AI Awareness, Job Insecurity, and the Protective Power of AI Literacy in Pakistani Universities

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Abstract: Artificial intelligence, smart technology, robotics, and algorithms (STARA) are infiltrating universities; before employees realise it, smart technology will begin to squeeze their jobs out of their hands. This study is aimed at investigating the effect of STARA awareness on the turnover intention of the higher education sector employees in Pakistan and the resources which can act as a roadblock. We draw on the Conservation of Resources (COR) theory to suggest that being aware of STARA results in job insecurity, which in turn leads to higher turnover intention, and that the effect of awareness on turnover intention is direct. We also explore the potential buffering effect of AI literacy for the first stage – and the potential buffering effect of perceived organizational support (POS) for the second stage. Partial least squares structural equation modeling (PLS-SEM) was used to analyze the data obtained from the performed survey. Lack of job security partially mediated the effect of STARA awareness on turnover intention, with approximately 40% of the total effect due to lack of job security. The buffering effect was more pronounced when this was channeled through the mediation of AI literacy, and this buffering was extended to the indirect effect. POS was related to a decrease in the overall turnover intention but did not moderate the link between insecurity and turnover. As a provider of knowledge education, it appears logical that it should gain the trust of employees, and organizational support is a helpful tool to retain employees.

Keywords: STARA Awareness, Job insecurity, Turnover Intention, AI Literacy, Perceived, Organizational Support, Higher Education, Pakistan, PLS-SEM

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1. Introduction

Artificial Intelligence (AI) is no longer an item of university teaching, but it is also a new tool used in the teaching, assessment, research, and administrative environment of a university. This belief has been dubbed STARA awareness by Brougham and Haar [1], and defines how workers think about the threat that their roles are at risk of being replaced by smart technology, AI, robotics, and algorithms. The next studies have linked this awareness to employees' intention to quit and burnout in the service, corporate, and hospitality sectors, respectively Kong [2], Li [3], Lingmont and Alexiou [4]. National targets for skills acquisition and utilization of AI and a key responsibility of education in the policy are laid out in the National AI Policy 2025 (Ministry of Information Technology and Telecommunication, 2025) [5]. In his wake, the Higher Education Commission has issued a draft policy urging universities to establish policies on AI, include

topics related to AI in their curriculum within two years, and train faculty, students, and staff on AI every year (ProPakistani) [6]. The changes provided little clue as to what the change meant to those who were part of the university, or whether it was a push to move out. The study highlights Pakistani university teachers as the direct focus and uncovers the relationship between inclusive leadership and innovative performance Irfan & Khan [7] and career sustainability Irfan [8], but not how the technology change is assessed. The study was motivated by the three gaps below. Most of the STARA literature is based on the higher education institutions of the hospitality and service sectors and few samples are from East Asia, Europe, and North America Başer & Büyükbeşe, [9] Li [3] and limited evidence from South Asia higher education Bhattarai & Shukla) [10]. Second, the threat to withdrawal has been recognized as a mechanism Shoss [11]; Sverke [12] that is seldom explored in a single model, along with the boundary conditions at various phases of the process. Third, AI literacy, an intervening variable between the source of the threat and insecurity-driven outcomes, is largely neglected in discussions on the digital-AI transition to insecurity-driven outcomes, but recent evidence shows that employees' AI literacy impacts this transition Sha & Chai [13]. We therefore explore a moderated mediation model that proposes that STARA awareness not only indirectly influences TINT through the intervening effect of job insecurity, but it will also directly affect TINT. The first stage (awareness to insecurity) is proposed to be weak because of AI literacy, and the second stage (insecurity to turnover intention) is proposed to be weak because of perceived organizational support (POS). The study's identification of the location of each resource also helps answer the question of technology change that is critical to COR research, and offers human resource (HR) and policy actors a more detailed understanding of where to act.

2. Theoretical Framework

2.1 Conservation of Resources Theory

The study is based on the COR theory, which posits that individuals become stressed to acquire, maintain, and defend resources and that the fear of losing resources is itself stressful Hobfoll [14]. Resources are objects, conditions, personal qualities, energies, etc., valued in themselves or for purposes of other valued resources; in organizations, they are things like job security, career opportunities, skills, and support Hobfoll [15]. Here the three assumptions of the theory are at the core. The first is the primacy of loss: loss has a greater psychological effect than an equal gain. What people do is use resources to prevent loss and to acquire more resources, and those who

have more resources have a greater ability to do so. The third is that, when there are not enough resources, individuals will implement defensive behaviors to protect the available resources Hobfoll [15]. The proposed model is clearly aligned with these tenets. Users' awareness of the possibility of algorithms replacing their jobs implies a threat to their livelihood and the career capital of it. Job insecurity experienced is the powerlessness to maintain desired continuity in a threatened job, or experienced job insecurity Greenhalgh & Rosenblatt, [16]; Shoss, [11]. Turnover intent is a defensive response that saves resources in the organization by shifting them to a safer alternative; it is a conscious desire to leave the organization. While it is possible to experience a loss in ways other than insecurity (e.g., through devalued skills, a loss of trust in the employer), the direct pathway from awareness to intention to turnover is predicted to remain.

2.2 Resource Caravans and the Buffering Logic

Building on this, in the COR theory, resources are not only flowing in caravans, but they can also interrupt the loss sequence if they are available Hobfoll [15]. This is the reasoning behind the two moderators, in terms of their origin as well as when they are expected to be applied. To meet the demand, AI literacy, which is the skills required to understand, use, critically assess, and ethically engage with AI Long & Magerko [17]; Ng [18], is a personal resource closely aligned with the demand. It is expected to be used at the beginning of the sequence to alter the perception of the technology's threat. Based on the transactional perspective of stress, which holds that individuals evaluate the stressor and their ability to manage it Lazarus & Folkman [19], a greater sense of coping ability should be gained, and therefore the extent of insecurity from awareness decreased through AI literacy. POS is a relational/organizational one, because it is the belief that the organization values employees' contributions and cares for their well-being Eisenberger [20]. It's supposed to appear at the end of the story when the employees are not as secure, and they would have a reason to stay. The resulting model is summarized in Figure 1.

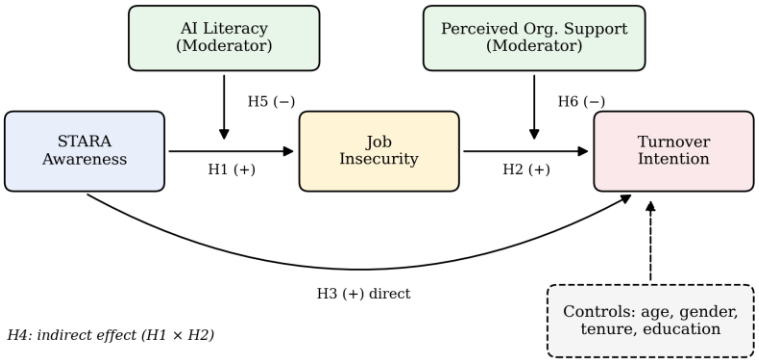


Figure 1: Conceptual Model of the Moderated Mediation Framework

Note. STARA = smart technology, artificial intelligence, robotics, and algorithms. Age, gender, tenure, and education were specified as controls on turnover intention.

3. Hypothesis Development

3.1 STARA Awareness, Job Insecurity, and Turnover Intention

The relationship between job insecurity and lower satisfaction, less commitment, poorer health, and higher withdrawal intentions is supported by Cheng & Chan [21], Jiang & Lavaysse [22], and Sverke [23]. STARA awareness provides a tangible, tech-based cue for employees to question the sustainability of their jobs, and empirical research confirms that STARA awareness positively correlates with employees' perceived job insecurity Lingmont & Alexiou, [4], while perceived job insecurity further drives the impact of technological disruption on their desire to leave their workplace Khalifa, [24]. The link between perceived changes in HR functions and employees' intention to use AI is not solely technical, as trust in AI technology buffers the relationship between the two Irfan & Ilyas, [25], indicating the significance of beliefs regarding AI's purpose. Turnover intention is the closest predictor of actual turnover Mobley, [26]; Tett & Meyer, [27]. Accordingly:

H1. STARA awareness is positively related to job insecurity.

H2. Job insecurity is positively related to turnover intention.

In addition to the explicit pathway of exit intention, awareness of STARA can also foster exit intentions indirectly, for example by raising concerns about career prospects, devaluation of one's skills, or loss of trust in the employer Brougham & Haar, [1]; Li [3]. Thus, one would

expect that a direct association would remain after accounting for insecurity. H1 and H2 together form an indirect pathway.

H3. STARA awareness is positively and directly related to turnover intention.

H4. Job insecurity mediates the relationship between STARA awareness and turnover intention.

3.2 AI Literacy at the First Stage

We draw upon four dimensions of AI literacy—awareness, usage, evaluation, and ethics—as proposed by Wang [28]. An employee who has a better understanding of the capabilities and limitations of AI, can leverage it, and can evaluate its results is better equipped to assess its impact on his/her job and adjust accordingly. Similarly, Sha and Chai [13] revealed that Job insecurity played a role in the operation of digital-AI transformation conditioned on AI knowledge. We therefore predict that STARA awareness will have a dampening effect on job insecurity, which in turn will be partially mediated by AI literacy.

H5. AI literacy negatively moderates the relationship between STARA awareness and job insecurity, such that the relationship is weaker at higher levels of AI literacy.

3.3 Perceived Organizational Support at the Second Stage

According to the meta-analyses, the results indicated that POS is related to lower turnover intention due to the fact that support makes employees feel obliged and gives them the sense that there is a future for them in the organisation Kurtessis [29]; Rhoades & Eisenberger [30]. In the context of the STARA, POS has been explored as a boundary condition and as an intervening variable Başer & Büyükbeşe, [9]; Li [3]. We find its buffering role at the second stage: when employees feel insecure, they should feel supported by an organization in which this is the norm, and they shouldn't feel like leaving.

H6. POS negatively moderates the relationship between job insecurity and turnover intention, such that the relationship is weaker at higher levels of POS.

4. Method

4.1 Participants and Procedure

The study was cross sectional which involved academic and administrative staff of public and private higher educational institutions at six major cities of Pakistan: Islamabad, Rawalpindi, Peshawar, Karachi, Lahore and Quetta. These cities have a high density of universities and cover the federal capital and the 4 provinces. Due to the lack of an available sampling frame for higher education employees, we opted for non-probability purposive sampling and convenience access

to respondents, with recruitment taking place via institutional contacts and professional networks by the authors [data collection period, ethics approval to be added]. Respondents completed the questionnaire online (n = 316, 87.8%) or on paper (n = 44, 12.2%). The study was anonymous and voluntary. There were no missing data, no duplication, and no implausible completion times (range = 250–1,500 s; M = 639.5, SD = 229.7) on completion of two attention checks by all respondents. A final sample consisted of N = 360 employees. The sample is adequate based on the inverse square root method Kock & Hadaya, [31] where approximately 200 cases are sufficient to detect the path .18 with 80% power and α = .05.The sample is described in Table 1. Respondents were mostly male (56.9%), aged 31–40 years (41.7%), and held a master's degree (42.2%). The average duration of organizational tenure was 4.16 years (SD = 3.18), and the average hours spent using AI tools was 6.56 hours per week (SD = 4.82).

Table 1: Demographic Profile of Respondents (N = 360)

Characteristic	n	%
Gender		
Male	205	56.9
Female	146	40.6
Prefer not to say	9	2.5
Age (years)		
21–30	114	31.7
31–40	150	41.7
41–50	81	22.5
51 and above	15	4.2
Highest education		
Bachelor's	121	33.6
Master's	152	42.2
MS/MPhil	74	20.6
PhD	13	3.6
Survey mode		
Online	316	87.8
Paper	44	12.2

Note. All respondents were employed in higher education; the sector was therefore constant and was not entered as a control. Mean organizational tenure = 4.16 years (*SD* = 3.18); mean AI tool use = 6.56 hours per week (*SD* = 4.82).

5. Measures

All items were measured using a 5-point scale (strongly disagree to strongly agree). Following Brougham and Haar [1], four items were used to assess STARA awareness. Job insecurity was measured using 4 items from the measures already available in the literature, e.g., Hellgren [23]. Three items taken from the Michigan Organizational Assessment Questionnaire Cammann [32] were used to measure turnover intention. AI literacy was measured using the 12-item AI Literacy Scale by Wang [28] which has 3 items for each scale including awareness scale and uses scale and ethics scale. The 8-item short form modified from Eisenberger [20] was used to measure POS. The variables that were controlled to minimize the risk of bias are: age band (dummy coded with < 20 years as the reference category; 20–30 years; 31–40 years; > 40 years), gender (dummy coded with female as the reference, male), organizational tenure (in years) (dummy coded with 0–20 years as the reference, 20–30 years; 31–40 years; > 40 years) and education (dummy coded with "bachelor's" as the reference, "master's", "MS/MPhil", "PhD").

6. Data Analysis

The selection of the estimation method was based on Partial Least Squares Structural Equation Modeling (PLS-SEM), which is suitable for prediction-oriented models with latent variables and interaction terms Hair [32-44]. The path weighting scheme was applied to the standardized indicators with Mode A outer path weighting, with the help of a custom Python routine. AI literacy was defined as a second-order construct and was specified by a repeated-indicators approach as done by Sarstedt [34]. For estimating the interactions, a two-stage approach Henseler & Fassott [35] was employed, and the product terms, STARA awareness × AI literacy and job insecurity × POS, were used as structural equations for the first-stage latent scores, which were standardized. The significance was assessed with 5,000 bootstrap resamples that re-estimated the whole procedure, and 95% percentile confidence intervals are reported with two-tailed bootstrap p-values. Moderated mediation was calculated following the method described by Hayes [36], and the conditional effect of the mediator using the moderator was calculated at −1 SD and at +1 SD and the mean of the moderator following Preacher and Hayes [37] and Zhao [38], respectively. Effect sizes (f^2) followed Cohen's [39] benchmarks (.02, .15,.35). The quality of measurements was assessed based on indicator loadings ≥ .70, Cronbach's α, ρA and composite reliability (CR ≥.70), average variance extracted (AVE ≥ .50), the Fornell–Larcker criterion Fornell & Larcker, [40] and the heterotrait–monotrait ratio (HTMT<.85; Henseler [41].

The collinearity was checked with variance inflation factors (VIFs< 3). Harman's one-factor test and structural model VIFs Kock [42]; Podsakoff [43] were used to analyze the common method variance.

7. Results

7.1 Measurement Model

The results in Table 2 indicate that all indicator loadings are greater than .70 (range .73 to .86). All Cronbach's αs ranged from .78 to .90, with ρA values of .79 to .91 and CR values of .86 to .92, all above .70, and AVE values of .59 to .74, all above .50, which indicated convergent validity. The second-order construct's loadings for the four AI literacy dimensions ranged from .73 to .80. Discriminant validity was supported: Table 3 shows that the square root of each construct's AVE was higher than the square root of all the other constructs' AVEs, and the HTMT values were all below .85. The inner VIF values and the indicator VIF values were not greater than 1.22 and 2.17, respectively, so there was no problem with collinearity. Common method variance is not likely to have affected the results because the first unrotated factor in Harman's test explained only 19.4% of the variance, well below the 50% criterion.

Table 2: Reliability and Convergent Validity of the Measurement Model

Construct	Items	Loadings	α	ρA	CR	AVE
STARA awareness	4	.80–.85	.84	.85	.90	.68
Job insecurity	4	.77–.83	.80	.80	.87	.63
Turnover intention	3	.82–.86	.79	.79	.88	.70
Perceived organizational support	8	.73–.80	.90	.91	.92	.59
AI literacy (second-order)	4[a]	.73–.80	.78	—	.86	.60
Awareness	3	.85–.86	.82	.82	.89	.74
Usage	3	.85–.86	.81	.81	.89	.73
Evaluation	3	.82–.85	.78	.78	.87	.70
Ethics	3	.84–.86	.81	.81	.89	.72

Note. α = Cronbach's alpha; ρA = reliability coefficient rho A; CR = composite reliability; AVE = average variance extracted. [a] The second-order construct is represented by its four dimensions; loadings are those of the dimension scores on the AI literacy score, and ρA is not reported.

Table 3: Descriptive Statistics, Correlations, and Fornell–Larcker Criterion

Construct	M	SD	1	2	3	4	5
1. STARA awareness	3.09	1.03	**.82**				
2. Job insecurity	2.96	0.95	.39	**.79**			
3. Turnover intention	3.09	1.02	.31	.40	**.84**		
4. AI literacy	3.10	0.83	.01	−.18	−.09	**.78**	
5. Perceived organizational support	3.00	0.94	−.08	−.18	−.28	.05	**.77**

Note. N = 360. Means and standard deviations are based on item averages on a five-point scale. Correlations are between latent variable scores. Bold diagonal values are the square roots of AVE.

7.2 Structural Model

Structural results are given in Table 4. The model explained modest but significant amounts of variance in the attitudinal outcomes, with 22% of the variance in job insecurity (adjusted R^2 = .21) and 26% of the variance in turnover intention (adjusted R^2 = .24). The results indicated a positive relationship between job insecurity and STARA awareness (β = .40, $p < .001$, f^2 = .20), which supported H1. The results showed that the job insecurity was positively correlated to turnover intention (β = .30, $p < .001$, f^2 = .10), so did the awareness of STARA to turnover intention (β = .18, $p < .001$, f^2 = .03). The indirect effect of Job insecurity on the attaining of second qualification was significant (β = .12, 95% CI [.08, .17]) and was in the same direction as hypothesized for H4. Both the direct effect ($\neq \beta$ = .44, 95% CI [.41, .46]) and indirect effects (through the complementary/partial mediators) were statistically significant with similar signs and accounted for about 40% of the total effect ($\neq \beta$ = .30, 95% CI [.21, .39]). There was also an interaction between AI literacy and awareness × job insecurity (β = −.16, $p < .001$, f^2 = .03), which supported H5, and direct negative associations between awareness and job insecurity (β = −.19, $p < .001$). AI literacy also interacted with work experience (β = .34, $p < .001$, f^2 = .11), confirming H6, although there was no interaction with either age or gender. The interaction of Job insecurity and POS was small and nonsignificant (β = −.07, 95% CI [−.16, .02], p = .131, f^2 = .01), thus limiting the feasibility of demonstrating that the impact would have differed between individuals who had low and high POS. When not supported, POS was directly associated with intent to turn down (β = −.20, $p < .001$). Of the controls, only organizational tenure was statistically significant (β = .13, p = .001) for turnover intent.

Table 4: Structural Model Results and Hypothesis Tests

Path	β	SE	t	p	95% CI	f^2
Hypothesized paths						
H1: STARA awareness → Job insecurity	.40	.04	9.54	< .001	[.32, .48]	.20
H2: Job insecurity → Turnover intention	.30	.05	5.91	< .001	[.20, .40]	.10
H3: STARA awareness → Turnover intention	.18	.05	3.59	< .001	[.08, .27]	.03
H4: Indirect effect via job insecurity	.12	.02	4.93	< .001	[.08, .17]	—
H5: STARA awareness × AI literacy → Job insecurity	−.16	.04	−3.68	< .001	[−.24, −.07]	.03
H6: Job insecurity × POS → Turnover intention	−.07	.05	−1.56	.131	[−.16, .02]	.01
Moderator main effects						
AI literacy → Job insecurity	−.19	.05	−3.83	< .001	[−.28, −.09]	—
POS → Turnover intention	−.20	.04	−4.77	< .001	[−.29, −.13]	—
Controls (on turnover intention)						
Age	−.06	.05	−1.31	.185	[−.15, .03]	—
Gender (male vs. female)	.04	.05	0.91	.364	[−.05, .14]	—
Gender (prefer not to say vs. female)	.01	.04	0.39	.712	[−.06, .09]	—
Tenure	.13	.04	3.09	.001	[.05, .22]	—
Education	.03	.05	0.59	.556	[−.07, .12]	—
Explained variance						
R^2 job insecurity	.22				[.16, .30]	—
R^2 turnover intention	.26				[.21, .35]	—

Note. $N = 360$. β = standardized coefficient; CI = percentile bootstrap confidence interval (5,000 resamples); POS = perceived organizational support; f^2 = effect size. Interactions were estimated with the two-stage approach. Total effect of STARA awareness on turnover intention = .30, 95% CI [.21, .39]. Adjusted R^2 = .21 (job insecurity) and .24 (turnover intention).

7.3 Conditional Effects and Moderated Mediation

The effects varied across levels of the moderators as shown in Table 5. The effect of STARA awareness on job insecurity also decreased with increasing levels of AI literacy, from β = .55 at low AI literacy (−1 SD) to β = .24 at high AI literacy (+1 SD), but the effect remained significant at every level of AI literacy, meaning that AI literacy only reduced the effect, but did not negate it. The pattern was the same for the conditional indirect effect (.17 at low versus .07 at high AI

literacy), and the moderated mediation index was significant (−.05, 95% CI [−.08, −.02]). In contrast, there was no reliable difference between the numerical values of the effect of job insecurity on turnover intention at high POS (.23) and at low POS (.37); and the moderated mediation model for POS did not reliably differ from zero (−.03, 95% CI [−.06, .01]).

Table 5: Conditional Effects and Conditional Indirect Effects

Moderator level	Effect	SE	t	95% CI
A. STARA awareness → Job insecurity, by AI literacy				
Low (−1 SD)	.55	.06	9.29	[.43, .67]
Mean	.40	.04	9.54	[.32, .48]
High (+1 SD)	.24	.06	4.02	[.12, .36]
B. Job insecurity → Turnover intention, by POS				
Low (−1 SD)	.37	.07	5.39	[.23, .50]
Mean	.30	.05	5.91	[.20, .40]
High (+1 SD)	.23	.07	3.42	[.10, .36]
C. Indirect effect on turnover intention, by AI literacy				
Low (−1 SD)	.17	.03	4.84	[.10, .24]
Mean	.12	.02	4.93	[.08, .17]
High (+1 SD)	.07	.02	3.31	[.03, .12]
Index of moderated mediation	−.05	.02	−3.04	[−.08, −.02]
D. Indirect effect on turnover intention, by POS				
Low (−1 SD)	.15	.03	4.70	[.09, .21]
Mean	.12	.02	4.93	[.08, .17]
High (+1 SD)	.09	.03	3.13	[.04, .15]
Index of moderated mediation	−.03	.02	−1.54	[−.06, .01]

Note. N = 360. Effects are standardized. CI = percentile bootstrap confidence interval (5,000 resamples); POS = perceived organizational support.

8. Discussion

Six hypotheses; five were supported. STARA awareness was correlated with more job insecurity and consequently more turnover intention, but not directly correlated. The awareness–insecurity link became weaker in the presence of AI, and so did the indirect link through the mediation of AI, while the insecurity–turnover link was not weakened in the presence of POS, although it was one of the strongest positive direct correlates of lower turnover intention.

8.1 Theoretical Implications

Firstly, the results are an addition to the STARA literature, which has been limited to a particular sector and region. The sequence of awareness, insecurities, and exit is similar to that found in studies of hospitality, service, and corporate workers Brougham & Haar, [1]; Li [3]; Lingmont & Alexiou [4] and the private sector in Egypt Khalifa, and aligns with COR theory, which explains that the expectation of losing valued resources triggers strain and withdrawal Hobfoll. The complementary mediation is an important but inadequate channel; the rest of the direct effect may be due to other appraisals, such as in the career or a devalued skill, that should be included in future research. This result is different from what was obtained by Bhattarai & Shukla with Nepali university teachers, where no difference in turnover intention was found in the group comparisons after STARA awareness. This difference may be due to different designs, contexts, and the importance of testing the mechanism as well as the bivariate association. Second, the study has a concept of AI literacy as a boundary condition, which matches with the source of the threat. The negative interaction ($\beta = -.16$) aligns with the COR's personal resources buffering perspective, and with the transactional focus on coping appraisals Lazarus & Folkman, as well as with the recent findings of the interaction between digital-AI knowledge and the insecurity pathway of digital-AI change Sha & Chai. Results showed that this threat remains significant even with high AI literacy ($\beta = .24$), indicating that AI literacy lowers but does not eliminate this threat. The result is consistent with the multidimensional concept of AI literacy Long & Magerko; Ng; Wang. All four dimensions loaded on the higher-order AI literacy construct. Third, it is important to read the null finding result for POS carefully. Although the hypothesized direction was correct ($\beta = -.07$), there was overlap with zero, and the effect size was very small ($f^2 = .01$). Power of about .18 allows for a small buffering effect to not be excluded. However, turnover intention was shown to be negatively predicted by POS ($\beta = -.20$), which is in line with the meta-analytic results of the relationship between support and retention Kurtessis; Rhoades & Eisenberger. One explanation is that support is an additive resource which reduces baseline motivation to leave; another possibility is that once employees are motivated to leave, general support is not a viable alternative to motivation to leave. Inclusive leadership has also been found to be another relational resource and is found to be an important aspect of leadership behavior as opposed to overall support Irfan & Khan; thus, the relationship behaviors of the leaders may be the channel through which the security is communicated. In summary, it seems that the stage of

the intervention is significant: The appraisal of the technology was changed by the introduction of AI-literacy, while POS was related to the outcome irrespective of the insecurity. Another result not hypothesized in our model that we found was that organizational tenure was positively related to turnover intention (β = .13).

8.2 Practical Implications

Based on the findings, there are three recommendations for university leaders and policymakers. First, AI upskilling can have a retention function, as well as a productivity function. Building awareness, use, evaluation, and ethical judgement, as envisioned in the Higher Education Commission's draft policy ProPakistani, is likely to be the most protective approach, if possible, reaching employees who already have concerns about the impacts of automation. Second, communication around AI adoption should be clear on what is changing and what is not being impacted by AI. Trust and faith in the technology are important here Irfan & Ilyas, and a culturally inclusive and intellectually stimulating management style can help the staff consider AI as a developmental opportunity Irfan & Khan. Third, organizational support has to be developed, but it must not be assumed to be enough to eliminate insecurity; specific guarantees on job security, re-employment, and retraining will be likely necessary.

8.3 Limitations and Future Research

There are a few caveats to note. The cross-sectional, self-reported design makes drawing causal inference difficult, and the order of awareness, insecurity, and intention to turn over is speculative. The Harman's test and the VIFs based on the structural model did not show method variance, but time-lagged or multi-source designs would be more powerful. The sample was non-probabilistic, and the data were collected from six cities, which restricted generalizability; the data did not distinguish between faculty members and administrative staff, or public and private institutions. The self-assessment of AI literacy was conducted. Out-of-sample predictive power (e.g., PLSpredict) was not evaluated, and for a customized PLS implementation, replication in dedicated PLS software is recommended. Future studies could include a longitudinal design and collect data on the use of AI instead of perceptions, as well as compare employees from public and private universities.

9. Conclusion

When algorithms are introduced in Pakistani universities, employees' sense of security will diminish in a stealth-like manner, and thus their commitment to stay. This study reveals that the

damage is not certain: the more skilled employees are in AI literacy, the less they link being aware of STARA to job insecurity, and the less the employees link being aware of STARA to turnover intention; the lower the indirect cost of awareness on turnover intention is. Organizational support was linked to a decrease in the intention to leave, but did not influence the transformation of insecurity to intention to leave. AI literacy should be considered a component of workforce retention and partnering with workforce support and explicit future of work guarantees.

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