The Influence of Instructional Leadership on the Use of Artificial Intelligence Applications among Vocational College Lecturers in Sarawak Zone

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DOI: https://dx.doi.org/10.47772/IJRISS.2026.10200559

Received: 02 March 2026; Accepted: 09 March 2026; Published: 20 March 2026

ABSTRACT

The integration of artificial intelligence (AI) in technical and vocational education and training (TVET) has gained increasing attention due to its potential to enhance instructional effectiveness. However, the level of AI application usage among vocational college lecturers remains uneven, particularly in less developed regions. This study examines the influence of instructional leadership on the use of AI applications among vocational college lecturers in the Sarawak Zone, guided by an integrated framework incorporating Instructional Leadership Theory, Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Self-Efficacy Theory. A quantitative cross-sectional design was employed involving 120 lecturers. Data were collected using a structured questionnaire and analysed using descriptive and inferential statistics. The findings indicate that instructional leadership, technology acceptance, and self-efficacy significantly influence AI application usage, with technology acceptance emerging as the strongest predictor. The model explains a substantial proportion of variance in AI usage, highlighting the combined role of leadership and psychological factors. The study provides empirical support for an integrated perspective of AI adoption, emphasising that effective AI integration in vocational education is shaped not only by technological factors but also by leadership practices and lecturers' readiness.

Keywords: Instructional Leadership; Artificial Intelligence; Vocational Education; Vocational College Lecturers; TVET; Sarawak

INTRODUCTION

The Fourth Industrial Revolution (IR 4.0) has accelerated the integration of advanced digital technologies in education, particularly artificial intelligence (AI), which is increasingly recognised as a transformative tool for enhancing instructional effectiveness, personalising learning experiences, and supporting data-driven decision-making (Zawacki-Richter et al., 2019; Hwang et al., 2021). AI applications such as adaptive learning systems, intelligent tutoring platforms, automated assessment tools, and learning analytics enable educators to monitor student performance and implement targeted instructional interventions more effectively (Tsai et al., 2022).

In technical and vocational education and training (TVET), AI integration is especially relevant due to its alignment with industry demands and skills-based learning. AI-driven tools, including simulation-based environments and intelligent assessment systems, support practical skill development and workplace readiness (Zhang et al., 2021; Che Mat & Abd Aziz, 2024). However, despite these advantages, the adoption of AI among vocational college lecturers remains uneven, particularly in less-developed regions such as Sarawak (Rahman & Ismail, 2023).

Existing studies have largely examined AI adoption from technological and individual perspectives, focusing on factors such as perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003). While valuable, these approaches often overlook the role of instructional leadership and psychological mechanisms in shaping lecturers' readiness to integrate AI. Additionally, research on instructional leadership and technology adoption has frequently been conducted in isolation, resulting in a fragmented understanding of AI integration.

Instructional leadership is essential in shaping instructional practices, fostering innovation, and supporting professional development (Hallinger & Murphy, 1985; Hallinger & Wang, 2020). In technology-driven contexts, leaders influence not only organisational readiness but also lecturers' confidence and perceptions of technology. Technology adoption models such as TAM and UTAUT explain how perceptions and social factors influence usage behaviour (Davis, 1989; Venkatesh et al., 2003), while Self-Efficacy Theory highlights the role of individual confidence in adopting new technologies (Bandura, 1977).

Despite these perspectives, empirical research integrating instructional leadership, technology acceptance, and psychological factors in explaining AI application usage in vocational education remains limited, particularly in the Sarawak context.

Therefore, this study aims to examine the influence of instructional leadership on AI application usage among vocational college lecturers in the Sarawak Zone using an integrated framework. This study contributes by providing empirical evidence on how leadership practices and psychological factors jointly influence AI integration in vocational education.

LITERATURE REVIEW

Instructional Leadership in Technology-Driven Educational Contexts

Instructional leadership is widely recognised as a key determinant of instructional quality, pedagogical innovation, and organisational effectiveness. Based on Hallinger and Murphy (1985), it encompasses defining instructional goals, managing instructional programmes, and promoting a positive learning climate. In technology-driven educational environments, instructional leadership extends to facilitating digital transformation and supporting innovation in teaching practices (Hallinger & Wang, 2020).

Empirical studies indicate that instructional leadership significantly influences teachers' instructional practices, professional engagement, and readiness to adopt educational technologies (Leithwood et al., 2021; Nguyen et al., 2022). In TVET contexts, where instructional practices must align with evolving industry demands, leadership plays a crucial role in fostering technology-oriented instructional cultures and supporting the integration of emerging technologies such as AI (Zhang et al., 2021; Sun et al., 2021).

Artificial Intelligence Integration in Vocational Education

Artificial intelligence (AI) has transformed educational practices through adaptive learning, automated assessment, and data-driven decision-making (Zawacki-Richter et al., 2019; Chen et al., 2023). In vocational education, AI applications such as simulation-based learning environments, intelligent tutoring systems, and learning analytics enhance skills-based learning and workplace readiness (Zhang et al., 2021; Che Mat & Abd Aziz, 2024).

However, AI integration in TVET remains uneven. Lecturers often utilise AI tools at a basic level due to constraints such as limited digital literacy, inadequate infrastructure, insufficient training, and uncertainty regarding pedagogical value (Rahman & Ismail, 2023; Hassan et al., 2023). These challenges highlight that AI adoption is influenced not only by technological factors but also by leadership and organisational conditions.

Technology Acceptance and AI Adoption

Technology adoption in education is commonly explained using the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM emphasises perceived usefulness and perceived ease of use (Davis, 1989), while UTAUT incorporates social influence and facilitating conditions (Venkatesh et al., 2003).

Empirical studies show that lecturers are more likely to adopt AI technologies when they perceive clear instructional benefits and ease of implementation (Rajapakse et al., 2024; Tsai et al., 2022). However, these models primarily focus on individual perceptions and provide limited explanation of how leadership and organisational contexts shape technology adoption, necessitating integration with broader perspectives.

Psychological Mechanisms: Self-Efficacy, Intrinsic Motivation, and Job Satisfaction

Psychological factors play a critical role in technology adoption. Self-efficacy influences lecturers' confidence in using AI technologies and their willingness to adopt innovative instructional practices (Bandura, 1977; Basir et al., 2023). Intrinsic motivation drives lecturers to engage in meaningful instructional innovation, while job satisfaction enhances professional commitment and openness to change (Mohd Faizal & Norita, 2024; Kim et al., 2023). These psychological factors are closely linked to leadership practices. Instructional leaders who provide professional development, support, and collaborative environments can enhance lecturers' confidence, motivation, and job satisfaction, thereby facilitating AI integration.

Organisational Conditions: Technological Infrastructure and Institutional Support

Organisational conditions are essential in enabling AI adoption. Technological infrastructure, including access to digital systems and technical support, determines the feasibility of implementing AI in instructional settings (Hassan et al., 2023). Institutional support, such as policies, training programmes, and leadership initiatives, further strengthens educators' readiness to adopt digital technologies (Nguyen et al., 2022). These factors may function as moderating variables that influence the effectiveness of instructional leadership in promoting AI integration.

Synthesis and Research Gap

Overall, the literature indicates that AI adoption in education is influenced by the interaction of leadership practices, technological perceptions, psychological readiness, and organisational conditions. However, existing studies often examine these factors separately, resulting in a fragmented understanding of AI integration, particularly in vocational education contexts.

Furthermore, limited empirical research has explored the combined influence of instructional leadership, technology acceptance, and psychological factors on AI application usage in TVET, especially within the Sarawak context. Therefore, this study adopts an integrated framework to provide a more comprehensive understanding of how these factors jointly influence AI integration among vocational college lecturers.

METHODOLOGY

This study was guided by an integrated theoretical and conceptual framework adapted from Instructional Leadership Theory, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and Self-Efficacy Theory, as illustrated in Figure 1 and Figure 2. The proposed framework conceptualises instructional leadership as a key organisational factor influencing the integration of artificial intelligence (AI) in teaching, both directly and indirectly through psychological mechanisms.

The full conceptual model includes multiple mediating factors, namely self-efficacy, intrinsic motivation, and job satisfaction, as well as moderating variables such as technological infrastructure and institutional support. However, due to the scope and design of the present empirical study, the analysis focuses on a partial model by examining the direct effects of instructional leadership, technology acceptance, and self-efficacy on AI application usage among vocational college lecturers.

This approach allows for an initial empirical validation of key components of the proposed framework while providing a foundation for future studies to test the full model using more advanced analytical techniques such as structural equation modelling (SEM).

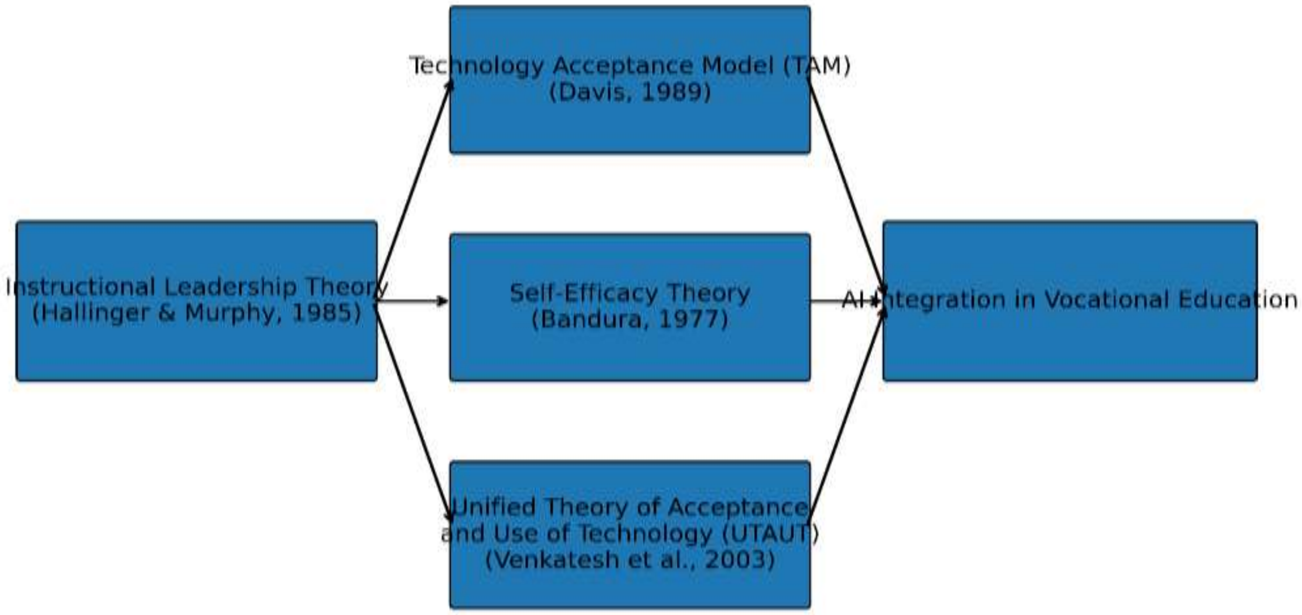

Figure 1 : The Theoretical Framework used in the research

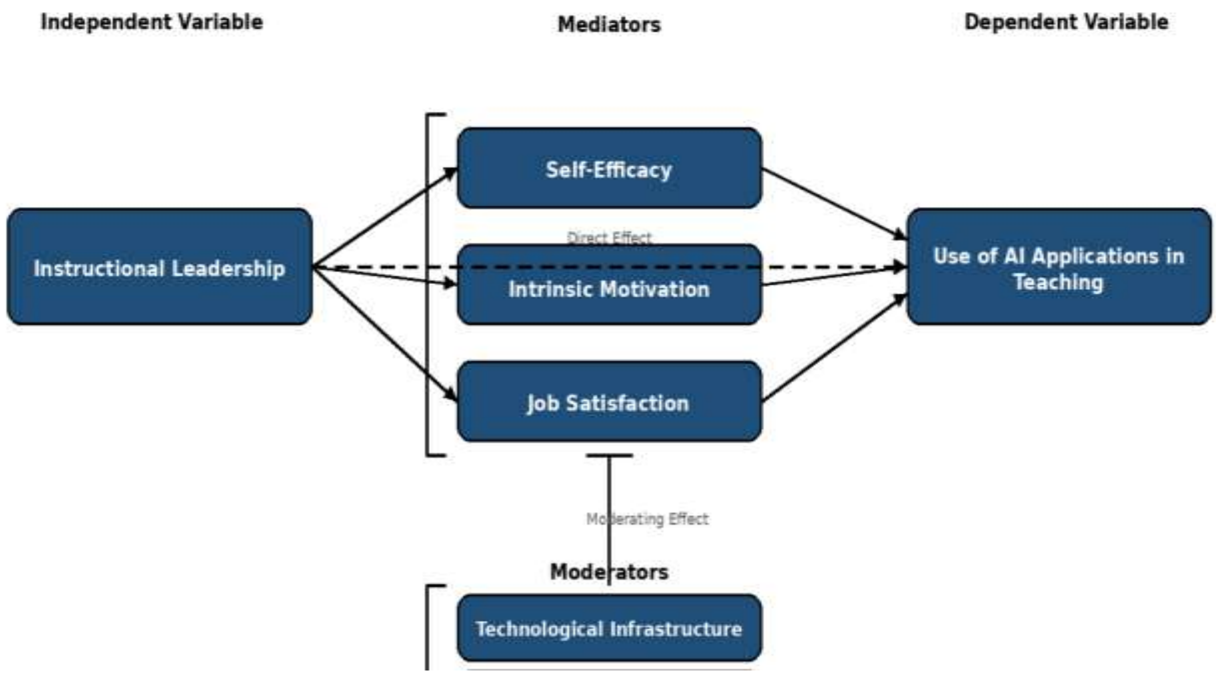

Figure 2: The Conceptual Framework used in the research

Population and Sample

The population of this study consisted of lecturers from vocational colleges in the Sarawak Zone who are actively involved in teaching and learning activities. These lecturers were selected as they play a central role in instructional delivery and are directly engaged in the integration of digital and AI-related technologies in vocational education.

A purposive sampling technique was employed to ensure that respondents met specific inclusion criteria, including having active teaching responsibilities and exposure to digital or AI-supported instructional tools. This approach is consistent with prior studies in educational technology adoption, where respondents are selected based on their relevance to the research context (Nguyen et al., 2022).

A total of 120 lecturers participated in the study, which is considered adequate for regression-based analysis and comparable to sample sizes used in similar empirical studies in educational leadership and technology adoption research. The focus on the Sarawak Zone provides important contextual insights, particularly given the region's geographical dispersion and varying levels of technological infrastructure, which may influence the adoption of AI in vocational education.

Measures and Operationalization of Variable

Data were collected using a structured questionnaire developed based on established and validated instruments from prior studies in educational leadership and technology adoption. The instrument was designed to reflect the key constructs in the proposed conceptual framework, with selected variables operationalised for empirical analysis.

1. Instructional leadership was measured using items adapted from established instructional leadership models, focusing on dimensions such as defining instructional goals, managing instructional programs, and promoting a supportive learning climate (Hallinger & Murphy, 1985).

2. Artificial intelligence (AI) application usage was operationalized by assessing the extent to which lecturers utilize AI-related tools in teaching and learning, including adaptive learning systems, automated assessment tools, and learning analytics applications.

3. Technology acceptance was measured based on constructs derived from TAM and UTAUT, including perceived usefulness, perceived ease of use, social influence, and facilitating conditions (Davis, 1989; Venkatesh et al., 2003).

4. Self-efficacy was measured to capture lecturers' confidence in their ability to effectively use AI applications in instructional practices (Bandura, 1977).

Although the conceptual framework includes additional psychological constructs such as intrinsic motivation and job satisfaction, as well as organisational factors such as technological infrastructure and institutional support, the present study focuses on selected variables that are directly aligned with the scope of the empirical analysis.

1) Validity and Reliability

To ensure content validity, the questionnaire items were developed and adapted from established instruments in instructional leadership and technology adoption literature. The instrument was reviewed by subject matter experts in educational leadership and educational technology to evaluate clarity, relevance, and alignment with the study constructs. Revisions were made based on expert feedback to ensure the adequacy of content representation. Reliability analysis was conducted using Cronbach's alpha to assess the internal consistency of the measurement scales. All constructs recorded alpha values exceeding the acceptable threshold of 0.70, indicating satisfactory reliability. The use of validated measurement items adapted from prior studies further supports the construct validity of the instrument in capturing the underlying theoretical constructs.

2) Data Analysis

The collected data were analysed using IBM SPSS Statistics Version 29.0. Descriptive statistics were first employed to summarise respondents' demographic characteristics and to determine the overall levels of instructional leadership, technology acceptance, self-efficacy, and AI application usage. Subsequently, Pearson correlation analysis was conducted to examine the relationships among the study variables. Multiple regression analysis was then performed to determine the predictive effects of instructional leadership, technology acceptance, and self-efficacy on AI application usage. This analytical approach is consistent with the study's objective of examining the direct relationships among key constructs within a partial model of the proposed conceptual framework. A significance level of $p < .05$ was adopted for all inferential analyses.

RESULT

This section presents the empirical findings of the study based on data collected from 120 vocational college lecturers in the Sarawak Zone. The analysis is structured to align with the study's conceptual framework, focusing on the relationships between instructional leadership, technology acceptance, self-efficacy, and AI application usage. The results are presented in three stages: reliability analysis, descriptive analysis, and inferential analysis.

Reliability Analysis

The internal consistency of the measurement scales was assessed using Cronbach's alpha, as presented in Table 1.

Table 1 : Cronbach's Alpha Reliability Coefficients (N = 120)

Construct	*Number of Items*	*Cronbach's Alpha*
Instructional Leadership	12	0.91
Technology Acceptance	12	0.88
Self-Efficacy	6	0.87
AI Application Usage	8	0.85

All constructs recorded Cronbach's alpha values above 0.70, indicating satisfactory internal consistency. Instructional leadership demonstrated the highest reliability ($\alpha = 0.91$), followed by technology acceptance ($\alpha = 0.88$), self-efficacy ($\alpha = 0.87$), and AI application usage ($\alpha = 0.85$). These results confirm that the measurement items are reliable and suitable for subsequent analysis.

Descriptive Statistics of Study Variables

The descriptive results indicate that all variables are at a moderate level. Instructional leadership recorded the highest mean (M = 3.67), suggesting that leadership practices are generally present within vocational colleges. Technology acceptance (M = 3.59) and self-efficacy (M = 3.62) also show moderate levels, indicating that lecturers possess a reasonable level of confidence and positive perception towards AI technologies.

However, AI application usage recorded the lowest mean (M = 3.41), suggesting that the actual integration of AI in instructional practices remains limited. This pattern reflects a gap between readiness (perception and confidence) and actual usage, highlighting the importance of translating psychological readiness into practical implementation.

Table 2: Descriptive Statistics of Study Variables (N = 120)

Variable	*Mean*	*Std. Deviation*
Instructional Leadership	3.67	0.54
Technology Acceptance	3.59	0.58
Self-Efficacy	3.62	0.56
AI Application Usage	3.41	0.61

Correlation Analysis

To examine the relationships among the study variables, Pearson correlation analysis was performed. The results are presented in Table 3.

Table 3 : Pearson Correlation Matrix

Variable	*IL*	*TA*	*SE*	*AIU*
Instructional Leadership (IL)	1			
Technology Acceptance (TA)	.62**	1		
Self-Efficacy (SE)	.58**	.65**	1	
AI Application Usage (AIU)	.54**	.67**	.60**	1

Note: p < .01

The Pearson correlation analysis shows significant positive relationships among all variables. Instructional leadership is moderately correlated with AI application usage ($r = .54$, $p < .01$), indicating that stronger leadership is associated with higher levels of AI integration.

Technology acceptance demonstrates the strongest correlation with AI usage ($r = .67$, $p < .01$), followed by self-efficacy ($r = .60$, $p < .01$). These findings suggest that lecturers' perceptions of AI usefulness and their confidence in using technology are critical factors influencing actual usage.

In addition, instructional leadership is significantly correlated with both technology acceptance ($r = .62$, $p < .01$) and self-efficacy ($r = .58$, $p < .01$), indicating that leadership practices may indirectly influence AI usage by shaping lecturers' perceptions and confidence. This finding provides preliminary support for the proposed conceptual framework, which emphasises the role of psychological mechanisms in mediating leadership influence.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

Regression Analysis

The regression model is statistically significant ($F(3,116) = 49.21$, $p < .001$), explaining 56% of the variance in AI application usage ($R^2 = .56$). Technology acceptance emerged as the strongest predictor ($\beta = .41$, $p < .001$), followed by self-efficacy ($\beta = .31$, $p < .001$) and instructional leadership ($\beta = .28$, $p < .001$). These findings indicate that while leadership plays an important role, lecturers' perceptions of AI usefulness and their confidence in using technology have a more direct influence on AI application usage.

Table 4 : Multiple Regression Analysis Predicting AI Application Usage

Predictor	*β*	*T*	*p*
Instructional Leadership	.28	3.64	.000
Technology Acceptance	.41	5.21	.000
Self-Efficacy	.31	4.02	.000

$R^2 = .56$, $F(3,116) = 49.21$, $p < .001$

From a theoretical perspective, these results align with TAM and UTAUT, which emphasise perceived usefulness and facilitating conditions as key determinants of technology adoption. At the same time, the significant effect of self-efficacy supports the role of psychological readiness in influencing lecturers' willingness to adopt AI technologies.

Importantly, the continued significance of instructional leadership suggests that leadership functions as an enabling factor that shapes both technological perceptions and psychological readiness. This supports the integrated framework proposed in this study, where leadership influences AI adoption both directly and indirectly through psychological mechanisms. This suggests a potential mediating mechanism, which warrants further investigation using SEM.

DISCUSSION

This study provides empirical support for the integrated framework, demonstrating that instructional leadership, technology acceptance, and self-efficacy significantly influence AI application usage among vocational college lecturers.

Technology acceptance emerged as the strongest predictor, indicating that lecturers are more likely to adopt AI when they perceive clear instructional value and relevance. This finding is consistent with TAM and UTAUT, which emphasise perceived usefulness as a primary determinant of technology adoption (Davis, 1989; Venkatesh et al., 2003). Self-efficacy also plays a significant role, highlighting the importance of lecturers' confidence in using AI technologies. This supports Self-Efficacy Theory (Bandura, 1977) and suggests that psychological readiness is essential for effective technology integration. Instructional leadership, although a comparatively weaker predictor, remains significant, indicating its role as an enabling factor that shapes both lecturers' perceptions and confidence. This suggests that leadership influences AI adoption both directly and indirectly, consistent with the proposed conceptual framework. An important finding is the gap between lecturers' readiness and actual AI usage, where moderate levels of leadership, acceptance, and self-efficacy do not fully translate into implementation. This implies that organisational conditions, such as technological infrastructure and institutional support, may influence the effectiveness of AI integration.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

Overall, the findings highlight that AI adoption in vocational education is not solely determined by technological factors but is shaped by the interaction between leadership practices and lecturers' psychological readiness.

Summary of Empirical Findings

To provide a clear synthesis of the study's key results, Table 4 summarises the main empirical findings based on the statistical analyses presented earlier.

Table 5 : Summary of Key Empirical Findings

Construct	*Key Finding*	*Theoretical Interpretation*
Instructional Leadership	Significant positive effect	Supports Instructional Leadership Theory – leadership shapes instructional innovation
Technology Acceptance	Strongest predictor	Consistent with TAM & UTAUT – perceived usefulness drives adoption
Self-Efficacy	Significant predictor	Supports Self-Efficacy Theory – confidence influences usage
AI Application Usage	Moderate level	Indicates gap between readiness and implementation
Overall Model	$R^2 = 0.56$	Demonstrates combined influence of leadership and psychological factors

This summary table consolidates the main findings and demonstrates coherence between the research objectives, conceptual framework, and statistical results.

Limitation of the Study

This study has several limitations. First, the scope of AI applications examined is relatively general, without focusing on specific tools or platforms and their pedagogical implications. Second, the use of a quantitative cross-sectional design limits the ability to capture in-depth experiences of lecturers in integrating AI into their teaching practices.

Third, the study is confined to vocational colleges in the Sarawak Zone, which may limit the generalisability of the findings to other educational contexts with different levels of infrastructure and institutional support. Finally, the reliance on self-reported data may introduce response bias, potentially affecting the accuracy of reported practices and perceptions.

Directions for Future Research

Future research should consider longitudinal designs to examine the development of AI adoption over time in vocational education. In addition, mixed-method approaches are recommended to provide deeper insights into lecturers' experiences, challenges, and institutional factors influencing AI integration.

Further studies may also extend the present model by incorporating additional psychological and organisational variables, such as intrinsic motivation, job satisfaction, technological infrastructure, and institutional support, using more advanced analytical techniques such as structural equation modelling.

CONCLUSION

This study examined the influence of instructional leadership on the use of artificial intelligence (AI) applications among vocational college lecturers in the Sarawak Zone using an integrated framework combining instructional leadership theory, technology acceptance models, and self-efficacy perspectives. The findings demonstrate that instructional leadership, technology acceptance, and self-efficacy are significant predictors of AI application usage, with technology acceptance emerging as the strongest determinant.

The study highlights that AI integration in vocational education is not solely a technological issue but is shaped by the interaction between leadership practices and lecturers' psychological readiness. While instructional leadership provides an enabling environment for innovation, lecturers' perceptions of usefulness and their confidence in using AI technologies play a more direct role in influencing actual adoption.

From a theoretical perspective, this study contributes by integrating leadership, technology acceptance, and psychological constructs into a unified empirical model, addressing the fragmented nature of prior research. From a practical perspective, the findings suggest that vocational institutions should strengthen instructional leadership practices, enhance professional development programmes, and promote positive perceptions of AI to support effective implementation.

Nevertheless, this study is limited by its focus on selected variables within a partial model and its reliance on cross-sectional survey data from a specific regional context. Future research should examine the full conceptual framework by incorporating additional psychological and organisational variables, such as intrinsic motivation, job satisfaction, technological infrastructure, and institutional support, using more advanced analytical approaches such as structural equation modelling.

ACKNOWLEDGMENT

The authors gratefully acknowledge the Ministry of Education Malaysia (MoE), under the Sarawak State Education Department (JPNSW9.700-4/1/5 (4-8), for the official reference and continued moral support, and for granting approval for a 30-day unrecorded leave over the one-year study period, which facilitated the conduct and completion of this research. We also extend our gratitude to Open University Malaysia for providing the necessary resources and facilities for this research.

Conflict Of Interest

The authors declare no conflict of interest with any party throughout the research and writing process of this paper.

Author Contributions

1) Azri bin Said: conceptualized the study, developed the methodology, conducted the formal analysis, and wrote the original draft of the manuscript

2) Md. Rosli bin Ismail : provided supervision, guidance on the research design, and critical review of the manuscript

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ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

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