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Innovation Climate, Autonomy, and Supervisory Support and Artificial Intelligence Integration Readiness among Academics in Higher Education: Does Training Matter?

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ABSTRACT

Artificial intelligence (AI) has moved from an emerging technology to an everyday workplace tool, yet its application in higher education, especially among academics in developing economies, remains uneven. While the factors influencing AI adoption from a technology acceptance perspective have been well documented, comparatively less is known about the organisational conditions that shape academics' willingness to incorporate these technologies into their work. Our study draws on Socio-Technical Systems Theory and the Ability–Motivation–Opportunity framework to investigate how innovation climate, autonomy, and supervisory support affect academics' AI integration readiness and whether training moderates these relationships. We collected cross-sectional survey data from 188 academic staff from three higher education institutions in Nigeria and analysed the data using partial least squares structural equation modelling. Our results showed that innovation climate and supervisory support were positively associated with AI integration readiness, whereas autonomy had no significant relationship. Contrary to our expectations, training did not significantly strengthen the relationships between any of the predictor variables and AI integration readiness. The study contributes to the AI adoption literature by reframing AI integration readiness as a socio-technical work behaviour and provides practical insights for higher education leaders and policymakers seeking to foster responsible AI integration.

Keywords: Artificial intelligence integration readiness; socio-technical systems; organisational climate; higher education; supervisory support; innovation climate

1. Introduction

In about half a decade, artificial intelligence (AI) has moved from an emerging technology to an everyday workplace tool. A 2025 global survey of 1,365 professionals across 29 countries found that 95% of organisations now use AI, with 58% reporting daily use (American Management Association, 2025). Higher education institutions (HEIs) are not left out of this transformation. Universities, polytechnics, and colleges are increasingly integrating AI into teaching, research, assessment, student support, and academic administration (Liang et al., 2025). Consequently, HEIs are investing heavily in AI technologies and encouraging academics to incorporate them into their daily work. A recent projection by Grand View Research (2024) indicates that the global AI in education market will exceed USD 47 billion by 2030.

This substantial investment demonstrates the growing recognition of AI's potential to improve how academic work is performed. Evidence suggests that AI can improve the efficiency of routine academic tasks,

support teaching and assessment, enhance research and scholarly workflows, and create opportunities for higher work engagement, creativity, productivity, and knowledge production (McClain, 2025; Renkema & Tursunbayeva, 2024; cf. Su et al., 2026; Zirar et al., 2023). However, these benefits are not experienced in the same way across institutions. AI integration remains uneven, with academics differing considerably in how readily they incorporate these technologies into their work (Baggia et al., 2026). This is particularly important in emerging economies such as Nigeria, where HEIs face increasing pressure to modernise teaching, research, and administrative processes while operating within significant resource and institutional constraints. Recent evidence indicates that while academics in Nigeria are engaging with AI technologies, concerns around academic integrity, responsible use, infrastructural challenges, and the need for greater institutional support and training remain evident (Abang, 2025; Eleje et al., 2025). The challenge, therefore, is no longer simply whether AI is available to academics, but what enables them to integrate it meaningfully into their work.

A number of studies have examined the factors influencing AI adoption in higher education. Much of this literature has been grounded in technology acceptance theories, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which explain adoption through perceptions such as usefulness, ease of use, social influence, trust, and behavioural intention (Davis, 1989; Venkatesh et al., 2003). While these theories have provided substantial insights into AI adoption behaviour and continue to feature prominently in higher education research (Acosta-Enriquez et al., 2024; Xue et al., 2026), they often approach AI use primarily as a technology adoption decision. In this study, we argue that AI integration in work organisations such as HEIs goes beyond the technology adoption decision typically made by students or consumers. This is because AI integration requires academics to redesign and adapt how they perform their work while navigating institutional expectations, exercising professional judgement, and complying with ethical standards (Liang et al., 2025; Nguyen et al., 2026) rather than merely deciding whether to use a new tool. Hence, perceptions such as usefulness and ease of use may not be sufficient to explain academics' readiness to integrate AI into their work. Accordingly, we propose that AI integration readiness should be understood not solely as an individual's acceptance of AI but also as a work behaviour embedded within the organisational and institutional context in which academic work is performed.

This perspective shifts attention from the technology itself to the organisational conditions that enable or constrain its use. Research in organisational behaviour and information systems suggests that workplace AI outcomes emerge through the interaction of technological, organisational, and human systems (Zirar et al., 2022; Pereira et al., 2023; Yu et al., 2023). Organisational conditions such as an innovation-supportive climate, autonomy in performing academic work, support from management and immediate supervisors, and opportunities for training may therefore influence whether academics feel ready to integrate AI into their teaching, research, and administrative responsibilities. Yet, compared with traditional technology acceptance explanations, these organisational conditions have received considerably less scholarly attention. This gap is particularly important in emerging economies such as Nigeria, where the successful integration of AI depends not only on access to technology but also on institutional capacity to provide support, guidance, and an environment in which academics can use AI responsibly and effectively (Abang, 2025; Eleje et al., 2025).

Socio-Technical Systems (STS) Theory provides a useful lens for understanding this challenge. According to STS, organisational outcomes depend on the alignment between technological and social systems (Emery & Trist, 1960). Guided by this perspective, we argue that AI integration is not simply a technology-choice problem but requires alignment between the technological system, the people using the technology, and the organisational environment within which academic work is performed. To complement STS theory, we draw on the Ability–Motivation–Opportunity (AMO) framework, which posits that employees are more likely to engage in desired work behaviours when they possess the necessary ability, motivation, and opportunity to do so (Appelbaum et al., 2000; Bos-Nehles et al., 2023). Building on this perspective, we argue that academics are more likely to develop AI integration readiness when their work environment provides the motivation, opportunity, and capability required for effective AI integration. Accordingly, this study examines how innovation climate, autonomy, and supervisory support influence AI integration readiness among academics in higher education and whether these relationships depend on training.

Our study contributes to the literature on AI adoption and applications in the workplace by providing evidence from HEIs in Nigeria, an underexplored but important emerging economy context, that AI integration is a socio-technical work behaviour and not solely a technology acceptance decision. This perspective demonstrates why organisational conditions deserve greater attention in explaining academics' AI integration and offers practical insights for higher education leaders and policymakers seeking to create organisational environments that support the effective integration of AI into academic work. By integrating Socio-Technical Systems Theory and the Ability–Motivation–Opportunity framework, we provide a more behaviourally grounded explanation of AI integration in higher education.

2. Theory and Hypotheses

2.1. AI Integration as a Socio-Technical Work Behaviour

Artificial intelligence (AI) integration readiness refers to academics' readiness and willingness to incorporate AI into the way they design learning activities, conduct research, assess students, support learning, and perform other aspects of their professional responsibilities (Yilmaz et al., 2024; Park et al., 2024; Pereira et al., 2023). Our central proposition in this study is that AI integration readiness is fundamentally a socio-technical work behaviour rather than merely a technology acceptance decision because it emerges through the continuous interaction between AI technologies, academics, and the organisational environment within which academic work is performed. To properly explain this relationship, we draw on Socio-Technical Systems (STS) Theory and the Ability-Motivation-Opportunity (AMO) framework.

Socio-Technical Systems (STS) Theory posits that organisational effectiveness depends on the alignment between technical and social systems rather than either system operating in isolation (Emery & Trist, 1960). Recent applications of STS similarly argue that successful digital transformation and AI implementation depend on how technological systems interact with organisational structures, work processes, leadership, and employees to produce organisational outcomes (Govers & Van Amelsvoort, 2023; Polojärvi et al., 2023; Yu et al., 2023). In this study, we conceptualise generative AI as the technical subsystem and the organisational work environment as the social subsystem. We further assert that STS's conceptualisation of joint optimisation of people and technology best explains this interaction between the technical and social subsystems because the effectiveness of a technology depends not only on its technical capabilities but also on how it is integrated with the social and organisational conditions in which work is performed. This interaction is particularly important for AI integration because the introduction of AI can alter work processes, task structures, roles, and patterns of human–technology interaction. Following this logic, we argue that the social subsystem is best understood through organisational climate because it reflects employees' shared perceptions of the organisational policies, practices, leadership behaviours, and work environment that shape how work is performed (Patterson et al., 2005; Schneider et al., 2013). We therefore argue that AI integration readiness depends not only on the capabilities of AI technologies but also on whether the organisational climate enables academics to meaningfully integrate those technologies into their everyday work. Accordingly, we use STS as the foundational theoretical framing of our study to explain why work environment factors matter during technology integration and assimilation.

While organisational climate consists of several dimensions (Patterson et al., 2005; Schneider et al., 2013), we focus on innovation climate, autonomy, and supervisory support for three interconnected reasons. First, AI use, like other forms of technology assimilation, requires a work environment in which experimentation, learning, and new ways of working are encouraged and supported (Bin-Nashwan & Li, 2025). Second, integrating a technology such as AI into established work practices involves individual judgement and agency because employees must decide how, when, and to what extent the technology is incorporated into their work, making sufficient discretion over how they organise and perform their work particularly important (Callari & Puppione, 2025; Hackman & Oldham, 1976; Xavier et al., 2025). Third, technology integration often involves uncertainty, learning demands, and changes to established work practices, making guidance, encouragement, and access to resources from immediate supervisors important conditions for employees' engagement with technological change (Fousiani et al., 2024; Zhang et al., 2025). Accordingly, we argue that these organisational climate dimensions represent three complementary organisational conditions through which HEIs influence academics' day-to-day technology-enabled work behaviour. Innovation climate reflects whether experimentation, creativity, and new ways of working are encouraged; autonomy reflects the degree of discretion academics possess in determining how they perform their work; while supervisory support reflects the guidance, encouragement, and resources provided by immediate supervisors as academics respond to technological change (Anderson et al., 2014; Eisenberger et al., 2002; Hackman & Oldham, 1976). From an STS perspective, these three organisational conditions represent important characteristics of the social subsystem because they influence whether AI technologies become meaningfully embedded within teaching, research, and other academic responsibilities across HEIs. Our interest in organisational climate also builds on earlier evidence from Nigerian higher education showing that organisational climate influences academics' intention to use generative AI, albeit indirectly through perceived usefulness (Abang, 2025). The present study extends this line of inquiry by examining how specific dimensions of organisational climate shape AI integration readiness and whether these relationships depend on training.

An important question that STS theory does not fully address is why some academics are more prepared than others to integrate AI, even when they operate within similar organisational environments. To answer

this question, we draw on the Ability-Motivation-Opportunity (AMO) framework, which proposes that employees are more likely to perform desired work behaviours when they possess the necessary ability, motivation, and opportunity to do so (Appelbaum et al., 2000; Bos-Nehles et al., 2023; Kundu & Gahlawat, 2018). Building on this perspective, we propose a conceptual model in which innovation climate primarily represents a motivational condition, while autonomy and supervisory support provide opportunities for AI integration. The ability component of the framework is examined in the next section, where we argue that training strengthens the extent to which these organisational conditions translate into AI integration readiness.

We consider innovation climate to be one of the most important organisational conditions shaping AI integration readiness because it represents employees' shared perception that experimentation, creativity, and the adoption of new ideas are encouraged and supported within the organisation (Anderson et al., 2014; Patterson et al., 2005). From a socio-technical systems perspective, introducing AI into academic work is largely an organisational change that requires academics to rethink established teaching practices, redesign assessment methods, experiment with new research workflows, and adopt new ways of interacting with students and colleagues. Such behavioural changes are unlikely to occur in organisational environments where innovation is discouraged or where employees perceive that deviating from established practices carries personal or professional risks. Rather, innovation-supportive climates signal that experimentation with new technologies is expected, valued, and institutionally supported, thereby reducing uncertainty and increasing employees' willingness to embrace new ways of working (Ali et al., 2022; Schneider et al., 2013). This proposition is also consistent with the motivational component of the AMO framework, which suggests that employees are more likely to engage in desired work behaviours when the organisational environment encourages and rewards those behaviours (Appelbaum et al., 2000; Bos-Nehles et al., 2023). Recent studies similarly suggest that organisational environments characterised by openness to innovation and digital transformation are more likely to facilitate AI implementation and other technology-enabled workplace behaviours (Mikalef & Gupta, 2021; Pereira et al., 2023; Yu et al., 2023). Accordingly, we expect academics who perceive a stronger innovation climate within their HEIs to exhibit greater AI integration readiness.

Hypothesis 1. Innovation climate is positively associated with AI integration readiness.

We view autonomy as another important organisational condition influencing AI integration readiness because it reflects the degree of discretion employees possess in deciding how they perform their work (Hackman & Oldham, 1976). Academic work is traditionally characterised by considerable professional autonomy, allowing academics to determine how they design courses, deliver instruction, conduct research, and assess students. However, integrating AI into these activities requires academics to exercise professional judgement regarding when, where, and how AI tools should be incorporated while balancing institutional expectations, disciplinary standards, and ethical considerations. From the perspective of STS theory, granting employees discretion over their work enables them to adapt technological innovations to local work requirements rather than merely complying with externally imposed technological changes. Autonomy therefore creates opportunities for academics to experiment with AI, learn from experience, and integrate emerging technologies into their work in ways that are both professionally appropriate and pedagogically meaningful. This reasoning is consistent with the opportunity component of the AMO framework, which proposes that employees are more likely to perform desired behaviours when their work environment provides sufficient opportunity to do so (Appelbaum et al., 2000; Bos-Nehles et al., 2023). Prior studies have similarly shown that greater job autonomy encourages experimentation, innovation, technology use, and proactive work behaviours (Parker, 2014; Vial, 2019; Sodiya et al., 2025). We therefore expect academics with greater work autonomy to report higher AI integration readiness.

Hypothesis 2. *Autonomy is positively associated with AI integration readiness.*

Similarly, we consider supervisory support to be an important organisational condition because immediate supervisors often represent employees' primary source of organisational guidance, encouragement, and access to resources during periods of technological change (Eisenberger et al., 2002). Within higher education institutions, departmental heads, deans, programme coordinators, and other academic leaders influence how academics interpret institutional priorities, respond to technological innovations, and navigate the uncertainties associated with emerging technologies. From an STS perspective, supportive leadership facilitates the alignment between technological and social systems by helping employees understand organisational expectations, reducing uncertainty, and creating an environment in which technological innovations can be successfully embedded into everyday work. Supervisory support also aligns with the opportunity dimension of the AMO framework because supportive leaders provide employees with encouragement, resources, feedback, and access to organisational support that facilitate desired work behaviours (Bos-Nehles et al., 2023). Studies have shown that supervisory support enhances employees' willingness to adopt organisational innovations, engage with digital technologies, and participate in

organisational change initiatives (Ali et al., 2022; Bevilacqua et al., 2025; Tarhini et al., 2015). We therefore expect academics who perceive greater supervisory support to exhibit stronger AI integration readiness.

Hypothesis 3. *Supervisory support is positively associated with AI integration readiness.*

2.2. The Ability, Motivation, and Opportunity to Integrate AI

While we have established in the preceding section that organisational conditions influence academics' readiness to integrate AI tools into their work, we further argue that supportive organisational conditions alone do not necessarily translate into AI integration readiness. Academics working within the same HEIs may experience similar levels of innovation climate, autonomy, and supervisory support, yet differ considerably in their readiness to integrate AI into their professional responsibilities. This suggests that organisational conditions may not exert uniform effects on all employees. Rather, their influence may depend on whether employees possess the ability required to translate those favourable organisational conditions into actual work behaviour. Following the logic of the Ability-Motivation-Opportunity (AMO) framework, we argue that motivational and opportunity-enhancing conditions may be insufficient if academics lack the knowledge, skills, and confidence required to integrate AI effectively into their work.

Within organisational settings, ability is commonly developed through training. This involves all structured organisational activities designed to develop employees' knowledge, skills, and capabilities required for effective job performance (Noe, 2023). Beyond improving technical competence, training can help employees develop the skills required to adapt to new technologies and changing work processes (OECD, 2025). Within HEIs, AI-related training enables academics to understand the capabilities, limitations, and appropriate applications of AI tools across teaching, research, assessment, and administrative activities. Consequently, academics who receive appropriate training should be better positioned to translate organisational support into meaningful AI integration than equally supported colleagues who lack such training. Recent studies similarly suggest that training and capability development strengthen employees' readiness to engage with AI and other digital technologies across organisational settings (Yu et al., 2026).

Building on this perspective, we propose that training functions as an ability-enhancing boundary condition that determines the extent to which organisational conditions are translated into AI integration readiness. Specifically, we expect the effects of innovation climate, autonomy, and supervisory support on AI integration readiness to be stronger when academics possess the skills to experiment with AI tools, use them effectively, and benefit from support provided by their institutions and supervisors. Accordingly, we hypothesise that:

Hypothesis 4. *Training positively moderates the relationship between innovation climate and AI integration readiness such that the relationship is stronger when training is high.*

Hypothesis 5. *Training positively moderates the relationship between autonomy and AI integration readiness such that the relationship is stronger when training is high.*

Hypothesis 6. *Training positively moderates the relationship between supervisory support and AI integration readiness such that the relationship is stronger when training is high.*

3. Methods

3.1. Participants and Procedure

We collected cross-sectional survey data from academic staff in three federal higher education institutions in Lagos, Nigeria using a structured self-reported questionnaire over a seven-week period between February to March 2026. We selected Lagos because it is Nigeria's leading academic and technological hub and hosts a large concentration of universities, polytechnics, and colleges of education. To ensure representation across the three principal categories of higher education institutions in Nigeria, we purposively selected the University of Lagos, Yaba College of Technology, and the Federal College of Education (Technical), Akoka. To ensure adequate statistical power, we first conducted an *a priori* power analysis using G*Power 3.1 software (Faul et al., 2009), complemented by PLS-SEM sample size recommendations (Kock & Hadaya, 2018), to determine the minimum sample required for the study. We assumed a medium effect size ($f^2 = .15$), statistical power of .80, a significance level of .05, with ten predictors being the most complex structural equation in the model. This indicated a minimum required sample of 118 participants. To improve estimation precision and account for possible non-response, we targeted a sample of 250 academic staff. The target sample from the three institutions was recruited in two stages. First, proportionate stratified sampling was used to allocate the target sample across the participating institutions based on their faculties or schools. Second, respondents

were recruited through convenience sampling because obtaining comprehensive staff lists required to construct a sampling frame for probability sampling was not feasible. Convenience sampling is commonly used in organisational research where access to complete sampling frames is constrained (Memon et al., 2025).

Since all study variables were collected from the same respondents, we implemented several procedural remedies to minimise the risk of common method bias following Podsakoff et al. (2024). Specifically, we assured respondents of anonymity and confidentiality, presented predictor and outcome variables in separate sections of the questionnaire, and carefully worded items to minimise ambiguity. In addition, to reduce evaluation apprehension, we informed respondents that there were no right or wrong answers.

3.2. Measures

We measured all study variables using established scales, with all items rated using a four-point ordinal response format ranging from 1 (*strongly disagree*) to 4 (*strongly agree*). We adopted a four-point response format to discourage neutral responding because the constructs examined in this study require respondents to express clear perceptions regarding their work environment and readiness to integrate AI. Previous methodological studies suggest that removing the neutral midpoint can improve measurement sensitivity by reducing respondents' tendency to default to neutral responses (Kankaraš & Capecchi, 2025). The questionnaire was administered in English, which was also the language in which the source instruments were originally developed; hence no translation was required. We made minor wording adjustments to improve contextual relevance to higher education institutions in Nigeria while preserving the original meaning of the items. The complete measurement items are provided in the Supplementary Material.

We measured *innovation climate, autonomy, supervisory support,* and *training* by adapting the innovation, autonomy, supervisory support, and training dimensions of the Organizational Climate Measure developed by Patterson et al. (2005). Innovation climate was measured with six items, autonomy with five items, supervisory support with five items, and training with four items. We measured *AI integration readiness* using the 20-item Generative Artificial Intelligence Acceptance Scale developed by Yilmaz et al. (2024). The scale assesses individuals' readiness and willingness to incorporate generative AI tools into their work activities. Minor wording modifications were made to reflect the higher education context.

Control variables. We controlled for tenure, discipline, and prior AI training because previous research suggests that these factors may influence employees' attitudes towards technology adoption and AI use in workplace settings (Park et al., 2024; Zhang et al., 2023).

3.3. Data Analysis

We first conducted data cleaning and preparation using SPSS version 27, which was also used to generate the descriptive statistics and correlation matrix. We then imported the data into SmartPLS 4.1 and estimated the measurement and structural models following the two-step approach recommended for PLS-SEM (Hair et al., 2019). The measurement model was first evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, after which the structural model was assessed. The significance of the direct and interaction effects were evaluated using bootstrapping with 5,000 resamples. Model quality was assessed using the coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2), following the recommendations of Ringle et al. (2020) and Hair et al. (2019). We adopted PLS-SEM because it is particularly well suited to prediction-oriented research and the estimation of interaction effects while imposing relatively few assumptions regarding data distribution (Kock & Hadaya, 2018).

4. Results

4.1. Respondents' Profile

Our final sample comprised 188 academic staff representing 75% usable response rate after screening the returned questionnaires for outliers and straightlining. Participants were predominantly male (75%), which is understandable considering the male to female ratio of academic staff distribution in Nigerian higher education institutions (Abang, 2025). Most academics were from the University of Lagos (50%), while the remainder were from Yaba College of Technology (30%) and the Federal College of Education (Technical), Akoka (20%). The largest proportion of respondents were Lecturer II/Lecturer III (28%), approximately one-third had between five and nine years of teaching experience (30%), and nearly two-thirds reported no prior

AI-related training (63%). Respondents also represented a broad range of academic disciplines, with Social and Management Sciences (29%) and Science/Technology/Engineering (26%) accounting for the largest shares of the sample.

4.2. Descriptive Statistics and Correlations

The means, standard deviations and intercorrelations among the study variables are displayed in Table 1. Supervisory support ($r = .495$, $p < .01$) had the strongest association with AI integration readiness, followed by innovation climate ($r = .436$, $p < .01$) and training ($r = .395$, $p < .01$). Autonomy exhibited a weaker but positive association with AI integration readiness ($r = .145$, $p < .05$). None of the control variables was significantly correlated with the study variables. Correlations among the focal variables were moderate, suggesting that problematic multicollinearity is unlikely. Furthermore, the square roots of the average variance extracted (AVE) exceeded the corresponding inter-construct correlations, providing support for discriminant validity based on the Fornell–Larcker criterion.

Variable	M	SD	1	2	3	4	5	6	7	8
1. Prior AI Training	0.42	0.49	—							
2. Tenure	2.55	1.11	−.007	—						
3. Discipline	3.47	1.61	.078	.056	—					
4. Innovation Climate	2.98	0.56	.007	.134	−.078	**(.847)**				
5. Autonomy	2.70	0.58	−.174*	.060	−.024	.180*	**(.844)**			
6. Supervisory Support	2.89	0.56	.014	.137	−.023	.378**	.245**	**(.858)**		
7. Training	2.61	0.57	.013	.121	.028	.442**	.124	.457**	**(.868)**	
8. AI Integration Readiness	3.00	0.53	−.053	.108	−.016	.436**	.145*	.495**	.395**	**(.811)**

Note. *p < .05, **p < .01. Values in bold parentheses on the diagonal represent the square root of the Average Variance Extracted (AVE).

Table 1. Descriptive Statistics and Correlations

4.3. Measurement Model

We assessed the measurement model following established guidelines for PLS-SEM (Hair et al, 2019). We first assessed indicator reliability using outer loadings. All indicators exceeded the recommended loading threshold of .70. As shown in Table 2, all constructs demonstrated satisfactory internal consistency reliability, with Cronbach's alpha and composite reliability values exceeding the recommended threshold of .70. Average variance extracted (AVE) values for all constructs were above the recommended .50 threshold (Hair et al., 2019). In addition to the Fornell-Larcker criterion reported in Table 1, we assessed discriminant validity using the Heterotrait–Monotrait (HTMT) ratio of correlations. As shown in Table 2, all HTMT values were below the conservative threshold of .85, indicating that the constructs were empirically distinct (Henseler et al., 2015).

4.4. Common Method Bias

We conducted a statistical assessment using the full collinearity variance inflation factor (VIF) approach to assess common method bias. All VIF values were below the recommended threshold of 3.3, indicating that common method bias is unlikely to pose a serious threat to the validity of the results (Kock, 2015). The full collinearity VIF approach simultaneously assesses both vertical and lateral collinearity and provides a more robust assessment of common method bias than Harman's single-factor test (Howard et al., 2024).

Latent Construct	Loadings	α	CR	AVE	INC	SS	TR	AIIR
Innovation Climate (INC)	.81–.87	.921	.939	.718	—			
Autonomy (AUT)	.80–.88	.902	.925	.712	.197	—		
Supervisory Support (SS)	.84–.91	.910	.933	.736	.412	.270	—	
Training (TR)	.84–.89	.891	.924	.753	.488	.144	.509	—
AI Integration Readiness (AIIR)	.77–.86	.973	.975	.658	.460	.156	.526	.425

Note. α = Cronbach's alpha; CR = Composite reliability; AVE = Average variance extracted. Values below the diagonal are HTMT ratios.

Table 2. Construct Reliability, Convergent Validity, and Discriminant Validity

4.5. Structural Model Assessment

To evaluate the structural model, we followed the criteria proposed by Ringle et al. (2020) and Hair et al. (2019). We assessed the coefficient of determination, effect sizes, and predictive relevance. The model explained 34% of the variance in AI integration readiness, indicating moderate explanatory power. Effect size estimates showed that supervisory support exerted the largest effect on AI integration readiness (f^2 = .131), followed by innovation climate (f^2 = .070). In contrast, the effects of training (f^2 = .019), autonomy (f^2 = .000), the three interaction terms (f^2 = .002–.003), and the control variables (f^2 = .000–.006) were negligible. Predictive relevance was supported, as the model yielded a positive Q^2 value (Q^2 = .238), indicating satisfactory predictive relevance. Overall, these results suggest that the explanatory and predictive power of the structural model is satisfactory.

4.6. Hypotheses Testing

Table 3 presents the results of the direct and moderating effects. Innovation Climate (β = .250, p < .001) and supervisory support (β = .347, p < .001) were positively associated with AI integration readiness, supporting H1 and H3. However, autonomy was not significantly associated with AI integration readiness (β = –.005, p = .941); therefore, H2 was not supported. None of the control variables had a statistically significant effect on AI integration readiness. Contrary to our expectations, training did not significantly moderate the relationships between innovation climate and AI integration readiness (β = –.045, p = .552), autonomy and AI integration readiness (β = –.036, p = .615), or supervisory support and AI integration readiness (β = .048, p = .544). Therefore, H4, H5, and H6 were not supported. The overall structural model with standardised path coefficients and explained variance is presented in Figure 2.

Hypothesis	Structural Path	β	t-value	p-value	95% CI	Decision
H1	INC → AIIR	.250	3.576	< .001	[.102, .380]	Supported
H2	AUT → AIIR	–.005	0.074	.941	[–.202, .090]	Not Supported
H3	SS → AIIR	.347	4.902	< .001	[.201, .479]	Supported
H4	INC × TR → AIIR	–.045	0.595	.552	[–.187, .108]	Not Supported
H5	AUT × TR → AIIR	–.036	0.504	.615	[–.166, .109]	Not Supported
H6	SS × TR → AIIR	.048	0.607	.544	[–.098, .216]	Not Supported

Note. INC = Innovation Climate; AUT = Autonomy; SS = Supervisory Support; TR = Training; AIIR = Artificial Intelligence Integration Readiness. β = standardised path coefficient; CI = bias-corrected bootstrapped confidence interval.

Table 3. Hypotheses Testing Results

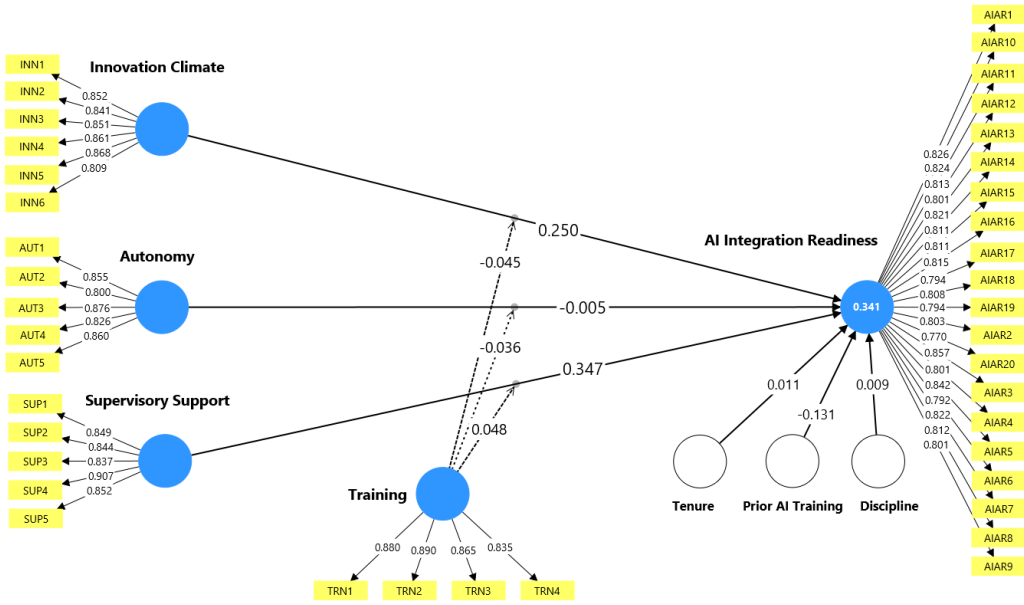


Figure 1. Structural Model Results

5. Discussion

This study provides empirical evidence that organisational context matters in AI integration readiness by academics in higher education. Specifically, our findings show that innovation climate and supervisory support significantly enhance academics' readiness to integrate AI into teaching, research, and other professional responsibilities, whereas autonomy does not. Contrary to our expectations, training did not strengthen any of these relationships. Together, these findings suggest that AI integration readiness is less a function of isolated organisational practices and more a reflection of the broader socio-technical environment within which academic professionals work.

Our findings also provide a more nuanced understanding of the role organisational climate plays in shaping AI integration within higher education. Consistent with Socio-Technical Systems (STS) theory, academics appeared more prepared to integrate AI when they worked in environments that encouraged experimentation and innovation and where supervisors actively supported technological change. These findings reinforce the central proposition of STS that technological innovations become embedded in organisations not because they are available but because the surrounding social system enables employees to incorporate them into their work. Within higher education, AI integration requires academics to rethink established teaching practices, redesign assessments, incorporate AI into research workflows, and exercise professional judgement in navigating emerging ethical and institutional expectations. Such changes are more likely to occur where the organisational climate encourages experimentation and where supervisors legitimise and support new ways of working. This agrees with recent findings by Bin-Nashwan and Li (2025) and Zhang et al. (2025), which highlight the importance of innovation-supportive organisational conditions and supervisory support in facilitating employees' engagement with AI and other digital technologies.

One finding that deserves particular attention is the non-significant effect of autonomy. Previous research generally suggests that autonomy encourages innovation and technology adoption because employees who enjoy greater discretion are more willing to experiment with new work practices (Sodiya et al., 2025). This outcome contrasts with the recent finding by Sodiya et al. (2025) that job autonomy was positively associated with both perceived usefulness and actual use of AI at work. Our findings suggest that although academics traditionally enjoy substantial autonomy over their teaching and research activities, this may not be sufficient to encourage AI integration. An important implication of this finding is that rather than asking whether academics are free to use AI, the more important question may be whether the organisational environment encourages, legitimises, and supports its responsible use. In other words, the freedom to integrate AI appears to matter less than the organisational signals academics receive regarding whether such behaviour is expected,

supported, and valued. This finding further reinforces our central argument that AI integration should be understood as a socio-technical work behaviour rather than simply an individual technology-use decision.

Perhaps the most unexpected finding was that training did not strengthen the relationships between organisational climate and AI integration readiness. From an AMO lens, and in line with the recent framework proposed by Yu et al. (2026), we expected training to function as an ability-enhancing condition that would enable academics to translate favourable organisational conditions into greater readiness to integrate AI. Instead, the results suggest that training alone may not be sufficient to strengthen the influence of innovation climate, autonomy, or supervisory support. One possible explanation is that the benefits of AI training depend less on its availability than on its quality, relevance, and alignment with academics' day-to-day work demands. Generic or one-off AI training programmes may increase awareness of AI tools without necessarily equipping academics to redesign their teaching, research, or administrative practices. However, a more plausible explanation may be that integrating AI into academic work involves more than acquiring technical competence. Academics must also navigate concerns relating to academic integrity, responsible AI use, professional judgement, and institutional expectations, all of which require organisational guidance beyond formal training (Coates et al., 2025; Vosloo et al., 2025). Under these conditions, training alone may be insufficient unless academics also perceive that their institution encourages responsible experimentation and provides visible supervisory support. Collectively, these findings suggest that organisational readiness for AI integration cannot be achieved simply by providing training. Rather, AI training is likely to be most effective when it forms part of a broader organisational climate that legitimises experimentation, provides supervisory support, and creates a clear institutional environment for responsible AI integration.

5.1. Theoretical Implications

This study provides evidence from the higher education setting in a developing economy that academics' AI integration readiness is better understood as a socio-technical work behaviour than merely a technology-acceptance decision. In doing so, it shifts attention from individual acceptance factors towards the organisational conditions that enable AI integration within everyday academic work. Relatedly, our findings provide a more behaviourally grounded application of Socio-Technical Systems Theory by demonstrating that not all elements of the social subsystem contribute equally to AI integration readiness. Specifically, innovation climate and supervisory support emerged as stronger organisational enablers than autonomy. Finally, our findings offer a more nuanced application of the Ability–Motivation–Opportunity (AMO) framework by suggesting that ability-enhancing practices such as training may not be sufficient to strengthen or buffer the effects of motivational and opportunity conditions on AI integration readiness. While AMO proposes that employees are more likely to engage in desired behaviours when ability, motivation, and opportunity are jointly present, our findings suggest that, in the context of AI integration, organisational signals that encourage experimentation and provide support may exert a stronger influence than formal training alone. This highlights the importance of viewing ability not in isolation but as part of a broader organisational context in which supportive work climates may be more instrumental in translating AI capabilities into everyday work behaviour.

5.2. Practical and Policy Implications

Our findings suggest that improving AI integration in higher education requires more than expanding AI training programmes. While developing academics' AI-related knowledge and skills remains important, universities, polytechnics, and colleges should give equal, if not greater, attention to creating organisational environments that encourage experimentation, legitimise responsible AI use, and provide visible supervisory support. Institutional leaders should therefore complement AI training with clear governance frameworks, practical guidelines for responsible AI use, and leadership practices that encourage academics to explore AI confidently within appropriate ethical and professional boundaries. This recommendation is particularly important in developing countries such as Nigeria, where institutional AI policies, digital infrastructure, and governance frameworks are still evolving. At the policy level, higher education regulators should move beyond promoting AI capacity building alone by supporting institution-wide strategies that integrate staff development, organisational support, and responsible AI governance. Such an approach is more likely to promote sustainable AI integration than focusing solely on technical training.

5.3. Limitations and Future Research Direction

This study has some limitations that should be considered when interpreting its findings. First, the cross-sectional design and reliance on single-source data limit causal inference and raise the possibility of common method variance, despite the procedural and statistical remedies we implemented. Future studies could employ longitudinal, multi-source, or experimental designs to strengthen causal conclusions. Second, although the study included academic staff from a university, a polytechnic, and a college of education, all participating institutions were located in Lagos State, Nigeria, and respondents were recruited through convenience sampling. This limited geographic coverage, use of non-probability sampling, and a sample size of 188 academics affect the generalisability of our findings. Future studies should employ probability sampling where feasible and examine whether the present findings generalise to other regions, institutional types, and national contexts. Finally, training was examined as a broad organisational practice. Future research could distinguish between different forms of AI training, such as technical skills development and ethical AI training, to determine whether particular forms of training are more effective in strengthening AI integration readiness. Future studies may also examine other organisational conditions, such as AI governance, institutional trust, digital infrastructure, or ethical climate, that may shape academics' readiness to integrate AI into their work.

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