How Artificial Intelligence (AI) Readiness Influences Academic Staff Retention: A Case from Higher Education (HE) in Egypt

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How Artificial Intelligence (AI) Readiness Influences Academic Staff Retention: A Case from Higher Education (HE) in Egypt

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Abstract

This research aims to investigate the influences of AI readiness on academic staff retention in the Egyptian HE context. A quantitative methodology was adopted. The sample consisted of 144 academic staff. They were asked to provide responses towards AI readiness in terms of cognition, ability, vision, and ethics; AI-enhanced innovation; perceived threats from AI; job satisfaction; and academic staff retention. The research outputs provide a clear understanding of HE insights regarding academic staff AI readiness in Egypt. Six hypotheses were investigated by employing correlation, simple and multi-regression, ending with supporting evidence for five out of the six research hypotheses. Accordingly, based on the outcomes, the current research conclusion, recommendation, and limitations were provided, offering the chief directions for future studies as well.

Keywords: Artificial Intelligence (AI) Readiness, Higher Education (HE), Academic Staff Retention, Egypt, Job Satisfaction

1. Introduction

Currently, the rising demand for AI applications creates an urgent need to educate individuals about AI usage and fully gain benefit from its potential and capabilities, especially in the education and training sectors, where significant implications must be addressed. As academic staff are on the front lines of AI implementation, it would be beneficial for academic staff to incorporate some AI technology into their teaching, as it would be beneficial for them to understand how AI can be achieved, as they are expected to develop an adequate understanding of AI and become educated users as well as academic staff. This requires applying practices such as curriculum development that incorporate AI literacy, critical thinking skill encouragement, and ensuring academic staff are well-equipped to smoothly deliver these concepts. The limited resources, infrastructure, and access to quality education were reported as chief challenges in HE in Egypt (Loveluck, 2012). Although there is a great paid effort in this sector observed in the increased number of new Egyptian or international universities in the last decade.

Academic staff are the most valuable asset of every educational institution. They contribute significantly to the organisation's success by bringing innovation and paving the road for sustainable development. May the academic staff's readiness to adopt such technology support these efforts and play a role in other factors in academic staff retention; thus, highlight the importance of investigating to what extent AI readiness impacts academic staff retention in the Egyptian HE context.

2. Literature Review

2.1 Information Technology (IT) and Artificial intelligence (AI) development and Impact

The development of information technology (IT) worldwide has brought about changes in people's educational activities (Xie et al., 2024). Amongst the early sectors influenced by the AI was education. The AI, a transformative force, significantly impacted education (Pence, 2019). More and more daily life activities have AI involvement. It exceeds the limit of specific and intentional tasks; it exceeds these and is being widely adopted in professional contexts, i.e., education (Chen et al., 2020).

A teacher's intention at their current school refers to "teacher retention intention" in the context of education (Van den Borre et al., 2021). According to Weiss (2002), job satisfaction refers to employees' positive or negative evaluations of their work, while Skaalvik and Skaalvik (2021) define teacher job satisfaction as teachers' affective reaction to their work or role. The concept extends beyond technological preparedness and involves a holistic view that includes mindset, skills, strategy, governance and cultural considerations, as it has multiple levels. The individual level is our concern here in this study as it relates to an individual's cognition, ability, vision and ethics.

2.2 AI Readiness

Based on Chen et al. (2023), digital readiness refers to the preparation of an individual, organisation, or society to tie together and become accustomed to digital innovations. The varied demographic backgrounds, particularly concerning gender and socioeconomic position amongst academic staff, propose various AI readiness, which have frequently been associated with dissimilarities in conventional technology usage (Beaunoyer et al., 2020). Meanwhile, academic staff' cognition, ability, vision, and ethical considerations with respect to the use of AI in education refer to the AI readiness term, which is defined as the state of preparedness of educators (Wang et al., 2023).

2.3 Adopting AI in HE

Higher education's future is tied to new technologies, innovation, development and intelligent adoption. It's clear that AI is already contributing to HE, by bringing new opportunities and challenges for these institutions (Hié & Thouary, 2023). Continuous evaluation of the emerging challenges and opportunities is an essential step before developing any acting plans toward them from the decision-making perspective. It might be claimed that the quality of the academic staff is perhaps the most essential variable impacting student achievement. Yearly, thousands of faculty members are hired around the world to guarantee that educational institutions are sufficiently staffed. As a result, this study was designed to investigate academic staff readiness for AI and whether there is a link between their readiness and academic staff retention.As a booming representative of Information Technology (IT), AI has significantly impacted education. In education, AI offers unique new perspectives on the core objectives of education and training. Based on the advantages of AI in teaching, there is an urgent need for AI to be introduced into the classroom, which results in a higher demand for teachers to master AI tools (Singh & Hiran, 2022) and (Chounta et al., 2022).

In Alnasib, (2023), a theoretical framework has been introduced with the following factors that might influence faculty members' readiness to integrate AI in an HE context: perceived benefits of AI in higher education, perceived benefits of AI in teaching, facilities and resources, attitude towards AI, behavioural intention. The independent variables were used: gender, age, academic rank, college type, and years of teaching experience.

Table 1 below summarises the key metrics for measuring AI readiness in associated studies performed from 2020 to mid-2025. As illustrated in Table 1, the amount of research conducted that considered measuring AI readiness has increased rapidly in recent years, which reflects awareness of its significance, impact, and initial acceptance somehow, regardless of the sector or technology professionalism in usage. This potential may support a rise in adoption levels.

Table 1: Key (Metrics) Factors Measuring AI Readiness in HE

Key Metrics Measuring AI Readiness	Author (s)	2020	2021	2022	2023	2024	2025
Organizational and Managerial Readiness	Jöhnk et al., 2021		√				
	Uren & Edwards, 2023				√		
	Essawi, 2024					√	
AI Literacy and Confidence	Dai et al., 2020	√					
	Zhong & Liu, 2025						√
Institutional Efficiency and Feedback Loops	Jöhnk et al., 2021		√				
	Essawi, 2024					√	
Cognition, Ability, Vision, and Ethics	Karaca et al., 2021		√				
	Wang et al., 2023				√		
Technological Readiness	Holmström, 2022			√			
	Martínez-Plumed et al., 2021		√				
	Uren & Edwards, 2023				√		
Staff and Faculty Readiness	Luckin et al., 2022		√				
	Ali, 2023			√			
	Bakry et al., 2024					√	
Optimism, Innovativeness, Discomfort, and Insecurities	Zaidi et al., 2024					√	
Economic and Financial Readiness	Abdel Rady, 2024					√	
Research and Development (R&D) Sector Improvement	Abdel Rady, 2024					√	
Personal Assets, Value-Cost Beliefs, and Contextual Resource Evaluations	Li & Liang, 2025						√
Trust and Perceived Usefulness	Nazaretsky et al., 2025						√

3. Research Problem and Objectives

Although employing AI in HE is significant, the efforts made in this area are insufficient and inadequate, given the increasing role of AI in developing the HE sector, taking into consideration the challenges facing the HE institutions and their expected roles in qualifying and preparing their students for the labour market and the faculty members' changing roles (Pence, 2019). The current research focusses on the Egyptian HE context, aiming to examine the influences of AI readiness on academic staff retention using mainly the scales created by Wang et al. (2023) and Chatzoudes & Chatzoglou, (2022).

The research objectives can be summarised as surveying the AI in Egypt in previous studies that covered the HE sector. Identifying the key components of the proposed framework; assessing and concluding the key findings based on the analysis conducted. In addition, the research investigates the perceptions of academic staff regarding their readiness to employ AI in their classes.

4. Research Methodology, Model, and Hypotheses

The research employed a quantitative methodology; a questionnaire was used to glean an understanding of academic staff beliefs. The researchers distributed a questionnaire to academic staff in different universities all over Egypt, trying to investigate their opinions and their readiness for the AI era and whether it has an impact on the way they practise their work. In addition to the eight variables in the questionnaire, the participants' demographic data were gathered. The item survey instrument variables were the four variables of AI readiness (cognition, ability, vision, and ethics), AI-enhanced innovation, perceived threats from AI, and job satisfaction and academic staff retention. A questionnaire was developed for a smooth data collection process. The items were rated on a five-point Likert scale, where one indicates "strongly disagree" and five indicates "strongly agree".

Table 2 below summarises the information associated with the research construct**s'** items source(s) and the number of corresponding items for each.

Table 2: Research Constructs' Items Source(s), and Number of Corresponding Items

<table>
<tr><th colspan="2">Construct</th><th>Items Source (s)</th><th>Number of Corresponding Items</th></tr>
<tr><td rowspan="4">AI-readiness (V9)</td><td>Cognition (V1)</td><td rowspan="4">Karaca et al. (2021)</td><td>5</td></tr>
<tr><td>Ability (V2)</td><td>6</td></tr>
<tr><td>Vision (V3)</td><td>3</td></tr>
<tr><td>Ethics (V4)</td><td>4</td></tr>
<tr><td colspan="2">Perceived threats from AI (V5)</td><td>Mirbabaie et al. (2022)</td><td>5</td></tr>
<tr><td colspan="2">AI-enhanced innovation (V6)</td><td>Popenici & Kerr (2017)</td><td>3</td></tr>
<tr><td colspan="2">Job Satisfaction (V7)</td><td>Frye et al., (2020)</td><td>5</td></tr>
<tr><td colspan="2">Staff Retention (V8)</td><td>Presbitero et al., (2016), Fletcher et al., (2018), Kundu & Lata, (2017), Haldorai, et al., (2019)</td><td>6</td></tr>
</table>

The research model is illustrated below in Figure 1. The research has six main hypotheses for the relationships between the constructs that were developed based on the research model, as follows:

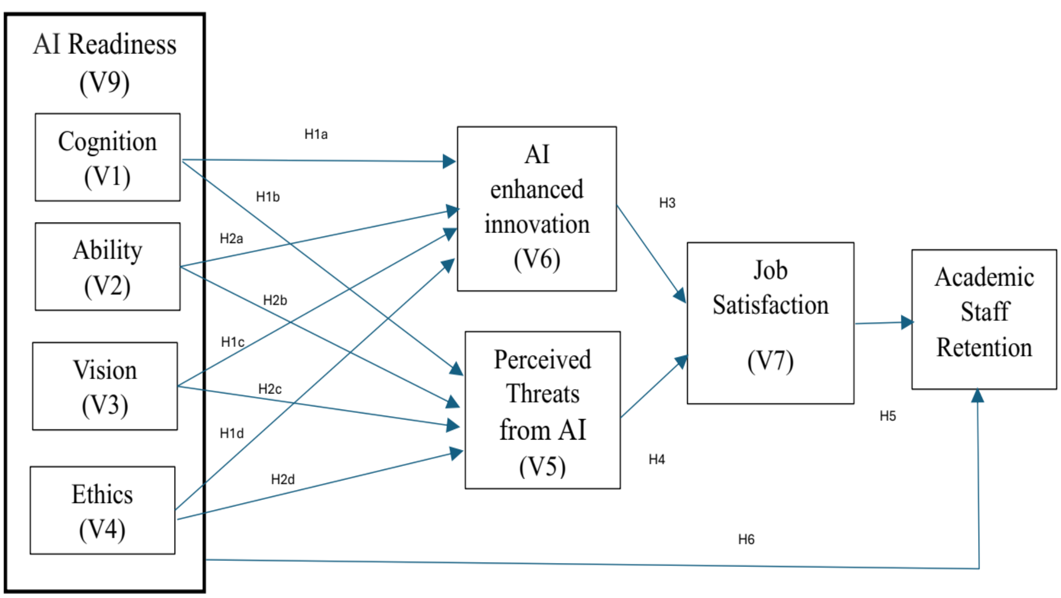

Figure 1: Research Model

H1 There is a significant relationship between V9 and V6

H1a There is a significant relationship between V1 and V6

H1b There is a significant relationship between V2 and V6

H1c There is a significant relationship between V3 and V6

H1d There is a significant relationship between V4 and V6

H2 There is a significant relationship between V9 and V5

H2a There is a significant relationship between V1 and V5

H2b There is a significant relationship between V2 and V5

H2c There is a significant relationship between V3 and V5

H2d There is a significant relationship between V4 and V5

H3 There is a significant relationship between V6 and V7

H4 There is a significant relationship between V5 and V7

H5 There is a significant relationship between V7 and V8

H6 There is a significant relationship between V9 and V8

4.1 Data Collection and Ethical Considerations

At the beginning of the questionnaire, the primary objective was stated to the target academic staff (participants). They were clearly requested to provide their consent for their demographic data and their opinions on the main research constructs for being investigated, and then at the end of the questionnaire, they were thanked for their participation (Raza et al., 2020). Having these early-mentioned declarations was intended to ensure transparency of the data-gathering process, apply ethical considerations in the same process, and encourage the participants to cooperate and be involved in the data collection process. The questionnaire was distributed to academic staff in several universities in Egypt in both the public and private sectors. The research was conducted during the spring 2025 semester. The Statistical Package for the Social Sciences (SPSS V26.0) has been used to analyse both the pilot study and the full sample.

4.2 The Pilot Study

A pilot study (40 participants) was done before the main study was initiated to make sure that research methodology was reliable and to be modified accordingly. Questionnaire questions were piloted to verify the wording, order of questions, and test data collection procedures. In addition to testing the internal consistency of questionnaire items, Cronbach's Alpha technique was employed. Cronbach's alpha value measuring reliability for all questions was .965, and N of items 37. Cronbach's alpha value indicates a high level of reliability within the studied items and dimensions, as its value is close to one. Moreover, Cronbach's alpha was calculated for each axis of the study to get the results shown in Table 3. It shows that the entire axis has high values for Cronbach's alpha for Job satisfaction (V7) and Ability (V2) with.956 and .937 in sequence.

Table 3: Reliability for the Study Axes

Reliability Statistics		
Axis	**Cronbach's Alpha**	**N of Items**
Cognition (V1)	.874	5
Ability (V2)	.937	6
Vision (V3)	.862	3
Ethics (V4)	.871	4
Perceived threats from AI (V5)	.898	5
AI-enhanced innovation (V6)	.815	3
Job satisfaction (V7)	.956	5
Academic staff retention (V8)	.622	6

5. Data Analysis

Before going on the analysis, the collected data was checked for the normality and descriptives of the sample. Table 4 summarises the demographic profile of the research sample. This research used convenience sampling in the participant selection. After excluding invalid responses, the present research retained valid responses from 144 participants.

Table 4: The Demographic Profile of the Research Sample

Value	%	Value	%
Educational Level		**University Category**	
BSc /BA	9%	Private	55.6%
Master	18.8%	Public	16.7%
PhD	72.2%	Other	27.7%
Most Experience is at		**University Location**	
Undergraduate Level	27.1%	Alexandria	63.9%
Post graduate Level	13.2%	Cairo	14.6%
Both	59.7%	Aswan	13.9%
Experiences in Years		Other	7.6%
Less than 10	23.6%	**Gender**	
Greater than 10 and less than 20	41%	Male	47.2%
Greater than 20	35.4%	Female	52.8%
Job Tile		**Age**	
GTA/ Teaching Assistant	22.2%	Less than 30	18.8%
Teaching Associated	9.7%	Older than 30 and less than 40	31.3%
Assistant Professor	29.9%	Older than 40 and less than 50	25%
Associate Professor	16%	Older than 50 and less than 60	17.4%
Professor	22.2%	Older than 60	7.5%
Major			
Business Administration	36.1%		
Engineering and informatics	15.3%		
Logistics	26.4%		
Medical studies	9%		
Others	13.2%		

5.1 Correlations analysis

This section offers the Pearson correlation coefficients outcomes for the in-depth analysis of the relationships of research variables. Investigating two groups of inter-variable correlations: the first focusing on the higher-level construct (V9) and key variables (V5, V6, V7, V8). The correction results amongst five variables, V5, V6, V6, V7, V8, and AI readiness (V9), are illustrated in Table 5 below. The second involves the disaggregated dimensions of AI readiness (V1, V2, V3, V4) in association with other constructs. The reasonableness of the proposed model and hypotheses H1 to H5 are statistically assessed through this analysis. Table 6 demonstrates the correlations for all research variables excluding AI readiness (V9).

Table 5: Correlations among V5, V6, V7, V8 and V9

Correlations						
		V5	V6	V7	V8	V9
V5	Pearson Correlation	1	.107	.201*	.458**	.083
	Sig. (2-tailed)		.203	.016	.000	.322
V6	Pearson Correlation	.107	1	.309**	.353**	.533**
	Sig. (2-tailed)	.203		.000	.000	.000
	N	144	144	144	144	144
V7	Pearson Correlation	.201*	.309**	1	.355**	.547**
	Sig. (2-tailed)	.016	.000		.000	.000
V8	Pearson Correlation	.458**	.353**	.355**	1	.304**
	Sig. (2-tailed)	.000	.000	.000		.000
V9	Pearson Correlation	.083	.533**	.547**	.304**	1
	Sig. (2-tailed)	.322	.000	.000	.000	
	N	144	144	144	144	144
*. Correlation is significant at the 0.05 level (2-tailed).						
**. Correlation is significant at the 0.01 level (2-tailed).						

5.1.1. Correlations Tests: Interpretation of Significant Findings

The following lines provide an interpretation of key outcomes of the conducted tests.

H1: A strong positive correlation was observed between V9 and V6. Where $r = .533$, $p < .001$, which indicates that AI readiness (V9) significantly contributes to the perceived threats (V6). As a result, H1 is supported by the test outcome.

H2: In contradiction to H2, an insignificant correlation between V9 and V5 was reported. The value of $r = .083$ and $p = .322$, reflecting that AI readiness is not basically translated into perceived threats.

H3 is confirmed through a significant moderate association between V6 and V7. With r = .309 and p < .001, this suggests that AI-enhanced innovation is more likely to affect the academic staff's job satisfaction.

H4: Although the reported weak significant association between the two constructs V5 and V7, the value of r = .201 and p = .016, H4 is confirmed, reflecting that AI-enhanced innovation may also demonstrate an effect on academic staff job satisfaction.

H5 is supported by a moderately significant relationship that was reported between V7 and V8, where r = .355 and p < .001. The position that job satisfaction (V7) is a critical predictor of academic staff retention (V8) is indicated through the finding of hypothesis 5 testing.

H6: A positive and significant association between V9 and V8 was observed at the 0.01 level, which implied that the two constructs, AI readiness (V9) and academic staff retention (V8), have a moderate relationship, as AI readiness increases academic staff retention.

5.1.2 Correlations for all variables without AI readiness (V9)

Table 6: Correlations between V1, V2, V3, V4 and Core Variables V5, V6, V7, and V8

Correlations									
		V1	V2	V3	V4	V5	V6	V7	V8
V1	Pearson Correlation	1	.678**	.558**	.549**	.113	.452**	.463**	.271**
	Sig. (2-tailed)		.000	.000	.000	.179	.000	.000	.001
V2	Pearson Correlation	.678**	1	.670**	.572**	.058	.551**	.445**	.213*
	Sig. (2-tailed)	.000		.000	.000	.492	.000	.000	.010
V3	Pearson Correlation	.558**	.670**	1	.614**	.045	.377**	.435**	.286**
	Sig. (2-tailed)	.000	.000		.000	.590	.000	.000	.001
V4	Pearson Correlation	.549**	.572**	.614**	1	.069	.411**	.492**	.252**
	Sig. (2-tailed)	.000	.000	.000		.414	.000	.000	.002
V5	Pearson Correlation	.113	.058	.045	.069	1	.107	.201*	.458**
	Sig. (2-tailed)	.179	.492	.590	.414		.203	.016	.000
V6	Pearson Correlation	.452**	.551**	.377**	.411**	.107	1	.309**	.353**
	Sig. (2-tailed)	.000	.000	.000	.000	.203		.000	.000
V7	Pearson Correlation	.463**	.445**	.435**	.492**	.201*	.309**	1	.355**
	Sig. (2-tailed)	.000	.000	.000	.000	.016	.000		.000
V8	Pearson Correlation	.271**	.213*	.286**	.252**	.458**	.353**	.355**	1
	Sig. (2-tailed)	.001	.010	.001	.002	.000	.000	.000	
	N	144	144	144	144	144	144	144	144
**. Correlation is significant at the 0.01 level (2-tailed).									
*. Correlation is significant at the 0.05 level (2-tailed).									

5.1.3 Interpretation of V1, V2, V3, and V4 Relationships

A strong inter-correlation was reported between the AI readiness components: V1, V2, V3, and V4. The value of r ranged from .549 to .678 and $p < .001$. This confirms the AI readiness components' rationality as a construct (V9). A significant correlation was shown for each of the AI readiness dimensions (V1, V2, V3, and V4) with AI-enhanced innovation (V6), with r = .452, .551, .377, and .411 and $p < .001$, respectively. H1a, H1d were supported by these outcomes. Meanwhile, for H2a, H2d is not supported, as the observed relationships between dimensions of AI readiness (V1, V2, V3, and V4) and perceived threats from AI (V5) were proven not to be significant.

These findings reflect that perceived threats from AI (V5) is not influenced by AI readiness. Moderate to strong correlations were found between dimensions of AI readiness (V1, V2, V3, and V4) and job satisfaction (V7), where the r value ranged from r = .435 to .492 ($p < .001$). This result supports the impact of AI readiness dimensions on job satisfaction (V7).

Small-to-moderate significant correlations were proven between each AI readiness dimension (V1, V2, V3, and V4) and academic staff retention (V8). This proposed a possible indirect impact of AI readiness dimensions on academic retention (V8).

A summary of the study hypotheses testing results is presented in Table 7. As it shows, five out of the six research hypotheses were supported by the evident outcomes.

Table 7: Summary of Hypothesis Testing

Hypothesis Description	Hypothesis	Hypothesis Test Result
V9 → V6	H1	**Supported**
V1 to V4 → V6	H1a–H1d	**Supported**
V9 → V5	H2	**Not Supported**
V1 to V4 → V5	H2a–H2d	**Not Supported**
V6 → V7	H3	**Supported**
V5 → V7	H4	**Supported**
V7 → V8	H5	**Supported**
V9 → V8	H6	**Supported**

5.2 Descriptive and Correlation Outcomes

The mean score for V9 – AI readiness dimensions (M = 3.79, SD = 0.69) based on the conducted descriptive statistics exceeds that of V8 (M = 3.16, SD = 0.65), which indicates that the participant academic staff reported more agreement or higher levels on the V9 construct compared to V8. Considering the positions of V9 in the proposed conceptual model as a predictor variable and V8 – academic staff retention as an outcome variable. Where a predictor likely represents conditions such as institutional support, infrastructure, or readiness, and an outcome variable reflecting intention to stay – academic staff retention in educational contexts, which has meaning differences conceptually.

The Pearson correlation coefficient between V9-AI readiness dimensions and V8-academic staff retention ($r = .304$, $p < .001$) is positively significant at the 0.01 level. A moderate association between these two constructs was reflected. Indicating that as V9– AI readiness dimensions increase, V8 – academic staff retention reported an increase as well.

5.3 Model and Hypotheses Connection

Based on previous analyses, V9 was shown to significantly predict V8 both directly and potentially indirectly via mediators (V5, V6, V7); H6 is supported by the bivariate correlation. The hypothesis assumes that V9 significantly predicts V8. Having those mediators or other confounding variables is not controlled through correlation. It represents, without dividing into direct and indirect, the total impact of V9 – AI readiness dimensions on V8 – academic staff retention.

Thus, this result is aligned with and strengthens the theoretical justification of the inclusion of such a path in the proposed conceptual model through confirming the foundational linear relationship exists between these variables.

The hypothesised model's key portions were validated through the correlation analyses. Although the direct correlation between perceived threats from AI (V5) is not significant, the model is supported by the significant relationships between AI readiness dimensions (cognition (V1), ability (V2), vision (V3), and ethics (V4)), AI-enhanced innovation (V6), job satisfaction (V7), and academic staff retention (V8). These joint results propose a mediated impact pathway, where AI readiness dimensions enhance V6, which raises V7, which improves V8; AI readiness dimensions enrich V8 as well.

5.4 Regression Analysis

The following section illustrates the multi-level regression analysis done during the study amongst the examined variables.

5.4.1 Regression Analysis Predicting (V6) from AI Readiness Dimensions (V1, V2, V3, V4)

This study investigated the four AI readiness dimensions (V1, V2, V3, V4) predicting (V6), where H1a to H1d hypotheses are tested.

Model summary: based on a multiple linear regression conducted with the dependent variable (V6) and predictors of four AI readiness dimensions, a moderate overall fit for the model was illustrated, with a multiple correlation coefficient of $R = .570$ and an R Square of .325, indicating that the combination of the four AI readiness dimensions are approximately explained 32.5% of the variance in V6. Having .306 for the adjusted R Square indicates that the model retains good explanatory power after accounting for the predictors number (Field, 2018). The model is significant according to the ANOVA test that revealed $F(4, 139) = 16.751$, $p < .001$, which confirmed that AI readiness dimensions significantly predict V6.

5.4.2 Predictors and Hypothesis Testing

The individual predictors analysis revealed a positive standardised coefficient of $\beta = .438$, $t(139) = 4.014$, $p < .001$. That means, with other variables kept constant, V2 was the only significant predictor of V6. This implies that each one standard deviation increase in V2 rises by approximately 0.438 standard deviations in V6. Thus, emphasising V2's serious influence in raising V6 and supporting hypothesis H1b for the three AI-readiness dimensions. They did not significantly predict V6 within this model. Where V1 ($\beta = .116$, $p = .243$), V3 ($\beta = -.064$, $p = .534$), and V4 ($\beta = .136$, $p = .150$). The hypotheses H1a, H1b, H1c, and H1d are supported by these outcomes in partial form, which means not all AI-readiness dimensions contribute with the same value to AI-enhanced innovation (V6). The strong effect of ability (V2) aligns with highlighting the significance of engagement forms in association with perceived threats from AI (V5) rise.

These results support that development of strategies to enhance specific AI readiness dimensions (V2 in particular) and potentially more effectively encourage V6. The customised involvement in these AI readiness aspects in the educational sector may improve academic staff skills and change engagement behaviours.

5.4.3 Regression Analysis Predicting V5 from AI readiness Dimensions (V1, V2, V3, V4)

The AI readiness dimensions V1, V2, V3, and V4 predictive impact on perceived threats from AI (V5) were investigated, which directly addresses H2a to H2d. Significant relationships between each AI readiness dimension and V5 were indicated.

Model summary: A multiple linear regression test with the dependent variable V5 and independent variables (V1, V2, V3, V4) – the four AI readiness dimensions. A weak overall fit of the model was observed with an R of .118 that reflects a low correlation between the outcome and predictors. The R-Squared value of .014 means that only 1.4% of the variance in V5 is explained by this collection of predictors. Additionally, the negative adjusted R Square (–.014) indicates that no better explanatory power than a simple mean-based prediction can be provided by the model (Field, 2018).

The model was not significant based on the ANOVA with $F(4, 139) = 0.490$, $p = .743$, demonstrating that V5 is not significantly predicted by the group of four AI readiness dimensions.

5.4.4 Individual Predictors and Hypothesis Testing

The regression coefficients showed that none of the predictors significantly contributed to the model. Where V1 ($\beta = .132$, $p = .272$)à(positive, non-significant), V2 ($\beta = –.032$, $p = .809$)à (small negative, non-significant), V3 ($\beta = –.025$, $p = .838$)à (negative, non-significant), and V4 ($\beta = .030$, $p = .793$) à(very small positive, non-significant).

The previous findings contradicted hypotheses: H2a to H2d

As these hypotheses predicted, a significant association between each AI readiness dimension and V5. Considering the lack of significant impact, results may be attributed to factors such as sample characteristics or contextual factors affecting academic staff behaviour, thus justifying conducting more investigations with larger sample sizes or considering other variables. Practically, both academic staff and policymakers should consider that only enhancing AI readiness may not serve to enhance V5.

5.4.5 Regression Analysis Predicting V5, V6 from V7

The H3 and H4 assume a significant association between V6 and V7 and V5 and V7 with respect to the order. Examining V5 and V6 impact on V7.

Model Summary: V7 as the dependent variable and V5 and V6 as predictors, a moderate fit with a correlation coefficient of R = .352 and an R Square = .124. The multiple linear regression model demonstrated that around 12.4% of the variance in V7 is explained by both V5 and V6. The model's explanatory power is still meaningful after adjusting for predictors the number, confirmed by R Square of .112 (Field, 2018). The overall regression model was proven significant based on ANOVA results, $F(2, 141) = 9.978$, $p < .001$, confirming that V5 and V6 together significantly predict V7.

5.4.6 Predictors and Hypothesis Testing

A significant positive effect on V7 was proved by both V5 and V6. V6 has a standardised coefficient of $\beta = .291$, $t(141) = 3.668$, $p < .001$, and is the stronger predictor. This result proposed that with V5 contacts, each one standard deviation rise in V6, V7 has an increase of 0.291 in correspondence. H3 is confirmed by this outcome. Additionally, H4 is confirmed true as V5 observed significantly and impacted positively on V7, with $\beta = .170$, $t(141) = 2.144$, $p = .034$. The outcome reflects that both V5 and V6 explain variance in V7 and contribution. Although the inequality of their contribution, as V6 has a larger impact.

The conceptual model was supported by results where V5 and V6 work as mediators, prompting V7. V6 has proven critical impact proposed its role in shaping associated outcomes of V7. On the other hand, the moderate impact and the explained variance proportion confirmed the existence of other factors rather than V5 and V6 influencing V7. Thus, calling for further research to discover the other predictors or moderators.

From the practical view, improving both V5 and V6 may result in a rise in V7. It proposes that targeted policymaking should consider the influences of these relationships in an effective way.

5.4.7 Regression Analysis Predicting V8 from V7:

H5 is confirmed through a proven significant positive association between V7 and V8. Model Summary: a moderate level of explanatory power resulted where R = .355 and an $R^2 = .126$. This means V7 explains 12.6% of the V8 variance. The adjusted R^2 value of .120 shows that this explanatory power remains strong after correcting for the sample size and complexity of the model (Field, 2018). The model significance is confirmed by the ANOVA test. Where $F(1, 142) = 20.498$, $p < .001$, reflecting that V8 is significantly predicted by the model.

5.4.8 Predictor Significance and Interpretation

A significant positive effect of V7 on V8 with $\beta = .355$, $t\ (142) = 4.528$, $p < .001$ demonstrating that each one standard deviation increases in V7, V8 rises by around 0.355 standard deviations, thus H5 is supported.

The B = 0.277 value for the unstandardised coefficient reflects that with all else constant, V8 increases by 0.277 for every one-unit rise in V7. A direct influence of V7 on V8 in practical terms is indicated.

The findings support the proposed theoretical framework where V7 acts as a predictor of V8. In practice, these suggest that a direct improvement could be observed directly on V8 based on strategies designed to enhance V7. Emphasising V7's played role as a key influence point in the broader scale model.

5.4.9 Regression Analysis of V9 Predicting V8

For assessing V9's direct impact on V8 where H6 is the corresponding hypothesis. Simple linear regression was employed.

Model Summary: with a value of $R = 0.304$ and $R^2 = 0.092$, V9 predicts V8 significantly. So, V9 can clarify approximately 9.2% of the V8 variance. With a modest but meaningful effect (Field, 2018). Meanwhile, adjusted $R^2 = 0.086$ indicates that this impact remains stable after adjustment of the model complication. The model significance is supported by the ANOVA where $F\ (1, 142) = 14.412$, $p < 0.001$, indicating that V9 predicts V8 reliably.

Regression Coefficients: Having a V9 standardised regression coefficient of $\beta = 0.304$ with a t-value of 3.796, $p < 0.001$, proposes evidence for H6 acceptance. The value of the coefficient suggests that a one-unit rise in V9 standard deviation associated with V8 standard deviation promotes 0.304. The B = 0.286 implies that having the other factors controlled, each one-unit V9 increases; V8 has an increase of 0.286 units in correspondence.

5.4.10 the Model Context Interpretation

The direct effect of V9 on V8 is stable within the theoretical framework where V9 acts as an independent predictor impacting the V8 outcome, which possibly reflects an external or control variable in the proposed model. This finding matches the mediated path through V7, suggesting that V8 has a joint indirect and direct impact. The indirect via mediators and directly by V9, stressing the complexity of the underlying mechanisms at play (Hayes, 2013).

Due to the complexity of the interplay between the variables V1 to V9, a chain of regression analyses was performed to provide critical insights amongst the study variables

(V1 to V9) and their impacts on the outcome variable V8, as assumed in the conceptual model.

1: Predicting Mediator V5 from V1 to V4: a non-significant model was yielded for the initial regression predicting the mediator V5 from the predictors V1 to V4.

2: Predicting Mediator V6 by V1 to V4: In opposition, the significant model clarified a meaningful variance proportion for the regression of V6 on V1 to V4.

3: Predicting V7 by Mediators V5 and V6: Succeeding regression analysis revealed that V7 is significantly predicted by both V5 and V6.

4: Predicting Outcome V8 by Mediator V7: The direct significant regression of V8 on V7 was confirmed.

5: Direct Effect of V9 on Outcome V8: V9's direct effect on V8 was significantly proven.

5.4.11 Summary of Mediation Effects

Combining these findings reveals the mediation model described in the following lines: the strongly supported pathway from V2 → V6 → V7 → V8 indicates that V6 and V7 are significant mediators for V2's impact on the outcome.

V5 has a weaker mediation potential role. As V1–V4 did not significantly predict it. Even with V5 contributing to V7, the possible existence of other variables mediating effects that were not captured or have more compound associations was indicated.

V9 impacted V8 directly; thus, the necessity of considering direct influences in conjunction with mediated paths in comprehensive structural models was emphasised.

5.4.12 Implications and Theoretical Contributions

The implications and theoretical contributions of these results can be summarised in: highlighting the value of concurrent multiple mediators testing to sort out the pathways concluded which predictors have impacted the outcomes, with mediation analysis modern approaches (Hayes, 2018). Through V6 and V7, significant mediation confirms the hypothesised model’s capacity to clarify a meaningful portion of V8 variance, V9 limited mediation gives emphasis to the model’s complexity. This approach aligns with contemporary structural equation modelling studies underlining the multiple mediators' simultaneous testing and direct paths to capture causal mechanisms (MacKinnon, 2012).

6. Discussion and Conclusion

Artificial intelligence (AI) has a rapidly unique adoption level amongst the available technological innovations and a high rate of involvement across sectors. All these are aligned with both opportunities and threats. Higher education (HE) is one of the sectors that has been strongly impacted by AI adoption. The readiness of academic staff is a centric dimension that has to be considered when deciding to use it.

Job satisfaction is essential to academic staff retention in higher education institutions. It has a larger and longer-term component than other elements. Overall, improved job satisfaction is closely related to enhanced job retention in HE. These findings are consistent with Rehman et al. (2020). The results also might not change with Asal et al. (2025), as AI readiness supports job retention through enhanced innovation. Academic staff with high AI readiness are more likely to innovate in their work.

This innovation may lead to enhanced job satisfaction as they adapt to and leverage AI opportunities, which is consistent with Wang et al. (2023) and Fu & Weng (2024). A considerable association between AI readiness and AI enhancement exists. Academic staff with high AI readiness have greater opportunities to enhance their practices in teaching experiences through AI technology, leading to teaching outcomes improvement as a result. This is aligned with the results of Wang et al. (2023) and Fu & Weng (2024) as well.

Meanwhile, the components of academic staff AI readiness, including cognitive abilities, vision, and ethics, are positively associated with AI innovation, which matches with the results (Fu & Weng, 2024) and (Ghiasvand & Seyri, 2025). AI readiness in HE is closely related to predicted threats. A greater awareness and familiarity with AI may reduce perceived risks, whereas visions of AI's future role might worsen them. The results may persist with Wang et al. (2023).

The findings of this study are intended to serve as a basis for a framework by which the HE. The study tests the role of AI readiness in academic staff retention, tested and proven by conducting multiple and intermediary analyses using corrections and multi-regression tests. Results showed that academic staff retention is significantly affected by AI readiness.

The goal of this study was to learn more about how artificial intelligence (AI) can operate and expand in educational institutions. It has been found that having suitable technology is not adequate; people also play important roles.

The results researchers obtained indicated that AI readiness, enhancing innovation, job satisfaction, and job retention all play an essential part, and these ideas are linked in meaningful ways. The survey questions were credible and successfully measured what researchers desired.

When looking at what most affects whether AI gets adopted in educational institutions, two factors stood out: the academic staff's readiness (such as having the ability, cognition, vision, and ethics) and job satisfaction with their AI experience. These elements play a crucial role in determining how effectively AI can be integrated into teaching and learning processes. In addition, fostering a supportive environment that encourages professional development and collaboration can enhance both readiness and satisfaction amongst educators in a significant way. Although the factors like AI-enhanced innovation and perceived threats serve as bridges that allow other influences to impact job satisfaction and employee retention.

The understanding of these dynamics can result in more effective strategies for settings AI in education. Highlighting concerns and AI benefits can help universities to develop a more positive outlook amongst educators, ultimately leading to outcomes enhancement for teachers and students as well. Encouraging an open communication environment and professional development can reduce AI technologies anxiety. This approach empowers educators and creates a culture of adaptability, change the view of the integration of AI from being a challenge to a collaborative enhancement.

More sophisticated statistical approaches should be in use in the upcoming studies to authenticate these outcomes and create deeper understanding. In addition, employees' readiness in other sectors is recommended to be the subject of examination in future research.

Educational institutions are recommended to invest not only in technology but also in training, leadership, and specific strategies. When institutions are truly ready, AI adoption is much more successful. People are more willing to use AI if they trust it and are confident in their skills. Being open about how AI works and providing training can go a long way.

7. Limitations and Future Directions

While this study provides useful insights, it should be noted that it is based on a single point in time and relies on people's self-reported judgments. Future studies could track individuals over the years to see how their opinions and efficacy shift. Interviews or focus groups might also show deeper attitudes regarding employing AI in education, including excitement and concern.

This study, while methodologically sound, is hampered by its cross-sectional design and reliance on self-reported data. Future research could use longitudinal designs to investigate the changing perceptions and effectiveness of AI in education. Furthermore, qualitative methodologies can supplement quantitative findings by providing deeper insights into reluctance or enthusiasm for AI integration.

The moderate impact and the explained variance proportion confirmed that the existence of perceived threats from AI and AI-enhanced innovation are not the only impacting factors on job satisfaction, which makes discovering the other predictors or moderators a subject of further studies.

In addition, the model clarifies a meaningful academic staff retention variance proportion. A considerable unexplained portion still exists, suggesting the impact of additional variables or mediators. Further studies are still needed to provide more accurate and deeper theoretical predictive understanding. Moreover, considering the data collection's frequent and impactful problems, i.e., non-respondent bias, common method bias, and small sample size issues, is mandatory during the processes of study design, appropriate statistical techniques, and transparent reporting as well.

The modest variance described by AI readiness recommends it is important but not a solo contributor to academic staff retention. More investigations should be conducted considering potential interactions or moderation impacts involving AI readiness for a better understanding of its role.

Future studies should employ more sophisticated statistical approaches to validate these findings and deepen our understanding, and also, the researchers recommend investigating the readiness of other employees in different sectors.

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