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The Human Side of AI Adoption: Leadership, Job Security, Psychological Need, and Employee Outcomes

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ABSTRACT

The rapid integration of artificial intelligence (AI) into the education sector has raised a question that goes beyond technology itself: When is AI's use beneficial to employees instead of a burden? The study builds on the theories of Self-Determination Theory (SDT), Social Exchange Theory (SET), and the Technology Acceptance Model (TAM) and proposes the following mediation model: AI Adoption Leadership Style influences Task Performance and Job Stress, with Perceived Job Security and Psychological Need satisfaction serving as the mediating psychological mechanisms.Based on the theories of SDT, SET, and TAM, this study proposes the following mediation model: AI Adoption Leadership Style affects Task Performance and Job Stress, while Perceived Job Security and Psychological Need satisfaction act as the psychological mediation pathway. A total of 359 respondents from the education sector of Punjab, Pakistan, were selected to collect the data and analyzed using partial least squares structural equation modeling (PLS-SEM) software, namely SmartPLS 4. Strong reliability and validity were obtained in the measurement model and good fit was achieved for the structural model (R^2 = 0.44-0.49, SRMR = 0.044). AI Adoption Leadership Style significantly and positively affected Psychological Need (β = 0.668) and Perceived Job Security (β = 0.663), and had significant direct effect on Task Performance (β = 0.433) and Job Stress (β = -0.503). The results showed that the mediation model for the relationship between Perceived Job Security and Task Performance was complementary partial mediation (β = 0.336) and the mediation model for the relationship between Psychological Need and Job Stress was complementary partial mediation (β = -0.246). All eight hypotheses were supported with both stress related pathways appearing in the hypothesized negative direction. The findings contribute to the existing human-resource and technology-adoption literature and have important implications for educational leaders who are tasked with leading change through the use of AI in an under-researched context of education in South Asia.

Introduction

The integration of artificial intelligence (AI) into the workplace is no longer an emerging trend but an integral part of an organization's functioning, and is transforming the way work is designed, monitored, and executed. The education industry is currently in the middle of a digital revolution, and AI is increasingly being integrated into the education support process, administrative processes, assessment and performance management. However, AI is not a panacea for all: equipping one institution with the same tools that increase productivity in another can lead to greater anxiety and resistance. But recent data have come in together to suggest a key takeaway: whether AI technology is adopted or not and its impact on outcomes is not their story, it is the story of the leadership that is introducing it (Gallup, 2026; Wang et al., 2025). Leaders are not just granting permission for AI tools, they are influencing the psychological and organizational landscape where employees are interacting with AI. According to Gallup's (2026) State of the Global Workplace report, there is a strong correlation between manager support for AI and employee experiences of a meaningful impact, with little to no impact on engagement or strain when employees are not supported in their manager's use of AI. Transformational and digital leadership styles foster adoption by establishing trust, support, and psychological safety without mandate (Gayathiri et al., 2026; Wang et al., 2025). This places AI Adoption Leadership Style as a key determinant in two key employee outcomes, Task Performance and Job Stress. The connection between leadership and employee outcomes is, however, not always a straightforward one (Saeed and Farooqi, 2014). The adoption of AI can also be met with resistance by employees, as they are not only worried about losing their job to AI, but also fear constant monitoring and the inability to keep up with new technology (Soulami et al., 2024). These fears are psychological in nature. The study is based on two theories, namely, Self-Determination Theory (Deci & Ryan, 2000) and Social Exchange Theory (Blau, 1964), which suggest that PJS and PN satisfaction are the intermediary processes between leadership behavior and performance outcome and stress reduction. Recent studies support the importance of this path: Psychologically safe AI adoption (PSAA) has been associated with increased levels of depression, which is partially mitigated by ethical, employee-centred leadership (Kim et al., 2025; Anum et al., 2017). If leaders create a safe, capable and valued work environment, employees will be more receptive to using AI effectively; if they do not, no tool, even a good one, will realize its potential.

This study falls within the education sector of Punjab, Pakistan, where digital transformation is happening at a fast pace, driven by the government, yet there is a lack of empirical research specifically focused on the human aspects of AI implementation. Much of the existing evidence originates from high-tech firms and East Asian samples (Gayathiri et al., 2026; Wang et al., 2025), leaving employees in developing-country education institutions largely unexamined a gap consistent with recent calls for context-specific tests of AI-adoption models outside high-tech and Western settings (Huang & Zhao, 2025). By testing a theoretically derived model of leadership, employee psychology, and outcomes in this setting, the study aims to explain not just whether AI improves organizational performance, but under what leadership and support conditions it does so.

Research Objectives

1. To examine the direct effect of AI Adoption Leadership Style on Task Performance and Job Stress among employees in the education sector of Pakistan.
2. To assess the effect of AI Adoption Leadership Style on Perceived Job Security and Psychological Need satisfaction.
3. To investigate the mediating role of Perceived Job Security and Psychological Need in the relationship between AI Adoption Leadership Style and employee outcomes.

Significance and Research Gap

This study theoretically and practically contributes to the existing literature and addresses three gaps in the currently available knowledge. It theoretically incorporates various theories, such as Self-Determination Theory, Social Exchange Theory, and the Technology Acceptance Model, into a single model to explain how and when AI Adoption Leadership influences employee outcomes, a combination that has not been attempted in previous studies, with most focusing on leadership, employee psychological needs, or technology adoption separately (Kim et al., 2025; Wang et al., 2025). There is empirical evidence that is focused on high-tech companies and economies in Asia, with no evidence found for the education sector in a developing South Asian economy; in this study, the model is tested in a context where digital transformation is accelerating but there is limited evidence at the employee level. Methodologically, it is addressing a gap by introducing and testing two different mediational pathways (Perceived Job Security and Psychological Need), instead of just direct effects. In practical terms, the results inform educational leaders and HR practitioners that the successful implementation of AI requires not only the technology but also the leadership and the psychological safety, providing specific insights into how to alleviate employee stress and boost productivity in the era of AI.

Literature Review

AI Adoption Leadership Style

AI Adoption Leadership Style is the mode of management that enables leaders to implement, advocate and integrate AI tools into day-to-day activities and work, while addressing the human side of change. It is not just about authorizing new technology, it's about communicating an AI strategy, making sure that the organization is set up to support that new technology, and ensuring that employees feel comfortable using new technology. Gallup (2026) used global workforce data to identify the characteristics of effective AI leadership, which they define as a clear company-wide strategy combined with managerial support, rather than the passive or unguided use of AI: Managers who actively support AI use are significantly more likely than those who do not to say that AI has changed the way they work. Wang et al. (2025) narrow this down to transformational leadership vision, motivation and individualized support finding that this directly predicts employee AI usage and that this plays a role indirectly via perceived organizational support, and Gayathiri et al. (2026) add the parallel construct of digital leadership, which combines the vision of technology with the management of people to enhance organizational performance through empowerment and engagement. The concept of the construct has been conceptually divided in these studies, with each using a different terminology for the leadership behavior, making it difficult to compare across studies and necessitating the present study's integrative treatment.

Task Performance and Job Stress

Task Performance is the efficiency and proficiency with which workers complete the specific tasks they have been assigned to complete, such as the ability to use AI tools to create higher-quality work in less time. Gayathiri et al. (2026) define it as an outcome of better digitally capable leadership, which can empower and engage employees to use performance systems based on AI, whereas Wang et al. (2025) consider it as the proximal driver of performance gains. On the other hand, Job Stress is the psychological stress that when the demands of AI use exceed the employee's perceived ability to handle them. The recent literature is clear that the impact of AI on stress is not guaranteed, but rather depends on the particular circumstances. Soulami et al. (2024) summarize in a bibliometric and systematic review, highlighting technological complexity, role ambiguity, and fear of displacement as the key stressors, and Kim et al. (2025) present direct longitudinal evidence that AI adoption in organizations increases the likelihood of depression, but this effect can be partially mitigated by ethical and supportive leadership. These findings suggest that leadership must be a key factor, not just a side moderator, in determining the impact AI will have on employees' well-being.

Perceived Job Security and Psychological Need

Perceived Job Security is a worker's personal feeling regarding the continuation of their job and its stability in the face of AI-driven change; it's a subjectively felt security, meaning two workers in the same situation who are being automated may have two entirely different perceptions of threat to their jobs. The literature is in consensus that people's resistance to AI is not because of lack of knowledge but rather due to concerns about being displaced, negatively evaluated, or unable to keep up with technology (Soulami et al., 2024). According to Self-Determination Theory (Deci & Ryan, 2000), Psychological Need refers to the basic needs of employees that need to be met for them to actively participate in AI without just complying or opting out.Psychological Need, rooted in Self-Determination Theory (Deci & Ryan, 2000), is the intrinsic need of employees to act autonomously, competently, and despite the presence of AI, in a way that is seen as meaningful. Given these three basic psychological needs, Huang and Zhao (2025) conducted a study of university faculty and revealed that these needs were most closely linked to work-life balance and job satisfaction by way of AI literacy. Psychological need satisfaction is also placed in the center of the adaptation process in the research conducted by Soulami et al. (2024), who claim that employees only "craft" their jobs when their psychological safety and support are present. The two mediators are described in the literature to some extent, but are occasionally combined in neighbouring concepts like support, empowerment or safety, and hence that is why the present study considers Perceived Job Security and Psychological Need as two distinct focal mediators.

Theoretical Foundation

Theoretically, the paths offered in this study are grounded in three complementary lenses. The psychological-need pathway is best accounted for by Self-Determination Theory (Deci & Ryan, 2000), which suggests that when these needs are met, individuals function at their best, and therefore, strain will be lower when leadership meets these needs. Social Exchange Theory (Blau,1964) explains the mutual causality of perceived ‘security’: if leaders invest in employees and demonstrate that their role is appreciated, employees respond with engagement and willingness to adapt to the situation to support performance. We must take into account the leadership formed environment in which the adoption behavior is occurring, in which perceived usefulness, perceived ease of use are embedded (Davis, 1989). These lenses help to understand not only the role of leadership, but the two paths it should take to increase performance and to decrease stress through need-satisfaction.

Hypothesis Development

Direct Effects of AI Adoption Leadership Style on Task Performance and Job Stress

In addition to the mediated pathways, the literature is finding both direct pathways between leadership and outcomes. Gayathiri et al. (2026) found that digital leadership positively impacts task performance through empowered and engaged employees and Wang et al. (2025) demonstrated a relationship between digital leadership and effective AI usage. The most direct evidence of negative consequences of using AI without psychologically supportive leadership comes from Kim et al. (2025), who find that AI without psychologically attentive leadership increases strain and risk for depression, and from Soulami et al. (2024), who find that levels of strain due to technological complexity are reduced by leadership and organizational support. Direct paths in the model are assumed to be partial, as well-evidenced mediators are also included in the model. Accordingly:

- H1: AI Adoption Leadership Style has a significant positive and direct relationship with Task Performance.
- H2: AI Adoption Leadership Style has a significant negative and direct relationship with Job Stress.

AI Adoption Leadership Style, Perceived Job Security, and Psychological Need

There is support in the literature for a positive impact of leadership on both mediators. Wang et al. (2025) show, using structural equation modeling, that perceived organizational support which is correlated with both security and need satisfaction is a partial mediator between transformational leadership and the motivational conditions of autonomy, competence, and relatedness, suggesting that feeling valued and supported by the organization reduces the threat perception and increases the motivational conditions associated with the three primary components of the model. This is further corroborated by Gallup (2026) which found that having a succinct AI strategy lowers uncertainty and re-gives a sense of control, which is essentially the restoration of security. The findings of Gayathiri et al. (2026) indicate that digital leadership creates empowerment and engagement, both of which are signs of the fulfillment of psychological needs. None of these studies operationalizes perceived job security or psychological need as an outcome variable of leadership with instruments used here, and there is a good motivation for the reversed direction of the relationship, but there is a lack of empirical evidence to establish the magnitude of the relationship in this specific model. Accordingly:

- ***H3:*** *AI Adoption Leadership Style has a significant positive and direct relationship with Perceived Job Security.*
- ***H4:*** *AI Adoption Leadership Style has a significant positive and direct relationship with Psychological Need.*

Perceived Job Security, Psychological Need, and Employee Outcomes

The model suggests that perceived job security can lead to the transmission of leadership influence into task performance: Secure workers are more likely to adopt and persist with AI tools and effective use of AI leads to performance improvements, a pathway that Wang et al. (2025) call from support to usage to outcomes. This is supported by Soulami et al. (2024) as they illustrate how employees who feel psychologically safe and secure in the workplace are more likely to engage in adaptive job crafting, which is fundamentally distinct from employee disengagement. A separate model proposes that psychological need satisfaction transmits the influence of leadership into job stress; there is comparatively direct evidence for this model as Huang and Zhao (2025) and Soulami et al. (2024) demonstrate that satisfied psychological needs lead to a decrease in strain and facilitate adaptation to technological change, which is predicted by SDT that thwarted needs are associated with ill-being while satisfied needs are associated with adaptive functioning. Accordingly:

- ***H5:*** *Perceived Job Security has a significant positive effect on Task Performance.*
- ***H6:*** *Psychological Need has a significant negative effect on Job Stress.*

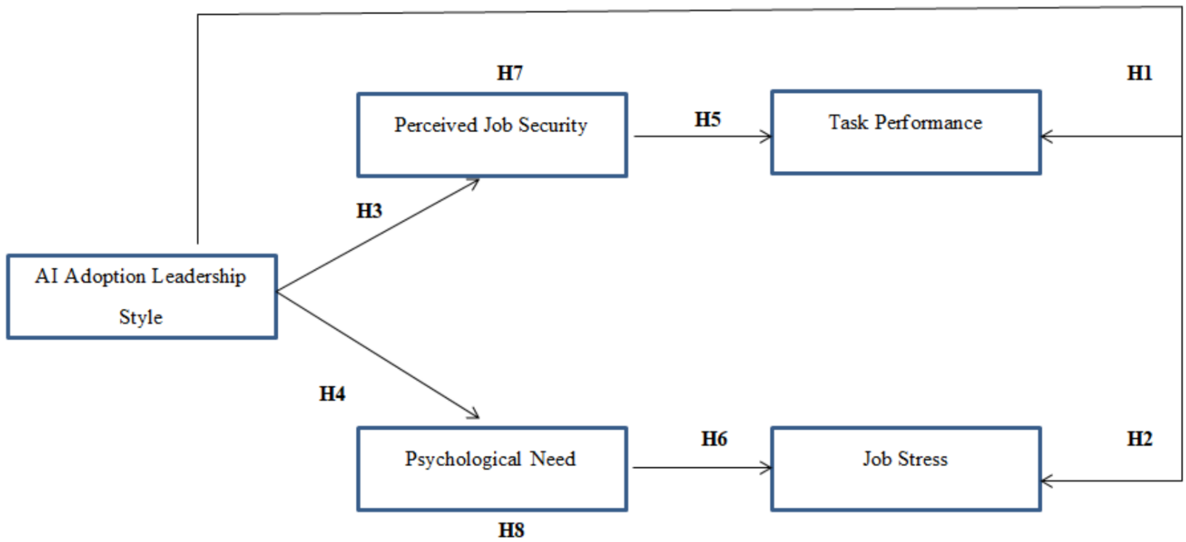
The Mediating Role of Perceived Job Security and Psychological Need

Combined, the evidence supports two mediating pathways which are leadership leads to perceived security and perceived psychological need which leads to performance and stress, respectively. Wang et al. (2025) test one closely related mediation with their findings that perceived organizational support partially mediates the leadership to AI-usage relationship, while Gayathiri et al. (2026) suggest that empowerment and engagement serve as the link between leadership and performance. The studies reviewed tend to mix up similar mediators (support, empowerment, engagement and safety all get used somewhat interchangeably and none studies security and need satisfaction as separate channels to distinct outcomes. It is analytically useful to assign security to performance and stress to need and a direct path indicates that part mediation is most likely to be expected, extending rather than simply repeating the existing evidence. Accordingly:

- ***H7:*** *Perceived Job Security mediates the relationship between AI Adoption Leadership Style and Task Performance.*

- ***H8:*** *Psychological Need mediates the relationship between AI Adoption Leadership Style and Job Stress.*

Figure 1. Hypothesized research model



Research Methodology

Research Approach and Design

This study used a quantitative positivist research approach, that is, the assumption of this research is that social reality is objective and can be measured in a systematic empirical study (Creswell & Creswell, 2018). The positivist epistemology is appropriate for using numerical data and statistical techniques to test hypotheses evolved from theory, and quantitative designs enable researchers to make precise statements about relationships between variables and to draw generalizations about them to other populations (Bryman, 2016). Because it was important to examine the relationship between the constructs within the population sample, the study employed a cross sectional survey design in which the data were gathered from participants at one time (Hair et al., 2019). The study had a deductive approach, with the eight hypotheses being formulated based on existing theoretical frameworks, such as the Self-Determination Theory (Deci & Ryan, 2000), Social Exchange Theory (Blau, 1964), and Technology Acceptance Model (TAM) (Davis, 1989), which served as a conceptual foundation for guiding the prediction of employee perceptions and performance outcomes within an AI-enabled organizational context.

Population and Sampling

The target population included full-time employees in the education sector of Punjab, Pakistan, who had either explicitly introduced AI tools in their work processes or were actively utilizing AI tools that had a significant impact on their job performance, whether directly or through AI-supported decision-making. The dynamic growth of Pakistan's economy and the introduction of digital transformation by the government have led to greater adoption of AI in the education sector, thus making this workforce a relevant and accessible population for analysis of the outcomes of AI application. To limit the accessible population, organizations with adequate organizational structures and formal AI governance were selected; as the constructs of interest (task performance, job stress, perceived job security and psychological need) are psychological and behavioral in nature, it was believed that these could best be captured at the individual level, consistent with Sekaran and Bougie (2016). The study used a purposive sampling approach with stratified sampling within selected education institutions that adopted the AI technology in the region, as there is no comprehensive sampling frame for all institutions. In combination, the selection of organizations within the purposive sampling that matched the inclusion criteria and participants who were aware of organizational leadership (Tongco, 2007) along with stratification per institution to ensure adequate representation across the sector, thereby combining the theoretical purposiveness with statistical representativeness (Etikan et al., 2016). The sample size for the study was determined by the proposed minimum ratio of 10 observations per structural path that points to any endogenous construct (Hair et al., 2019) and the proposed minimum sample size for mediation (Kline, 2016) which was 350 usable responses, given the six direct structural paths and 35 indicator items across five latent constructs. Thirty-five hundred and nine valid and complete responses were obtained in a final sample.

Measures and Data Collection

The data were gathered by using online-based self-administered structured questionnaire based on multi-items scales drawn from previously published peer reviewed literature, which were validated for content validity and reliability. The most widely used scale in organizational behavior research for item scoring is the Likert scale of 1 (strongly disagree) to 5 (strongly agree), with all items being scored on this scale (DeVellis, 2016). The eight items for AI Adoption Leadership Style were adapted from scales for transformational and digital-leadership (Gayathiri et al., 2026; Wang et al., 2025). The six items for Task Performance were adapted from Goodmann and Svyantek's (1989) task performance scale. The six items for Job Stress were adapted from Parker and DeCotiis's (1983) job stress scale, and the six items for Perceived Job Security were adapted from Ashford et al.'s (1989) job insecurity scale, but reverse coded for security. The nine items for Psychological Need satisfaction were adapted from the Basic Psychological Need Satisfaction scale (Gagné, 2003) based on Self-Determination Theory with three of each for autonomy, competence, and relatedness. Overall, the five constructs contained 35 indicator items. The questionnaires were sent out using Google Forms, through professional networks and through the HR offices of institutions. Each questionnaire was accompanied by a formal statement of informed consent that reiterated the voluntary nature of participation, the confidentiality of answers and the purely academic nature of the research, as per the American Psychological Association (2020) ethical practices. Three hundred and fifty-nine questionnaires were received and were complete and considered valid, and are presented by a demographic profile in Table 1.

Common Method Bias

Common method bias (CMB) was a potential methodological issue given the self-reported nature of all constructs and the measurement of these constructs all within the same time frame. Instead of the single factor test as has been criticized, which would be a comparatively poor diagnostic, the more rigorous full-collinearity approach advocated by Kock (2015) was used to evaluate CMB: If all constructs in the structural model have inner VIF values below 3.3, there should be no concerns about CMB. This procedural decision was backed up by design stage remedies such as previously validated scales, clear item wording, and providing assurance of respondent anonymity as recommended by Podsakoff et al. (2003).

Data Analysis Strategy

Data were analyzed using a combination of descriptive statistics and Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, following the two-stage procedure recommended by Hair et al. (2022): the measurement model was assessed first, followed by the structural model. PLS-SEM was selected because the model combines multiple latent constructs, two parallel mediation pathways, and a moderate sample size, conditions under which PLS-SEM is well suited relative to covariance-based SEM (Hair et al., 2019, 2022).

Results

Sample Profile

Data were gathered from 359 respondents working in the education sector of Punjab, Pakistan, using a structured, self-administered questionnaire. All study constructs were measured on 5-point Likert scales. The achieved sample size satisfies the requirements for stable PLS-SEM estimation established in Chapter 4. The demographic profile of the respondents is presented in

Table 1: Respondents' Profile (N = 359)

Variable	Category	n	%
Age	Under 25 years	74	20.6%
	25–34 years	129	35.9%
	35–44 years	90	25.1%
	45–54 years	48	13.4%
	55 years and above	18	5.0%
Gender	Male	216	60.2%
	Female	130	36.2%
	Non-binary / Gender diverse	7	1.9%
	Prefer not to say	6	1.7%

Variable	Category	n	%
Education	High school / Secondary certificate	24	6.7%
	Bachelor's degree	131	36.5%
	Master's degree	158	44.0%
	Doctoral degree (PhD or equivalent)	24	6.7%
	Professional certification / Diploma	22	6.1%
Experience	Less than 1 year	32	8.9%
	1–3 years	114	31.8%
	4–7 years	111	30.9%
	8–12 years	54	15.0%
	More than 12 years	48	13.4%
City	Islamabad	32	8.9%
	Gujranwala / Sialkot	74	20.6%
	Lahore	94	26.2%
	Gujrat	110	30.6%
	Khariyan	49	13.6%
AI Familiarity	Not at all familiar	21	5.8%
	Slightly familiar	59	16.4%
	Moderately familiar	120	33.4%
	Very familiar	108	30.1%
	Extremely familiar / Expert user	51	14.2%

Note. Percentages are rounded and may not sum exactly to 100%.

Measurement Model Assessment

Indicator reliability was evaluated through the outer loadings, using the criterion of loadings > 0.708 recommended as a rule of thumb, with items retained on composite-reliability grounds where slightly lower (Hair et al., 2022). As shown in Table 2, all 35 indicators loaded satisfactorily, with loadings ranging from 0.707 to 0.844; no item fell meaningfully below the benchmark, so the full instrument was retained. Internal consistency reliability was confirmed using Cronbach's alpha and composite reliability (ρa and ρc), all between 0.86 and 0.93, and convergent validity was established through the average variance extracted (AVE), which ranged from 0.596 to 0.647. Item-level skewness and kurtosis remained within ±0.6, indicating approximately normal distributions.

Table 2: Descriptive Statistics, Reliability, and Convergent Validity

Construct / Item	Mean	SD	Skewness	Kurtosis	Loading	α	ρa	ρc	AVE
AI Adoption Leadership Style						**0.916**	**0.919**	**0.932**	**0.632**
AALS1	3.755	0.813	-0.244	-0.421	0.783				
AALS2	3.752	0.800	-0.215	-0.244	0.841				
AALS3	3.738	0.811	-0.213	-0.441	0.751				
AALS4	3.760	0.811	-0.167	-0.362	0.760				
AALS5	3.749	0.808	-0.185	-0.472	0.825				
AALS6	3.716	0.837	-0.228	-0.369	0.805				
AALS7	3.741	0.800	-0.224	-0.391	0.841				

Construct / Item	Mean	SD	Skewness	Kurtosis	Loading	α	ρa	ρc	AVE
AALS8	3.738	0.786	-0.366	0.183	0.749				
Perceived Job Security						**0.879**	**0.881**	**0.909**	**0.624**
PJS1	3.588	0.820	-0.267	0.009	0.820				
PJS2	3.591	0.792	-0.316	0.017	0.804				
PJS3	3.585	0.817	-0.367	0.216	0.814				
PJS4	3.579	0.855	-0.234	0.067	0.763				
PJS5	3.593	0.869	-0.211	-0.261	0.734				
PJS6	3.588	0.803	-0.255	0.259	0.801				
Psychological Need						**0.915**	**0.917**	**0.930**	**0.596**
PN1 (AUT1)	3.621	0.836	-0.200	-0.233	0.740				
PN2 (AUT2)	3.585	0.831	-0.154	-0.235	0.739				
PN3 (AUT3)	3.641	0.830	-0.159	-0.231	0.766				
PN4 (COM1)	3.616	0.841	-0.113	-0.435	0.774				
PN5 (COM2)	3.646	0.826	-0.249	-0.148	0.773				
PN6 (COM3)	3.574	0.829	-0.192	-0.356	0.779				
PN7 (REL1)	3.630	0.811	-0.046	-0.525	0.836				
PN8 (REL2)	3.624	0.781	-0.045	-0.429	0.756				
PN9 (REL3)	3.591	0.810	-0.105	-0.473	0.779				
Task Performance						**0.864**	**0.874**	**0.898**	**0.597**
TP1	3.825	0.755	-0.089	-0.520	0.724				
TP2	3.850	0.769	-0.179	-0.269	0.809				
TP3	3.861	0.764	-0.136	-0.540	0.741				
TP4	3.852	0.750	-0.111	-0.511	0.801				
TP5	3.833	0.755	-0.065	-0.577	0.707				
TP6	3.813	0.795	-0.288	-0.337	0.844				
Job Stress						**0.891**	**0.891**	**0.917**	**0.647**
JS1	2.936	0.905	-0.009	-0.304	0.841				
JS2	2.930	0.899	0.137	-0.097	0.833				
JS3	2.939	0.863	-0.039	0.008	0.773				
JS4	2.925	0.883	-0.146	-0.247	0.785				
JS5	2.939	0.876	0.044	-0.276	0.816				
JS6	2.897	0.851	0.116	-0.280	0.776				

Note. α = Cronbach's alpha; ρa, ρc = reliability coefficients; AVE = average variance extracted. All loadings exceed .70; all α/ρa/ρc values exceed .70; all AVE values exceed .50 (Hair et al., 2022).

Indicator-level collinearity was examined next. As shown in Table 3, all item VIF values ranged from 1.539 to 2.612, below the 3.3 threshold, indicating no problematic collinearity among indicators.

Table 3: Indicator Collinearity (VIF)

Item	VIF	Item	VIF	Item	VIF
AALS1	2.110	PN1	1.842	TP4	1.953
AALS2	2.612	PN2	1.831	TP5	1.539
AALS3	1.875	PN3	2.044	TP6	2.224
AALS4	1.939	PN4	1.999	JS1	2.365
AALS5	2.409	PN5	1.997	JS2	2.249
AALS6	2.219	PN6	2.051	JS3	1.839
AALS7	2.567	PN7	2.577	JS4	1.892
AALS8	1.840	PN8	1.926	JS5	2.170
PJS1	2.117	PN9	2.047	JS6	1.827
PJS2	2.000	TP1	1.618		
PJS4	1.745	TP2	1.975		
PJS5	1.668	TP3	1.669		
PJS6	1.992				

Note. All item VIF values fall below the 3.3 threshold (Kock, 2015), indicating no problematic indicator-level collinearity.

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT). As shown in Table 4, none of the values exceeded the 0.85 threshold (the highest being 0.738), confirming that the five constructs are empirically distinct (Henseler et al., 2015).

Table 4: Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)

Construct	(1)	(2)	(3)	(4)
(1) AI Adoption Leadership Style	-			
(2) Job Stress	0.738	-		
(3) Perceived Job Security	0.737	0.527	-	
(4) Psychological Need	0.727	0.644	0.578	-
(5) Task Performance	0.732	0.559	0.707	0.530

Note. All HTMT values fall below the 0.85 threshold, confirming discriminant validity among the five constructs (Henseler et al., 2015).

Model fit was examined via the standardized root mean square residual (SRMR) and two supplementary discrepancy indices. As shown in Table 5, the saturated-model SRMR was 0.041 and the estimated-model SRMR was 0.044, both well below the 0.08 threshold conventionally used to indicate acceptable fit (Hu & Bentler, 1999).

Table 5: Model Fit Indices

Index	Saturated Model	Estimated Model
SRMR	0.041	0.044
d_ULS	1.048	1.238
d_G	0.371	0.376

Note. Chi-square and NFI were not part of the exported bootstrapping/algorithm report and are not reported here; SRMR, d_ULS, and d_G are the fit indices produced by SmartPLS for this run, and all indicate good fit (Hu & Bentler, 1999).

Common Method Bias

Because the data were self-reported, common method bias (CMB) was assessed using the full-collinearity approach (Kock, 2015) described in Chapter 4. All inner variance inflation factor (VIF) values fell below the 3.3 threshold (range 1.000-1.808; Table 6), indicating that CMB is unlikely to materially affect the structural estimates.

Table 6: Inner-Model Collinearity (VIF)

Path	VIF
AALS → PJS	1.000
AALS → PN	1.000
AALS → TP	1.785
PJS → TP	1.785
AALS → JS	1.808
PN → JS	1.808

Note. All inner VIF values fall below the 3.3 threshold, so multicollinearity is unlikely to affect the structural estimates.

Structural Model Assessment

The model explains a moderate-to-substantial share of variance in the endogenous constructs (Table 7): 48.0% of Job Stress, 49.4% of Task Performance, 44.7% of Psychological Need, and 44.0% of Perceived Job Security.

Table 7: Coefficient of Determination (R^2)

Construct	R^2	Adjusted R^2
Job Stress	0.480	0.477
Task Performance	0.494	0.491
Psychological Need	0.447	0.445
Perceived Job Security	0.440	0.438

Note. R^2 values in the 0.44-0.49 range indicate a moderate-to-substantial share of explained variance (Hair et al., 2019).

Effect sizes (Table 8) confirm that AI Adoption Leadership Style is the dominant force in the model, with large effects on Psychological Need (f^2 = 0.808) and Perceived Job Security (f^2 = 0.785), and small-to-medium effects on the remaining paths (Cohen, 1988).

Table 8: Effect Size (f^2)

Path	f^2	Effect
AALS → PN	0.808	Large
AALS → PJS	0.785	Large
AALS → JS	0.269	Medium
AALS → TP	0.208	Medium
PJS → TP	0.125	Small
PN → JS	0.065	Small

Note. Benchmarks: .02 = small, .15 = medium, .35 = large (Cohen, 1988).

Hypothesis Testing

The significance of the structural paths was assessed through bootstrapping (5,000 resamples). As shown in Table 9, four of the six direct paths were positive and two AALS → Job Stress and Psychological Need → Job Stress were negative, exactly as hypothesized; all six were significant at p < .001, and no bias-corrected confidence interval contained zero. Figure 2 depicts the estimated structural model with its standardized path coefficients.

Table 9: Structural Path Coefficients (Direct Effects)

Path	β (O)	STDEV	T	95% CI
AALS → PJS	0.663	0.029	22.874	[0.603, 0.717]
AALS → PN	0.668	0.031	21.517	[0.600, 0.723]
AALS → TP	0.433	0.051	8.575	[0.332, 0.530]
PJS → TP	0.336	0.052	6.530	[0.234, 0.436]
AALS → JS	-0.503	0.053	9.455	[-0.605, -0.398]
PN → JS	-0.246	0.056	4.385	[-0.354, -0.132]

Note. Bootstrapped output, 5,000 resamples; all paths significant at p < .001. AALS = AI Adoption Leadership Style; PJS = Perceived Job Security; PN = Psychological Need; TP = Task Performance; JS = Job Stress.

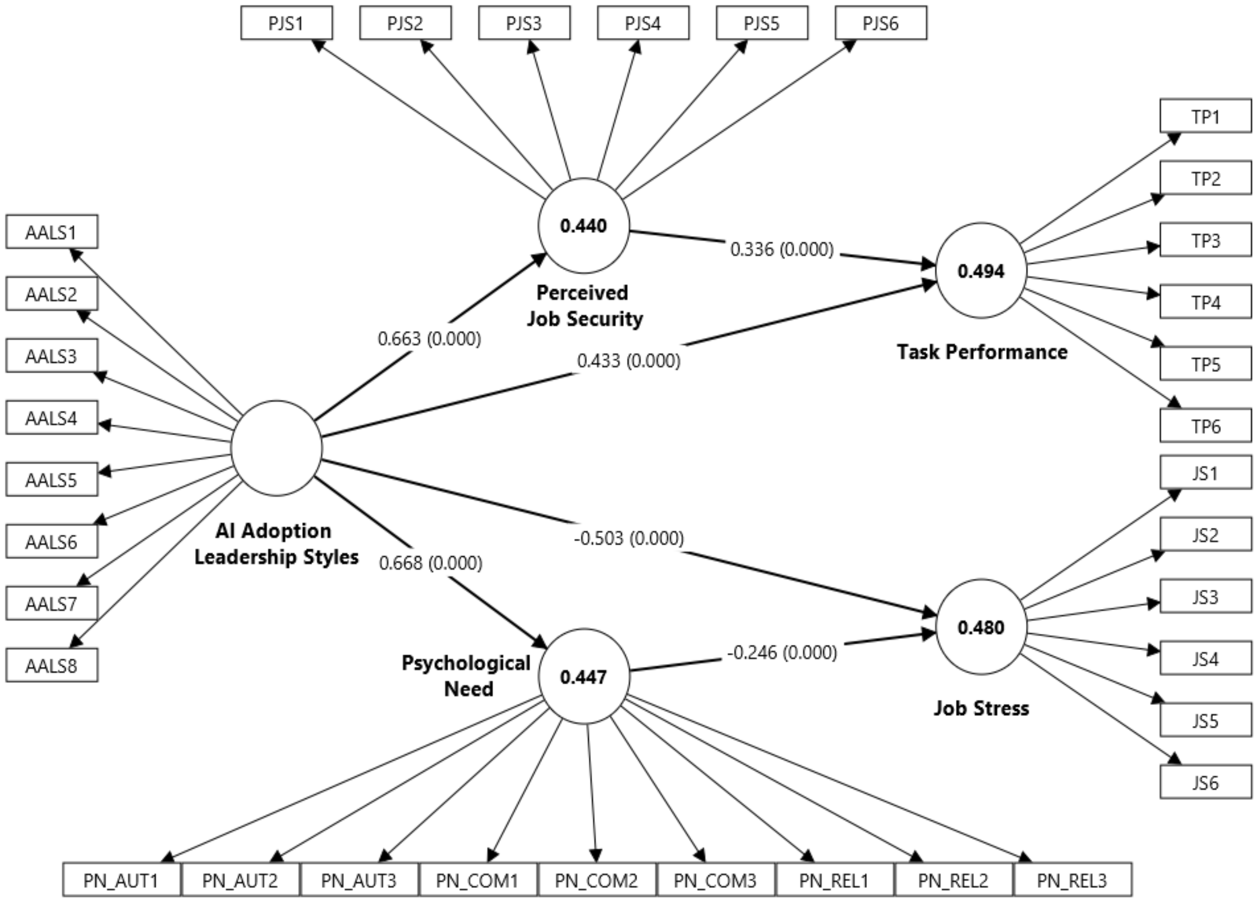


Figure 2. Estimated structural model with standardized path coefficients.

Both specific indirect effects tested for mediation were significant (Table 10). Because the corresponding direct effects (AALS → Task Performance; AALS → Job Stress) also remained significant, both mediation pathways represent complementary partial mediation (Hair et al., 2022) rather than full mediation.

Table 10: Specific Indirect Effects (Mediation)

Indirect Path	β (O)	STDEV	T	p
AALS → PJS → TP	0.223	0.036	6.163	< .001
AALS → PN → JS	-0.165	0.039	4.240	< .001

Note. Bootstrapped indirect effects, 5,000 resamples (Preacher & Hayes, 2008; Hayes, 2018). Both direct effects remained significant after the mediator was entered, indicating complementary partial mediation (Hair et al., 2022).

As summarized in Table 11, all eight hypotheses were supported, with both Job Stress paths (H2, H6) confirmed in their hypothesized negative direction.

Table 11: Summary of Hypothesis Testing

H	Hypothesized Relationship	β / p	Decision
H1	AALS → Task Performance (+)	0.433 / < .001	Supported
H2	AALS → Job Stress (–)	-0.503 / < .001	Supported
H3	AALS → Perceived Job Security (+)	0.663 / < .001	Supported
H4	AALS → Psychological Need (+)	0.668 / < .001	Supported
H5	Perceived Job Security → Task Performance (+)	0.336 / < .001	Supported
H6	Psychological Need → Job Stress (–)	-0.246 / < .001	Supported
H7	PJS mediates AALS → Task Performance	0.223 / < .001	Supported (partial)
H8	PN mediates AALS → Job Stress	-0.165 / < .001	Supported (partial)

Note. AALS = AI Adoption Leadership Style; PJS = Perceived Job Security; PN = Psychological Need.

Discussion and Conclusion

Discussion of Findings

The results align with the core argument of this research: it is not the technology per se that matters but how the leaders deal with its introduction in the learning environment. Supportive, well-communicated AI Adoption Leadership Style significantly increased Perceived Job Security (β = 0.663) and Psychological Need satisfaction (β = 0.668) and directly drove up Task Performance (β = 0.433) as well as indirectly through Perceived Job Security (β = 0.336). This corresponds to Social Exchange Theory, as well as with Wang et al. (2025) who established that POS is a very similar exchange mechanism that can be used to promote employee use of AI, with transformational leadership stimulating POS partially. AI Adoption Leadership Style (β = -0.503) and Psychological Need satisfaction (β = -0.246) significantly reduced Job Stress (H2, H6), as predicted. This aligns with Huang and Zhao's (2025) research indicating that autonomy, competence and relatedness satisfaction are major benefits of AI literacy for faculty well-being, and contrasts with Kim et al.'s (2025) results showing that without psychological leadership, faculty members' psychological safety will be reduced and depression risk will increase. Together, these results validate that the leadership practices observed here serve as the missing protective condition from less successful AI rollouts as described by Kim et al. (2025) and that supportive AI leadership and needs-satisfaction are indeed more than engagement-enhancing; they are also stress-reducing in this sample. Both mediation pathways were meaningful but partial: In the first case, Perceived Job Security accounted for a meaningful proportion of the effect of AI Adoption Leadership Style on Task Performance, and in the second case, Psychological Need accounted for a meaningful proportion of the effect of AI Adoption Leadership Style on Job Stress, while both direct paths remained significant when accounting for their respective mediators. This complementary partial-mediation pattern is consistent with Wang et al.'s (2025) finding that perceived organizational support only partially not fully mediates the leadership-to-AI-usage relationship, and it extends that evidence by showing that leadership's influence on employee outcomes travels through two theoretically distinct, empirically separable channels rather than a single undifferentiated support mechanism.

Theoretical and Practical Implications

Theoretically, the study integrates Self-Determination Theory, Social Exchange Theory, and the Technology Acceptance Model to explain how leadership reaches employee outcomes through two distinct psychological channels security toward performance, and need satisfaction toward stress confirming partial mediation on both routes. This extends recent single-mechanism accounts (Kim et al., 2025; Wang et al., 2025) by demonstrating that AI-adoption leadership operates through parallel rather than unitary pathways, and it does so in an education-sector, South Asian setting that has received little empirical attention relative to the high-tech and East Asian contexts that dominate the current literature (Gayathiri et al., 2026; Huang & Zhao, 2025; Wang et al., 2025).

In reality, AI adoption in education should be seen as a leadership and communication challenge rather than a technical one, which falls to the responsibility of both educational leaders and HR practitioners. The present findings reinforce Gallup's (2026) workforce data, which indicates that employees' experiences of AI as a true transformative or an imposed change depend most strongly on whether managers use AI appropriately. The findings of this study illustrate the specific ways in which increasing perceived job security and meeting employee needs for autonomy, competence and relatedness are the managerial levers most likely to ensure that the adoption of AI leads to better performance and healthier responses to stress. Institutions that are implementing AI tools should consider the psychological component of their employees' jobs as secondary and communicate explicitly with their leaders.

Limitations and Future Research

There are some restrictions to these results. This study is a self-reported cross-sectional data, though common method bias was not a significant threat as the three-wave design employed by Kim et al. (2025) was employed, future studies may employ time-lagged or multi-source designs to bolster causal inferences. R^2 for endogenous constructs were moderate (44-49%) and could be further expanded with more leadership and/or individual difference variables that were not measured such as AI literacy (Huang & Zhao, 2025), or ethical leadership (Kim et al., 2025) in future research. Last, the sample is limited to the education sector of one Pakistani province, which would be improved by sector, regional, and country replication in order to increase generalizability and determine if the pattern of complementary partial mediation found in this study would replicate in other institutional and cultural settings.

Conclusion

This research was designed to test the integrated mediation model of which AI Adoption Leadership Style have direct effect on Task Performance and Job Stress, as well as indirect effect on Task Performance and Job Stress through Perceived Job Security and Psychological Need respectively among 359 employees of Education Sector of Punjab, Pakistan. Both the measurement model was reliable and valid, and all hypothesized relationships were supported: AI Adoption Leadership Style significantly predicted Task Performance (H1, H2), and Perceived Job Security significantly predicted Task Performance (H5) and Psychological Need significantly predicted Job Stress (H6) in both directions; mediation through both pathways was significant, representing partial complementary mediation (H3, H4) and (H7, H8). The findings expand Self-Determination Theory, Social Exchange Theory, and the Technology Acceptance Model to a context education-sector Pakistan that has been comparatively less empirically explored and provide educational leaders with a scientifically valid perspective on the use of AI as a leadership and psychological-security issue instead of a technical one.

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