	0.018	1.286	1.264
OC	0.038	0.055	2.016	1.912
PI	0.012	0.048	2.007	1.915
SE	0.240		1.428	

PLSpredicts & Cross-Validated Predictive Ability Test (CVPAT)

The model's inferences and managerial implications were thoroughly evaluated using out-of-sample predictive analysis via the PLSpredict method, as Shmueli et al. (2016, 2019) advocated. As shown in Table 6, the application of PLS-SEM yielded significantly better Q^2 predictions (>0) than naive mean predictions, consistently achieving lower Root Mean Square Error (RMSE) values compared to linear model (LM) benchmarks, highlighting its robust predictive capabilities. Remarkably, in six instances, RMSE values from PLS-SEM predictions surpassed those from the LM prediction benchmark, emphasising the proposed model's predictive strength, as outlined in Table 6. The development of the Cross-Validated Predictive Ability Test (CVPAT) by Hair et al. (2022), along with its integration with PLSpredict analysis by Liengaard et al. (2021), represents significant advancements in predictive modelling. Furthermore, Table 7 corroborates the superior predictive abilities of PLS-SEM, showing lower average loss values against indicator averages and LM benchmarks, providing compelling evidence of its enhanced predictive performance.

Table 6
PLS Predicts

	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLS-LM
INT1	0.332	0.631	0.629	0.002
INT2	0.230	0.623	0.628	-0.005
INT3	0.256	0.679	0.696	-0.017
INT4	0.173	0.717	0.717	0.000
SE1	0.228	0.620	0.619	0.001
SE2	0.180	0.624	0.638	-0.014
SE3	0.148	0.676	0.678	-0.002
SE4	0.145	0.683	0.696	-0.013
SE5	0.188	0.615	0.629	-0.014

Table 7
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-value	p-value
INT	-0.145	6.625	0.000
SE	-0.089	5.040	0.000
Overall	-0.114	6.847	0.000

Importance-Performance Map Analysis (IPMA)
The Importance-Performance Map Analysis (IPMA) conducted by Ringle and Sarstedt (2016) and Hair et al. (2018) offers valuable insights into prioritising improvements for factors affecting performance. Table 8 reveals that self-efficacy, while having the highest total effect (0.408) among variables, shows the lowest performance score (60.548). This suggests a significant opportunity for enhancement. Strategies such as targeted training programs to boost confidence and operational skills, mentorship initiatives, and creating supportive environments should be implemented to improve self-efficacy. Additionally, fostering a culture that encourages risk-taking and recognises individual achievements can enhance self-efficacy, ultimately improving overall performance.

Table 8
Importance-Performance Map Analysis (IPMA)

	Total Effect	Performance
LS	0.259	66.582
OC	0.302	67.523
PI	0.209	66.583
SE	0.408	60.548

Discussion & Conclusion
Discussion
To positively influence employees' intention to accept AI-enabled transformation, airline companies should strategically enhance peer influence, organisational culture, and leadership style, utilising self-efficacy as a mediator. As revealed in the hypotheses testing, self-efficacy holds a substantial beta value (0.408), indicating its critical role in mediating the effect of these variables on employees' acceptance of transformation. Firstly, fostering peer influence (Beta: 0.253) can significantly elevate self-efficacy. This can be achieved by encouraging knowledge-sharing and collaboration among employees, where more experienced individuals guide their peers in AI applications (Durkin et al., 2021). Creating peer learning groups or forums can boost confidence and diminish resistance to new technologies as employees receive first-hand support and validation from their colleagues (Nurjanah & Harsono, 2024). Enhancing organisational culture (Beta: 0.270) involves cultivating an environment that values innovation and continuous improvement. Airlines should implement initiatives that reward experimentation and allow for safe failures, enhancing self-efficacy by empowering employees to engage with AI without fear of negative repercussions (Martínez et al., 2024). Additionally, transparent communication regarding the benefits and implications of AI implementations can alleviate uncertainties, promoting a culture of trust and openness necessary for technological adoption (Jain et al., 2024). Regarding leadership style (Beta: 0.125), transformational leadership approaches should be adopted where leaders act as role models by embracing AI technologies and championing such transformations (Kaur & Kaur,

2024). Leaders should provide vision-driven goals that inspire and motivate employees, aligning AI initiatives with overarching organisational goals. By offering regular feedback and recognising achievements, leaders can enhance employees' self-efficacy, fostering an optimistic outlook toward AI-enabled transformation (Chi et al., 2022). The effective enhancement of these strategic areas leads to increased employee self-efficacy, significantly affecting their intention to accept AI transformations within the airline industry. This integrated approach aligns with the statistical significance found in the study results. It provides a roadmap for airlines to drive AI transformation with minimal resistance and maximal engagement, securing competitive advantages and innovation within the industry.

Theoretical Implications

The theoretical implications of this research are firmly rooted in the framework of Transformational Leadership Theory, which supports understanding the variables and dynamics within our research model. Transformational Leadership Theory posits that leaders who inspire, motivate, and foster an environment of innovation can significantly influence their followers' attitudes and behaviours (Bass & Riggio, 2006). In the context of this study, such leadership practices are essential in enhancing employees' intention to accept AI-enabled transformations, with self-efficacy serving as a critical mediator. Transformational leaders effectively elevate self-efficacy by articulating compelling visions and providing individualised support, which helps reduce employees' resistance to change and fosters an internal drive to adapt (Eisenbeiss et al., 2008). This aligns with our findings that highlight leadership style's positive impact on self-efficacy and its influence on the intention to accept AI transformations. When organisational culture encourages transformational leadership qualities, it further strengthens this relationship, resonating with Chi et al.'s (2022) view on the role of leadership in facilitating technology acceptance. Additionally, peer influence within this dynamic is underpinned by the transformational leader's ability to cultivate a supportive and collaborative organisational culture (Jain et al., 2024). As employees engage in shared learning experiences, their self-efficacy is enhanced, increasing their willingness to embrace AI transformations (Nurjanah & Harsono, 2024). In essence, Transformational Leadership Theory provides a coherent lens through which the interaction between leadership, organisational culture, peer influence, and self-efficacy can be viewed. This theoretical grounding ultimately enriches understanding of factors driving acceptance of technological change in the airline industry. This theoretical grounding supports the research model and offers strategic insights into balancing leadership and cultural dynamics for successful AI implementation.

Practical Implications

The practical implications of this study are significant for airline companies pursuing AI-enabled transformations. First, by leveraging Transformational Leadership Theory, these companies can address leadership's critical role in fostering an environment conducive to technological change. Leaders should be trained to inspire and motivate employees, which enhances their self-efficacy and openness to AI adoption (Bass & Riggio, 2006; Eisenbeiss et al., 2008). Additionally, airline companies should focus on developing a supportive organisational culture that values innovation and collaboration. Such an environment not only boosts individual self-efficacy but also reinforces the positive impacts of peer influence as employees learn and adapt together (Jain et al., 2024). This can be implemented through workshops, peer mentoring, and collaborative platforms encouraging knowledge-sharing about new technologies. Furthermore, companies must recognise the importance of self-efficacy as a mediator in technology acceptance and provide resources and support to boost this confidence (Nurjanah & Harsono, 2024). This might include training programs, clear communication about AI benefits, and fostering a psychologically safe space for experimentation and learning. By strategically enhancing leadership practices, organisational culture, and self-efficacy, airline companies can improve employee acceptance of AI technologies, leading to smoother transitions and more effective implementations.

Suggestions for Future Study

Future studies should explore the longitudinal effects of transformational leadership on self-efficacy and AI adoption within the airline industry. Researchers can assess how sustained leadership practices influence technological adoption and employee adaptation to AI changes by examining these dynamics over time. Additionally, it would be beneficial to explore how different dimensions of organisational culture specifically contribute to enhancing self-efficacy and openness towards AI, thereby providing more granular insights into which cultural aspects have the most significant impact. Research could also extend to comparing results across various geographical regions and sectors within the airline industry to determine whether cultural or sectoral differences affect the relationships indicated in this study. Finally, incorporating qualitative methods, such as interviews or focus groups, can provide deeper insights into employee perceptions and experiences of leadership and AI integration, offering a more comprehensive understanding of the psychological and social factors influencing technology acceptance.

Conclusion

This study underscores the pivotal role of transformational leadership in facilitating AI-enabled transformations within the airline industry. Leaders can significantly influence employees' willingness to embrace technological changes by enhancing self-efficacy and cultivating a supportive organisational culture. This approach aligns with the theoretical foundations of Transformational Leadership Theory and provides practical pathways to address challenges in technology adoption. Contextually, as airlines increasingly integrate AI to optimise operations and customer service, fostering an environment that supports learning and collaboration becomes essential. The study's findings highlight the importance of strategic leadership development and cultural initiatives that bolster employee confidence and adaptability. These insights are crucial for airline companies aiming to navigate the complexities of AI implementation effectively. By focusing on leadership, culture, and peer dynamics, airlines can enhance their competitive edge and ensure the successful integration of AI technologies, ultimately driving innovation and operational excellence in a rapidly evolving industry.

References

Abd El Kafy, J. H., Eissawy, T. M., & Hasanein, A. M. (2022). Tourists' Perceptions Toward Using Artificial Intelligence Services in Tourism and Hospitality. *Journal of Tourism, Hotels and Heritage*, *5*(1), 1-20.

Bai, X., Guo, R., & Gu, X. (2024). Effect of teachers' TPACK on their behavioural intention to use technology: chain mediating effect of technology self-efficacy and attitude toward use. *Education and Information Technologies*, *29*(1), 1013-1032.

Bass, B. M., & Riggio, R. E. (2006). Transformational Leadership (2nd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Bayraktar, S., & Jiménez, A. (2020). Self-efficacy as a resource: a moderated mediation model of transformational leadership, extent of change and reactions to change. *Journal of Organizational Change Management*, *33*(2), 301-317.

Cheriyan, A., Sharma, R. K., Joseph, A., & Kappil, S. R. (2022). Consumer acceptance towards AI-enabled chatbots; case of travel and tourism industries. *Journal of Positive School Psychology*, *6*(3), 3880-3889.

Chi, O. H., Gursoy, D., & Chi, C. G. (2022). Tourists' attitudes toward using artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking. *Journal of Travel Research*, *61*(1), 170-185.

Chughtai, M. S., Syed, F., Naseer, S., & Chinchilla, N. (2023). Role of adaptive leadership in learning organizations to boost organizational innovations with change self-efficacy. *Current Psychology*, 1-20.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112, 155–159. doi:10.1037/0033-2909.112.1.155

De Cannière, M.H., De Pelsmacker, P., Geuens, M. (2009) Relationship quality and the theory of planned behaviour models of behavioral intentions and purchase behavior. J. Bus. Res., 62, 82–92.

Duong, C. (2023). A moderated mediation model of perceived barriers, entrepreneurial self-efficacy, intentions, and behaviors: A social cognitive career theory perspective. *Oeconomia Copernicana*, *14*(1), 355-388.

Durkin, K., Williford, D. N., Turiano, N. A., Blank, M. D., Enlow, P. T., Murray, P. J., ... & Duncan, C. L. (2021). Associations between peer use, costs and benefits, self-efficacy, and adolescent E-cigarette use. *Journal of Pediatric Psychology*, *46*(1), 112-122.

Eisenbeiss, S. A., van Knippenberg, D., & Boerner, S. (2008). Fostering team innovation: How leader behaviour influences integrating different team member perspectives. Research on Managing Groups and Teams, 11, 211-233.

Gelaidan, H. M., Al-Swidi, A. K., & Al-Hakimi, M. A. (2024). Servant and authentic leadership as drivers of innovative work behaviour: the moderating role of creative self-efficacy. *European Journal of Innovation Management*, *27*(6), 1938-1966.

Geske, A. M., Herold, D. M., & Kummer, S. (2024). Artificial Intelligence as a driver of efficiency in air passenger transport: A systematic literature review and future research avenues. *Journal of the Air Transport Research Society*, 100030.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, CA: SAGE.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3 ed.).* Thousand Oaks, CA: Sage.

Hair, J.F., M. Sarstedt, C.M. Ringle, and S.P. Gudergan. (2018). *Advanced issues in partial least squares structural equation modeling.* Thousand Oakes, CA: Sage Publications

Halawi, D. B. A., L., Miller, Ed D., M. D., & Holley, Ph D. S. J. (2024). Artificial Intelligence in Aviation: A Path Analysis. *Journal of Aviation/Aerospace Education & Research*, *33*(4), 10.

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling, *Journal of the Academy of Marketing Science,* 43(1): 115-135

Intaratat, K., Osman, Z., Nguyen, H. A. T., Suhandoko, A. D. J., & Sultana, N. (2024). Peer and tutor interaction effects on collaborative learning: The role of learning self-efficacy. *Edelweiss Applied Science and Technology*, *8*(4), 2108-2121.

Ivanov, D., Pelipenko, E., Ershova, A., & Tick, A. (2021, November). Artificial intelligence in aviation industry. In *International Scientific Conference Digital Technologies in Logistics and Infrastructure* (pp. 233-245). Cham: Springer International Publishing.

Jain, A., Damodaran, A., Kumar, R., & Bangwal, D. (2024). Stakeholder perception on challenges of artificial Intelligence implementation in Indian aviation industry: a focus group study. *International Journal of Business Innovation and Research*, *35*(1), 1-16.

Kang, Y-N., Chang, C-H., Kao, C-C., Chen, C. Y., Wu, C-C. (2019) Development of a short and universal learning self-efficacy scale for clinical skills. PLoS ONE 14(1): e0209155. https://doi.org/ 10.1371/journal.pone.0209155

Kaur, H., & Kaur, P. (2024). Paradoxes of Self-Service Technology Adoption: An Evidence from Airline Industry. *Saudi J Bus Manag Stud*, *9*(5), 96-103.

Kebah, M., Raju, V., & Osman, Z. (2019). Growth of online purchase in Saudi Arabia retail industry. *International Journal of Recent Technology and Engineering*, 8(3), 869-872.. ISSN: 2277-3878

Kebah, M., Raju, V., & Osman, Z. (2019). Online purchasing trend in the retail industry in Saudi. *International Journal of Recent Technology and Engineering (IJRTE)*, 8(3), 865-868. ISSN: 2277-3878

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1-10.

Kock, N., & Lynn, G.S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, 13(7), 546-580.

Le, T. T., Doan, X. H., & Duong, C. D. (2023). A serial mediation model of the relation between cultural values, entrepreneurial self-efficacy, intentions and behaviors: Does entrepreneurial education matter? A multi-group analysis. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(2), 100064.

Li, X. T., Rahman, A., Connie, G., & Osman, Z. (2020). Examining customers' perception of electronic shopping mall's e-service quality. *International Journal of Services, Economics and Management*, 11(4), 329-346.

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, Yet Forsaken? Introducing a Cross-validated Predictive Ability Test in Partial Least Squares Path Modeling. *Decision Sciences*, 52(2), 362-392.

Madlock, P. E. (2008). The Link Between Leadership Style, Communicator Competence, and Employee Satisfaction. *The Journal of Business Communication (1973)*, *45*(1), 61–78.

Martínez, B. M. T., Carmen Pérez-Fuentes, M., & Jurado, M. D. M. M. (2024). The influence of perceived social support on academic engagement among adolescents: the mediating role of self-efficacy. *Anales de Psicología/Annals of Psychology*, *40*(3), 409-420.

Meidute-Kavaliauskiene, I., Yıldız, B., Çiğdem, Ş., & Činčikaitė, R. (2021). The effect of COVID-19 on airline transportation services: A study on service robot usage intention. *Sustainability*, *13*(22), 12571.

Meyer-Waarden, L., Pavone, G., Poocharoentou, T., Prayatsup, P., Ratinaud, M., Tison, A., & Torné, S. (2020). How service quality influences customer acceptance and usage of chatbots?. *SMR-Journal of Service Management Research*, *4*(1), 35-51.

Naz, S., Li, C., Zaman, U., & Rafiq, M. (2020). Linking proactive personality and entrepreneurial intentions: A serial mediation model involving broader and specific self-efficacy. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 166.

Northouse, P. G. (2018). Leadership: Theory and Practice (8th ed.). Thousand Oaks, CA: Sage Publications.

Nurjanah, D. L., & Harsono, H. (2024). The Influence of Entrepreneurship Education, Peer Influence, and Self-Efficacy on Students' Entrepreneurial Intentions. *Indonesian Interdisciplinary Journal of Sharia Economics (IIJSE)*, *7*(3), 4476-4491.

Osman, Z., Mohamad, W., Mohamad, R. K., Mohamad, L., & Sulaiman, T. F. T. (2018). Enhancing students' academic performance in Malaysian online distance learning institutions. *Asia Pacific Journal of Educators and Education*, 33, 19-28.

Purnomo, E. N., Imron, A., Wiyono, B. B., Sobri, A. Y., & Dami, Z. A. (2023). E-leadership, technology acceptance and technological self-efficacy: Its effect on teacher attitudes in virtual learning environments. *Pegem journal of Education and Instruction*, *13*(4), 189-198.

Ringle, C. M., (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems.* 116: 1865–1886.

Shmueli, G., Sarstedt, J.F., Hair, J.-H., Cheah, H., Ting, S., (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*. 53: 2322–2347.

Shmueli, G., Ray, J. M., Estrada, V., and Chatla, S. B. (2016). The elephant in the room: predictive performance of PLS models. *Journal of Business Research*, 69: 4552–4564.

Sreejith, P. M., & Sreejith, S. (2023). Exploring the role of cultural capital, ICT skills, and entrepreneurial self-efficacy in shaping entrepreneurial intention among women. *Journal of Telecommunications and the Digital Economy*, *11*(2), 151-179.

Stewart, D., McWhirter, J., Sun, J., & Stewart, D. (2007). Development of population-based resilience measures in the primary school setting. *Health education*.

Susanti, S., & Ardi, A. (2022). The Effect of Digital Transformational Leadership, Creative Self-Efficacy on Innovative Behaviour Mediated by Perceived Organizational Support. *JIIP-Jurnal Ilmiah Ilmu Pendidikan*, *5*(8), 3111-3120.

Trivedi, S. K., Patra, P., & Singh, S. (2022). A study on intention to use social media in higher education: the mediating effect of peer influence. *Global Knowledge, Memory and Communication*, *71*(1/2), 52-69.

Zou, Y., Liu, S., Guo, S., Zhao, Q., & Cai, Y. (2023). Peer support and exercise adherence in adolescents: the chain-mediated effects of self-efficacy and self-regulation. *Children*, *10*(2), 401.