Islamic Ethical Leadership and Employee Innovative Work Behavior in the AI Era

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Abstract: Universities are increasingly requiring their employees to be innovative, with a growing reliance on new digital tools, but it remains to be seen how innovation can be fostered by leaders demonstrating Islamic ethical values (justice, trustworthiness, consultation, truthfulness, and excellence) and whether the involvement of employees in the implementation of artificial intelligence (AI) in the workplace will make a difference. The present research involved 465 academic and administrative staff of public and private universities in eight cities of Pakistan. Based on social learning and social exchange theories, it mapped out the relationship between employees' perceptions of their leaders' behaviors and their perceptions of how safe they felt expressing unfinished ideas, and then how often they generated, championed, and implemented new ideas, and examined whether trust in the use of AI tools affected this process. A coherent picture began to emerge. Leaders who were described as fair, trustworthy, and consultative were seen to create a safe environment for others to share their ideas, and this created a small but strong influence on innovation; a direct leadership relationship still existed. Trust in AI was correlated with increased innovative behavior on its own, but did not obviously increase or decrease the relationship between psychological safety and innovative behavior; it seems that the two resources operated independently. The pattern was confirmed after adjusting for demographic factors and for institutions. Psychological safety then becomes a partial conduit for values-based leadership; AI trust becomes an additive but not a conditioning resource, but a single-source, single-time design can't establish causation.

Keywords: Islamic Ethical Leadership, Psychological Safety, AI Technology Trust, Innovative Work Behavior, Moderated Mediation, Higher Education, Pakistan

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1. Introduction

The purpose of a university is to create knowledge, change teaching, modernise administration, and incorporate rapid digital technologies simultaneously. These expectations rely on the innovative work behavior of employees, that is, the deliberate creation, promotion, and implementation of novel ideas in the workplace [1], [2], and on employees' assessment of whether it is safe to share unfinished ideas with management. It's a new era, especially since the introduction of generative AI and analytics in teaching and research administration and decision-making has put pressure on: when it comes to experimenting with such tools, it is not just a

question of the social climate; it's also one of willingness to trust imperfect, opaque technologies [3]. That's a climate that is set by leaders. Ethical leadership is correlated with various positive outcomes for followers [4], namely when leaders demonstrate normatively appropriate behavior and encourage followers to do so as well. Relationships between ethical leadership and other positive outcomes for followers [4] stem from the demonstration of normatively appropriate behavior by leaders and encouragement of followers to do the same. For Muslim-majority societies like the case of Pakistan where leadership expectations are largely voiced through Islamic norms of conduct (ethics), such as justice (adl), trustworthiness and stewardship (amanah), consultation (shura), truthfulness (sidq), and excellence (ihsan) [5]; [6]. The principles have scriptural anchors (The Qur'an, 4:58, 16:90, 42:38), but this study is based on the employees' perception of whether the leader acts in accordance with these principles or not, not on the leader's personal piety. The study of Islamic work ethics revealed that Islamic ethics could be applied not only to create positive attitudes among workers in the university but also to foster positive voices among workers in the university [7]. However, there are few empirical studies on the relation between Islamic ethical leadership and innovation. Research into Higher education in Pakistan started to capture the correlation of leader behaviour with innovation and career, but focused on thoughts and inclusion-related pathways. Similarly, [8] cited that inclusive leadership positively affected teachers' innovative performance via intellectual stimulation, while [9] identified a similar intellectual stimulation pathway from inclusive leadership to teachers' career sustainability. According to [10], inclusive leadership is an approach to protecting careers preventatively by reducing perceptions of discrimination. From a technology perspective, findings indicate that trust is related to the adoption of AI-related technology and is proximal to the psychological dimension of the perceived changes in HR functions: [11] proposed that AI-technology trust is the mechanism through which perceived changes in HR functions lead to employee adoption intentions. The question that has yet to be studied is whether a values-oriented leadership system relies on the interpersonal climate of psychological safety, and if trust in AI builds or conditions the above. There is also limited and conflicting information available on the safety pathway. Ethical leadership mediated the connection between ethical leadership and Pakistani software workers' innovation, between ethical leadership and Chinese service workers' innovation [12]; [13] and between EW and PS for the public university accountants in Malaysia [14]. Simultaneously, [15] revealed that employee AI trust is linked to innovative

behavior among employees, but the effect of AI trust in addition to leadership-generated climates is yet to be tested. This study addresses three questions: (RQ1) Is Islamic ethical leadership related to innovative work behavior, directly and through psychological safety? Whether AI technology is independently related to innovative work behavior or not? (RQ2) (RQ3): Will AI technology influence the relationship between safety and innovation and the indirect leadership influence? The study has three contributions. It builds on the innovation literature on ethical leadership by adding an Islamic values-based specification to the sample of large multi-city universities. It resolves conflicting results along the psychological safety continuum, has clear measurement diagnostics, effect sizes, and cluster-aware robustness checks, and has a design that aligns with that. Additionally, it combines the leadership and AI-trust literatures, testing if AI trust is a boundary condition, rather than assuming it is.

2. Theoretical Background and Hypotheses

2.1 Islamic Ethical Leadership and Psychological Safety

Social learning theory suggests that employees learn appropriate behaviour as a result of seeing acceptable role models; ethical leaders act as a role model in fair treatment, accountability, and ethical behaviour [16]. According to social exchange theory, workers respond to trust with openness and positive participation [17]. One plausible mechanism is psychological safety, which has been defined as a shared belief that the work setting is safe for interpersonal risk-taking [18]; leader behavior that promotes openness and availability for the leader, and consistent, just, and consultative leadership, signal to others that they can act without fear of harm or embarrassment, and reduce the perceived cost of raising concerns or confessing to errors [19]; [20]; [21]. There are also data that confirm the relationship between leadership and psychological safety as one of the strongest relationships that can be identified [22]. The consultation (shura) principle is particularly useful in a hierarchical academic environment, but it may not be more than symbolic. Hence:

H1: Islamic ethical leadership is positively related to psychological safety.

2.2 Psychological Safety and Innovative Work Behavior

Innovation involves sharing immature ideas, asking for materials, and experiencing some discoveries for which there is no explanation. Innovation involves sharing immature ideas, asking for materials, and experiencing some discoveries for which there is no explanation. Studies on ethical leadership and innovation in Pakistan [12] and China [13] support this logic,

as do findings by Pakistani teachers that resources given to them by school leaders promote innovative performance, consistent with evidence of psychological safety [8]. The result of the opposite study from Malaysia [14] indicates that it could be dependent on the measurements/ context, thus replication is informative.

H2: Psychological safety is positively related to innovative work behavior.

2.3 Direct and Indirect Effects of Islamic Ethical Leadership

Ethical leaders could also serve as an innovating agent directly by ascribing value to experimentation and by distributing decision-making responsibilities, as in the case of inclusive leadership and direct influence on innovative performance and career sustainability among Pakistani educators [8]; [11]. Ethical leadership has direct and indirect effects on the outcomes, so there is a possible partial mediation.

H3: Islamic ethical leadership is positively related to innovative work behavior.

H4: Psychological safety mediates the relationship between Islamic ethical leadership and innovative work behavior.

2.4 AI Technology Trust as a Boundary Condition

Trust in technology is the willingness to depend on a system, which is based on beliefs about its reliability and competence [23]; [24]; [25], and human–AI trust is not the same as uncritical acceptance but rather is related to task and context [3]. Calibrated trust in AI can expand the avenues for testing concepts, exploring options, and executing them when employees have the freedom to express their ideas, and safety becomes innovation. On the other hand, overtrust will reduce their critical thinking. [15] found that employees' trust in AI positively impacted their innovative behavior, while [11] included AI-technology trust as one of the mediating variables between employees' behavior and their intentions toward AI. However, neither study tested the moderating effect of a climate created by leadership. Similarly, data from the implementation of generative AI suggests that employee trust in AI tools is the bridge between their use of AI and increased engagement levels and productivity [26]. Therefore, the ‘moderation hypothesis’ is exploratory.

H5: AI technology trust positively moderates the psychological safety–innovative work behavior relationship, such that the relationship is stronger at higher levels of trust.

H6: The indirect relationship between Islamic ethical leadership and innovative work behavior through psychological safety is stronger at higher levels of AI technology trust (moderated mediation).

Figure 1 depicts the model.

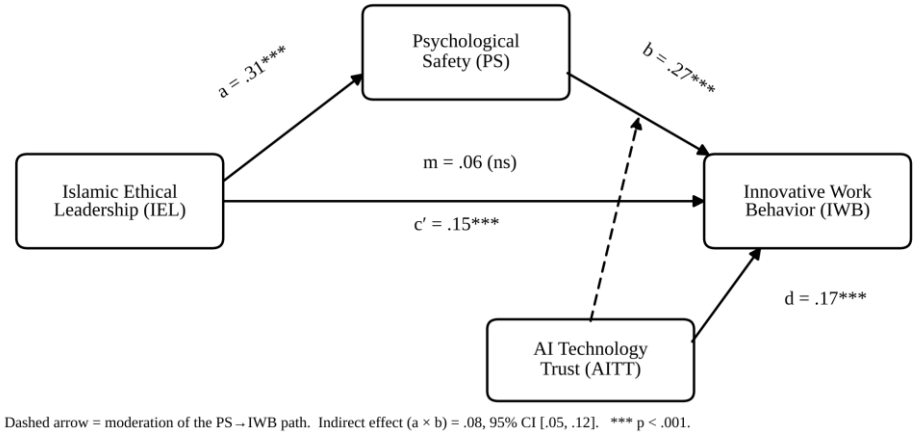


Figure 1: Estimated Moderated Mediation Model

Note. Standardized composite-score path estimates (N = 465). ns = not significant; the 95% bootstrap CI for m was [−.02, .13].

3. Method

3.1 Participants and Procedure

The analytic file contained 465 complete responses with no missing item data from employees of 32 higher education institutions (HEIs) in eight cities: Lahore (n = 100), Karachi (n = 99), Islamabad/Rawalpindi (n = 84), Peshawar (n = 52), Multan (n = 49), Faisalabad (n = 34), Quetta (n = 29), and Hyderabad (n = 18). As indicated in Table 1, 57.2% of them worked in public institutions, 42.8% worked in private institutions, and 69.7% worked in an academic position. The mean tenure of service was 13.6 years (SD = 7.3, range 2–26) for the organizations. A study protocol of full-time faculty and professional staff who have reported interacting with work-relevant AI tools within the past six months and have a clear supervisor or boss, using multi-stage stratification by city, sector, and role, but without imposing a religious affiliation question, was undertaken; the study in total was voluntary, anonymous, and did not involve religious affiliation. The sample was summarized according to its composition in Figure 2. The following is a list of all variables analyzed as a stand-alone wave, with the exception of wave-linking metadata, which were not saved in the analytic file.

Table 1: Sample Characteristics (N = 465)

Characteristic	*n*	%	Characteristic	*n*	%
Sector			City		
Public	266	57.2	Lahore	100	21.5
Private	199	42.8	Karachi	99	21.3
Role			Islamabad/Rawalpindi	84	18.1
Academic	324	69.7	Peshawar	52	11.2
Administrative	141	30.3	Multan	49	10.5
Age band (years)			Faisalabad	34	7.3
25–34	132	28.4	Quetta	29	6.2
35–44	190	40.9	Hyderabad	18	3.9
45–54	101	21.7	AI use frequency		
55+	42	9.0	Sometimes	172	37.0
			Often	204	43.9
			Very often	89	19.1

Note. Mean organizational experience = 13.64 years (*SD* = 7.31, range 2–26). Participants came from 32 institutions.

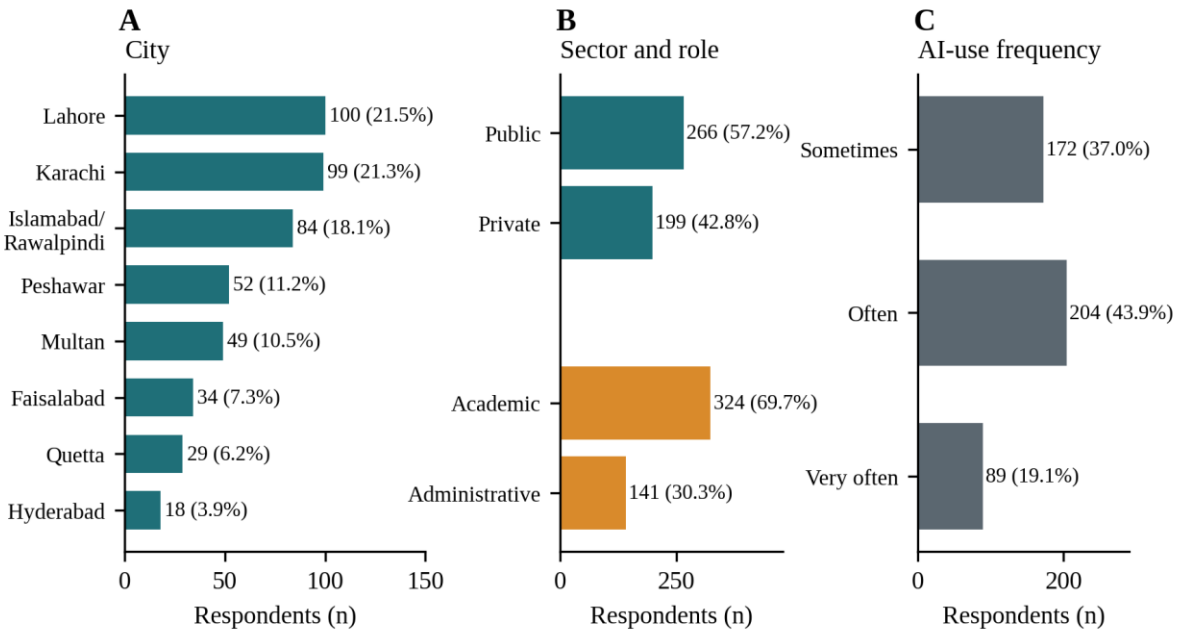


Figure 2: Sample Composition by City, Sector and Role, and AI-Use Frequency

Note. Percentages refer to the full sample (*N* = 465). Panel B shows two separate classifications (sector and role), each summing to 465.

3.2 Measures

Each of the constructs was measured using five items rated on a 5-point scale (1 = strongly disagree, 5 = strongly agree). Islamic ethical leadership was developed from the Islamic leadership model [5] and the ethical leadership literature [16] to reflect justice, trustworthiness, consultation, truthfulness, and excellence that were observed by the subordinates. The concept of psychological safety is based on [18]. AI technology trust was measured with measures adapted from trust-in-automation and trust-in-technology scales [27]; [25], as they are psychometrically sensitive in contexts of trust in AI [28], which is why their diagnostics are reported here. Idea generation, promotion, and realization were viewed as innovative work behavior [1]; [2]. The mean of all five items was taken as the construct score.

3.3 Analytic Strategy

The composite scores were standardized, and two Ordinary Least-Squares equations were estimated: $PS = a \cdot IEL + e1$ and $IWB = c' \cdot IEL + b \cdot PS + d \cdot AITT + m \cdot (PS \times AITT) + e2$. The moderated mediation index is am [29], and the conditional indirect effects are $a(b + mW)$. Percentile intervals were calculated from 5,000 case-resampling bootstrap draws (using seed = 42; [30] and were probed at ±1 SD of AITT [31]. All Effect sizes are [32] f2. As these are equal-weighted composite estimates and not the iterative algorithm of PLS-SEM software, the following limitations are noted: They are reported with this limitation in mind and in accordance with the recommendations of [33], [34] and [35] for transparent reporting of method choices. Cronbach's α, composite reliability (CR), and average variance extracted (AVE) were assessed from the first component of measurement factors; the heterotrait–monotrait ratio (HTMT; [36] was also used to assess the quality of measurements. Robustness checks included (a) controlling for sector, role, frequency of AI use, and experience, (b) a cluster bootstrap resampling of the 32 institutions (2,000 draws), and intraclass correlations (ICC[1]); (c) HC3 heteroscedasticity-consistent standard errors; and (d) Spearman correlations. Common method variance was investigated using Harman's one-factor test and collinearity statistics, which are considered to be weak diagnostics [37].

4. Results

4.1 Measurement Quality and Descriptive Statistics

Use of descriptive statistics and quality of measurement.Use of descriptive statistics and quality of measurement. Table 2 shows adequate internal consistency (α = .79–.82; CR = .85–.88) and

convergent validity (AVE = .54–.58, all above .50), with standardized loadings from .71 to .79. The distributions were roughly symmetrical, and the means were clustered around the median of the scale (2.95 – 2.98). Discriminant validity was indicated by HTMT values below the conservative threshold of .85 (shown in Table 3), and each construct's √AVE value (shown in Figure3) exceeded its correlations with other constructs (Table3: .10–.33). The 20-item correlation matrix had four eigenvalues greater than 1.0 (4.92, 2.57, 2.02, 1.77) with the fifth eigenvalue equaling .72, suggesting a four-construct solution. Scores did not differ by sector or role (all ps > .34), and AI-use frequency was unrelated to AITT, $F(2, 462) = 0.72$, $p = .486$.

Table 2: Descriptive Statistics, Reliability, and Convergent Validity of the Constructs

Construct	*M*	*SD*	Skewness	Kurtosis	α	CR	AVE	Loadings
IEL	2.96	0.78	0.13	−0.47	.79	.85	.54	.71–.76
PS	2.97	0.88	−0.01	−0.54	.82	.88	.58	.74–.79
AITT	2.98	0.83	0.03	−0.64	.80	.86	.55	.71–.77
IWB	2.95	0.85	0.09	−0.58	.81	.87	.57	.73–.77

Note. $N = 465$. IEL = Islamic ethical leadership; PS = psychological safety; AITT = AI technology trust; IWB = innovative work behavior. CR = composite reliability; AVE = average variance extracted. CR, AVE, and loadings are first-component approximations from composite-score analysis, not PLS-SEM software output.

Table 3: Correlations, Fornell–Larcker [38] Criterion, and Heterotrait–Monotrait Ratios

Construct	1	2	3	4
1. IEL	*.73*	.38	.28	.35
2. PS	.31***	*.76*	.12	.40
3. AITT	.23***	.10*	*.74*	.29
4. IWB	.28***	.33***	.23***	*.75*

Note. $N = 465$. Below the diagonal: Pearson correlations. Above the diagonal: HTMT ratios. Italic diagonal: square root of AVE. * $p < .05$. *** $p < .001$.

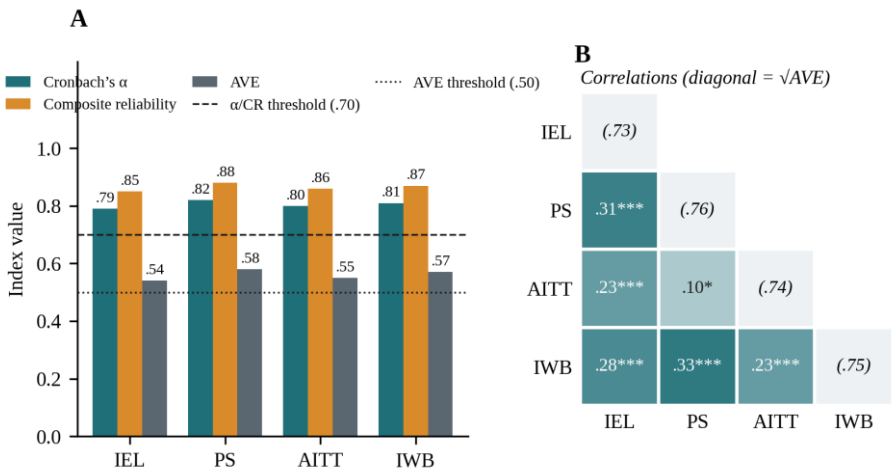


Figure 3: Reliability, Convergent Validity, and Inter-Construct Correlations

Note. IEL = Islamic ethical leadership; PS = psychological safety; AITT = AI technology trust; IWB = innovative work behavior; CR = composite reliability; AVE = average variance extracted. Panel B shows Pearson correlations below the diagonal and the square root of AVE on the diagonal. * $p < .05$. *** $p < .001$.

4.2 Tests of the Structural Model

Structural estimates are reported in Figure 1 and Table 4 and displayed with the corresponding effect sizes and confidence intervals in Figure 4. The collinearity was very small (max VIF = 1.16). The model contributed to the variance in PS accounted for 9.3% (adjusted R2 = .091), and the full model accounted for 17.3% (adjusted R2 = .166) of the variance in IWB. Supporting H1, IEL was positively related to PS (β = .31, 95% CI [.223, .387], f2 = .10). Supporting H2, PS was positively related to IWB (β = .27, [.174, .355], f2 = .08), and, supporting H3, IEL retained a direct association with IWB (β = .15, [.063, .237], f2 = .02). The total association of IEL with IWB was β = .28 (SE = .045, p < .001). This indirect effect via PS was .081 [.048, .120], suggesting partial mediation, thereby accounting for approximately 29.5% of the overall association and supporting H4. AITT had an independent positive association with IWB (β = .17, [.093, .254], f2 = .03).

Table 4: Bootstrapped Structural Estimates and Hypothesis Tests

Hyp.	Path	β	Boot *SE*	95% CI	*p*	f^2	Decision
H1	IEL → PS	.306	.042	[.223, .387]	< .001	.10	Supported
H2	PS → IWB	.266	.046	[.174, .355]	< .001	.08	Supported
H3	IEL → IWB (direct)	.151	.044	[.063, .237]	< .001	.02	Supported
H4	IEL → PS → IWB	.081	.018	[.048, .120]	< .001	–	Supported
H5	PS × AITT → IWB	.057	.038	[−.021, .129]	.147	.004	Not supported
H6	Moderated mediation index	.017	.012	[−.006, .041]	.147	–	Not supported
–	AITT → IWB	.172	.041	[.093, .254]	< .001	.03	Additive

Note. N = 465; 5,000 bootstrap resamples; percentile intervals; two-sided bootstrap *p-values* (minimum resolvable p = .0002). Point estimates are from the full sample. R^2 = .093 (PS) and .173 (IWB).

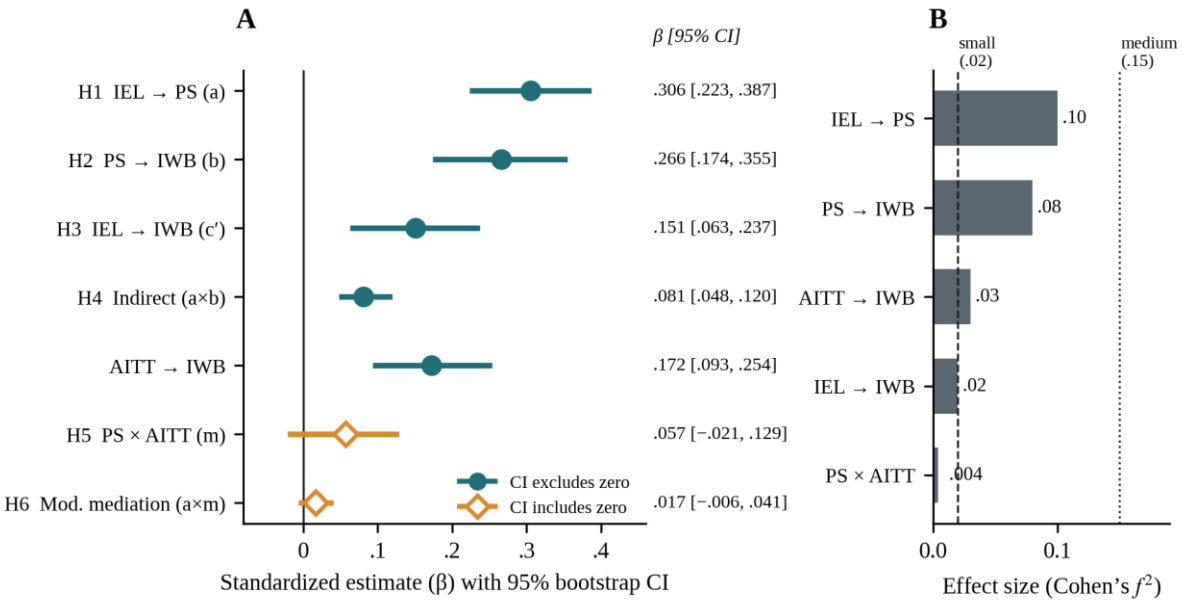


Figure 4: Bootstrapped Structural Estimates and Effect Sizes

Note. Panel A plots standardized estimates with 95% percentile bootstrap intervals (5,000 resamples; N = 465). Panel B shows Cohen's (1988) f^2 for each path; reference lines mark the conventional small (.02) and medium (.15) thresholds. An effect size is not defined for the indirect effect or the index of moderated mediation.

H5 and H6 were not enabled. The interaction was small and its interval included zero (β = .06, [−.021, .129], f2 = .004), as was the index of moderated mediation (.017, [−.006, .041]). Based on a sensitivity calculation, the sample size was approximately 80% power to detect f2 ≥ .017 for a single term; therefore, a population interaction of this magnitude would be difficult to find. As presented in Table 5, at each of the AITT levels (from −1 SD to the mean to +1 SD) the slope of the PS–IWB was positively sloped, and the conditional indirect effect was significant at each level (range: .064 to .099), though the interval was not statistically reliable.

Table 5: Conditional Effects of Psychological Safety and of the Indirect Effect at Levels of AI Technology Trust

AITT level	Slope PS → IWB	*SE*	*p*	Conditional indirect effect	95% CI (indirect)
−1 *SD*	.209	.059	< .001	.064	[.027, .108]
Mean	.266	.045	< .001	.081	[.048, .120]
+1 *SD*	.322	.062	< .001	.098	[.056, .145]

Note. Simple-slope standard errors are analytic; conditional indirect effects are $a(b + mW)$ with bootstrap percentile intervals (5,000 resamples).

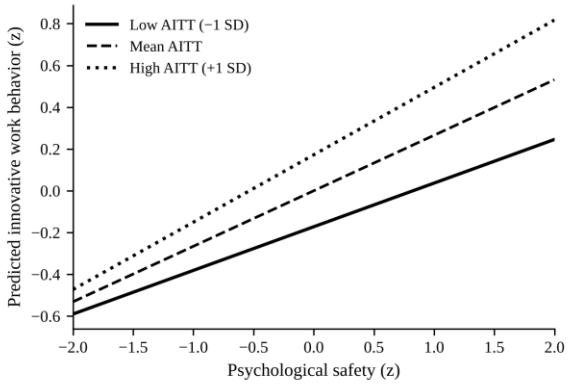


Figure 5: Simple Slopes of Psychological Safety on Innovative Work Behavior at Three Levels of AI Technology Trust

Note. Predicted values from the standardized model with IEL held at its mean. The slopes are nearly parallel, consistent with a non-significant interaction.

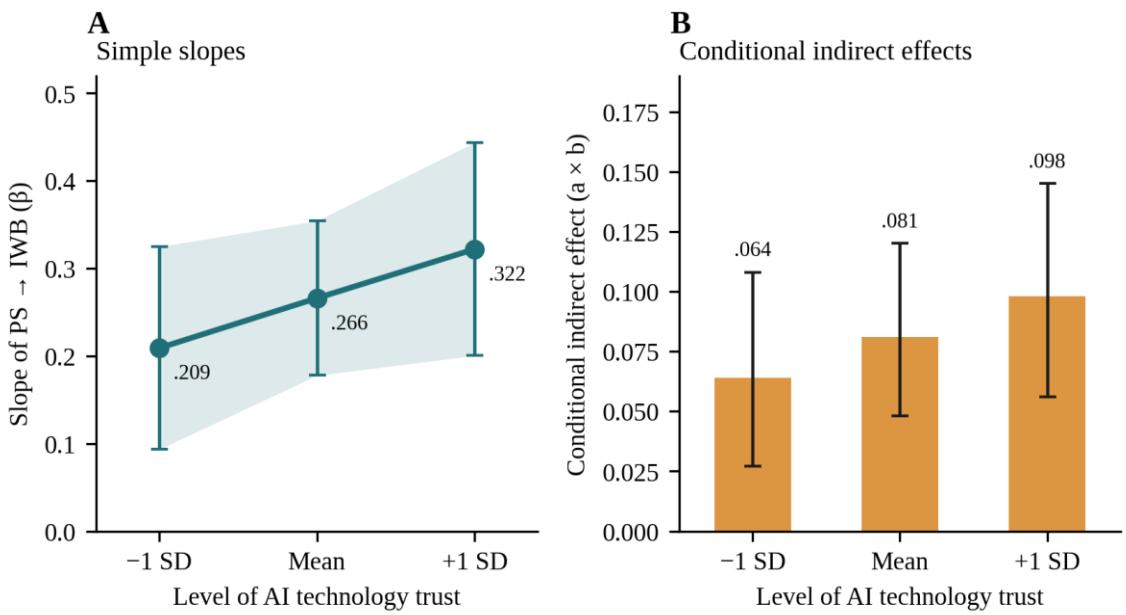


Figure 6: Conditional Effects of Psychological Safety and of the Indirect Effect at Levels of AI Technology Trust

Note. Panel A shows simple slopes with analytic 95% confidence intervals; Panel B shows conditional indirect effects with 95% bootstrap percentile intervals (5,000 resamples). Intervals overlap across levels of AI technology trust, consistent with the non-significant moderation.

4.3 Robustness Checks

A comparison of the results in Table 6 and Figure 7 with those in Table 5 and Figure 6 indicated no change in results when control of sector, role, frequency of AI use, and experience were added and when the institutions were resampled as clusters. This was the case with negligible clustering (ICC[1] = −.014, .021, .030, and −.001 for IEL, PS, AITT, and IWB, respectively), and the HC3 standard errors (.038–.046) were practically equal to the standard errors in the common method. Spearman correlations (.10 – .34) were similar to the Pearson coefficients. Harman's test revealed that the first factor had a variance of 24.6%, which is below the 50% limit, and due to low collinearity, there is no indication of dominant common method variance; however, single-source data cannot rule it out [39].

Table 6: Robustness of Key Estimates to Controls and Cluster-Level Resampling

Effect	Baseline β	With controls β (*p*)	Cluster-bootstrap 95% CI	Baseline 95% CI
IEL → PS (*a*)	.306	.301 (< .001)	[.242, .366]	[.223, .387]
PS → IWB (*b*)	.266	.266 (< .001)	[.161, .363]	[.174, .355]
IEL → IWB (*c′*)	.151	.149 (.001)	[.057, .242]	[.063, .237]
PS × AITT (*m*)	.057	.056 (.173)	[−.004, .124]	[−.021, .129]
Indirect effect (*ab*)	.081	–	[.047, .113]	[.048, .120]
Moderated mediation (*am*)	.017	–	[−.001, .038]	[−.006, .041]

Note. Controls: sector, role, AI-use frequency, and experience (R^2 for IWB = .177; for PS = .100). Cluster bootstrap: 2,000 resamples of 32 institutions.

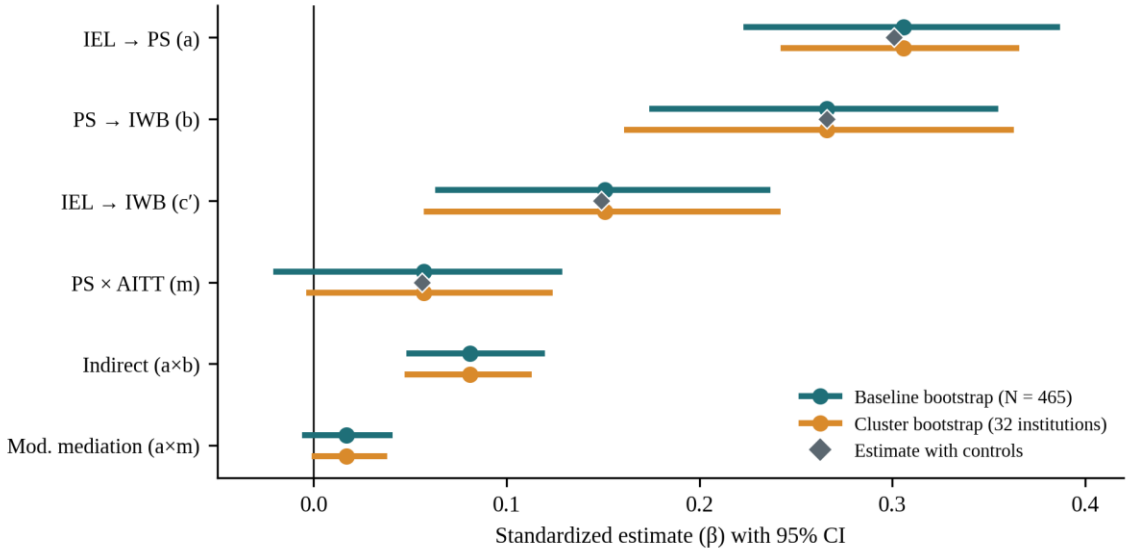


Figure 7: Robustness of Key Estimates to Controls and Cluster-Level Resampling

Note. Controls were sector, role, AI-use frequency, and experience. Cluster-bootstrap intervals resample the 32 institutions (2,000 draws). Estimates with controls were not computed for the indirect effect or the index of moderated mediation.

5. Discussion

This research investigates the relationship between Islamic ethical leadership and innovative work behavior among employees in Pakistani universities, with psychological safety and conditional upon employees' trust in Artificial Intelligence (AI). There are three highlights: First, when employees felt their leaders were just, trustworthy, consultative, truthful, and excellence-oriented, they felt that they could do this in a safer interpersonal climate and that their leaders acted more innovatively; approximately 30% of the overall leadership association was carried by psychological safety. Second, there was an independent link between AI technology trust and innovation. Third, no single-slope pattern could be identified for changes in the safety–innovation relationship and the indirect effect of leadership, respectively, with the inclusion of trust in AI. Third, there was no detectable single-slope pattern when trust in AI was included for the changes in the safety–innovation relationship and for the indirect effect of leadership, respectively.

5.1 Theoretical Implications

The partial mediation result is in line with social learning and social exchange accounts that hold that ethical leaders demonstrate behaviors that render disclosure less risky [39]; [17]; [16], and it is consistent with the safety pathway reported for employees in Pakistan and China [12]; [13]. It does not report negative or null estimates for Malaysian public universities, which may indicate that measurement or sample characteristics are causing the discrepancy from the results of [14], rather than the failure of the safety mechanism as a whole. The continuity of direct leadership association also suggests that there is no need to go through the path of safety: those leaders who consult and act justly can directly legitimize experimentation, similar to the direct and intellectual-stimulation-based association of safety and experimentation among Pakistani educators as observed by [8] and [9]. This study focused on an interpersonal climate, and the cognitive stimuli that were the focus of the earlier studies are a logical next step; hence, an integrative model with parallel cognitive and relational mediators. Similarly, if inclusive leadership mitigates against perceived discrimination leading to the protection of careers [10], one manifestation of such a protective climate might be psychological safety, as would be investigated directly in future research. The AI trust findings strengthen the distal trust/trust as a distal mediator perspective. AITT was found to have a small yet independent relationship with IWB, consistent with [15], who found that trust in AI is correlated with innovative behavior, and

with [11], who found that AI-technology trust relates to employee behaviors, including IWB, and with [26], who found that trust has a small yet significant association with employee perceptions of generative AI and its associations with employee engagement and performance. This does not indicate, however, that there is a synergistic relationship between interpersonal safety and technological trust, but that the two are complementary rather than additive: while employees don't seem to need high AI trust to reap the rewards of a safe climate, they also don't seem to reap more rewards from a safe climate enhanced by high AI trust. This aligns with the idea of "trust as task and system characteristics", which has been argued by [3] and [23]. This should be interpreted as not finding an effect, but does not necessarily mean that there is none, since the interaction interval allowed for small positive values.

5.2 Practical Implications

There are two parallel levers for University leaders. On the other hand, leadership development that's focused on observable fairness, actual consulting, and responsible stewardship is linked to safer climates and more innovation; this strong direct link implies that appropriate permission and resources for innovation should go hand in hand with leadership development that promotes such behavior. In isolation, institutions interested in leveraging AI to be productive should ensure that AI tools are reliable, transparent, and have good governance, and that use of them was linked to their ability to promote innovation, independently of leadership. Leaders can also get innovative performance and career sustainability benefits from their behavior, as evidenced by Pakistani teachers; leader behavior includes intellectual stimulation [8]; [9]; thus, elements of ethical, consolatory leadership can accompany deliberate intellectual stimulation in leadership development. Similarly, AI-technology trust relates to the perceived changes in human resource roles with employees' adoption intention scores [11], which shows that before the introduction of tools, universities should make clear to their employees the effect of these changes on their role using an open approach.

6. Limitations and Future Research

There are several caveats to these results. The data are cross-sectional and self-reported and thus causal ordering and common-source inflation have not been established; leadership and safety, AI trust and innovation, and innovation and objective outcomes may be related in each of the various ways, and if innovation outcomes could be measured by the supervisor would enhance inferences; The model is not estimated by the latent variables and the reliability and validity

indices are an approximation, so there is a need for replication using latent-variable PLS-SEM and covariance-based SEM, reliability and validity tests, and prediction assessment out of the sample such as PLSpredict [40]. IEL has not been validated in comparison to a general ethical leadership measure; therefore, there is no evidence of incremental and distinct contribution. Although psychological safety is a team-level construct [18], it was measured at the team level in this study; due to the 32-institution structure, there was little clustering to be detected and limited multilevel modelling. Submitting any sample should be accompanied by "sampling metadata", "response rates", and "ethics documentation", while the limits of sampling in one country restrict generalization to other Muslim-majority and non-Muslim settings. Future research could incorporate two or all three types of leadership (ethical, inclusive, and Islamic) at the same time in one model, test the parallel mediators like intellectual stimulation [8]; [9], consider different forms of AI trust (competence-based, integrity-based, or benevolence-based) as a mediator, and use multi-wave and multi-source designs to determine whether these different types of AI trust condition the link between safety and innovation or if they constitute a mediating state as suggested in [11].

7. Conclusion

Islamic ethical leadership was directly and indirectly correlated with innovative work behavior, and trust in AI did not condition the indirect pathway through psychological safety and, hence, brought an independent contribution to the model. In a multi-city sample of Pakistani university employees, religious-ethical leadership was correlated directly and indirectly with innovative work behavior, and trust in AI did not condition the pathway, so it added an independent contribution to the model. Thus, it seems that values-based leadership and technological trust are different, yet complementary; resources for innovation in the AI era need to be further substantiated using longitudinal multi-source data.

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