AI Adoption Readiness in Universities: A Multivariate Regression and Machine Learning Analysis of Malaysia and Indonesia

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ABSTRACT

This study investigates the determinants of AI adoption in higher education institutions in Malaysia and Indonesia using an integrated analytical framework that combines behavioral, institutional, and training-related factors. A quantitative cross-sectional survey was conducted in 2025, yielding 748 valid responses from academic staff and students (response rate: 34%). The analysis employed logistic regression, ordinal regression, structural path modeling, heatmap segmentation, and machine learning clustering. Results demonstrate that perceived ease of use and perceived usefulness are the strongest predictors of AI usage and user satisfaction, with standardized effects exceeding those of demographic variables. AI training significantly increases adoption likelihood, raising sustained AI usage probability by over 40% among trained participants. Malaysian institutions exhibit higher adoption maturity, with AI training participation of 68.3% compared to 54.1% in Indonesian institutions. However, satisfaction levels in both countries remain largely neutral to moderate, indicating that AI integration is still at a transitional stage. Compared with prior research, this study advances understanding of AI adoption by integrating advanced statistical modeling with machine learning methods, offering stronger empirical evidence for policy design and leadership decision-making in higher education.

Keywords: Artificial Intelligence Adoption; Higher Education; Technology Acceptance; AI Training; Machine Learning Segmentation

INTRODUCTION

Artificial intelligence (AI) is rapidly reshaping higher education by supporting teaching, learning, research, and institutional management. Universities worldwide are increasingly adopting AI-driven tools such as intelligent tutoring systems, learning analytics, academic chatbots, and generative AI platforms. These technologies offer substantial potential to enhance educational quality, personalize learning experiences, and improve institutional efficiency. However, despite this potential, AI adoption across higher education institutions remains uneven, with many universities still struggling to achieve meaningful and sustainable integration. Recent studies emphasize that AI adoption in higher education is not driven by technology alone but depends on a combination of behavioral, organizational, and policy-related factors. Perceived usefulness, perceived ease of use, institutional readiness, and training availability consistently emerge as key determinants shaping adoption decisions [1], [3], [6], [10]. In emerging higher education systems such as Malaysia and Indonesia, these factors are particularly important due to differences in digital infrastructure, governance maturity, and professional development capacity [17], [20].

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Although both countries have introduced national digital transformation strategies, the pace and depth of AI integration within universities vary substantially. Empirical evidence suggests that while awareness of AI is increasing, actual usage levels remain moderate and user satisfaction is mixed, reflecting the early stage of institutional AI maturity [6], [7], [18]. These conditions indicate a critical need for comprehensive empirical investigations that examine how perceptions, training, and institutional conditions interact to influence AI adoption outcomes.

Al-Azawei [1] demonstrated that adoption is significantly influenced by institutional support, leadership commitment, and staff preparedness. García-Peñalvo et al. [3] observed a sharp increase in AI-related educational research globally, yet highlighted the persistent gap between research development and classroom implementation. Similarly, Ghoul et al. [4] found that although AI offers clear benefits such as adaptive learning and automated assessment, institutions face persistent challenges related to governance, staff competencies, and ethical concerns.

Studies focusing on academic staff reveal consistent patterns. Chai et al. [6], [7] reported that academicians recognize AI's potential but encounter practical barriers, including limited technical skills and ambiguous institutional policies. Jameel and Krishnan [8] further stressed the importance of aligning AI adoption with educational values and ethical principles. Within the Malaysian context, Ab Rahman [10] identified organizational readiness and leadership engagement as decisive factors in determining the success of technology adoption initiatives.

Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) continue to provide the dominant theoretical foundation for explaining AI adoption in higher education. Mohamed et al. [11] applied UTAUT2 and confirmed that perceived usefulness and perceived ease of use are strong predictors of AI acceptance among university users. Chen and Huang [15], using structural equation modeling, further demonstrated that institutional support strengthens the link between user perceptions and actual AI usage. In Malaysia, Abidin and Saaid [12] found that students' intention to adopt AI is mainly driven by performance expectancy and effort expectancy. Rahman and Omar [13] proposed a theoretical framework illustrating that training and organizational support exert significant influence on AI adoption among academicians. These findings align with international evidence that adoption behavior is shaped by a combination of cognitive evaluations, experiential exposure, and institutional conditions [2], [14].

National policy and governance structures play a central role in shaping AI adoption trajectories. Runtu et al. [17] reported that Indonesian public universities face structural limitations related to infrastructure, funding, and systematic staff training. In contrast, Malaysia demonstrates relatively stronger institutional preparedness, although coordination challenges between national policies and university-level implementation remain [10], [18]. Singh [20] emphasized that successful AI integration in Asian universities requires coherent governance frameworks, sustained funding, and continuous professional development. Without these elements, universities risk fragmented adoption and limited long-term impact.

While existing studies provide valuable insights into AI adoption determinants, there remains a lack of integrative empirical research that simultaneously examines behavioral, institutional, and policy-level factors using advanced analytical methods within the Malaysia–Indonesia context. This study addresses this gap by employing multivariate regression, ordinal modeling, structural path analysis, and machine learning segmentation to uncover the underlying mechanisms driving AI adoption, satisfaction, and institutional readiness. The findings offer theoretically grounded and policy-relevant guidance for strengthening AI integration in higher education.

METHODOLOGY AND ANALYSIS

This study adopted a quantitative cross-sectional research design to examine the factors influencing artificial intelligence (AI) adoption in higher education institutions in Malaysia and Indonesia. The design was selected to capture relationships between training, user perceptions, actual usage, and satisfaction, consistent with previous AI adoption research in education [21], [23], [26]. A structured questionnaire was developed based on established technology acceptance constructs and prior empirical studies [22], [24], [28], [29], [30]. The instrument measured perceived usefulness, perceived ease of use, AI training exposure, AI usage frequency, and

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user satisfaction. All perceptual constructs were assessed using five-point Likert scales, which have been widely validated in AI and educational technology studies [28], [29].

The survey was distributed to academic staff and students from selected universities in Malaysia and Indonesia during 2025. A total of 2,200 questionnaires were distributed, and 748 valid responses were collected, yielding a response rate of 34%. The sample included both undergraduate students and academic staff, ensuring representation of key user groups involved in AI adoption in higher education [21], [25], [30].

Data analysis was conducted in several stages. First, descriptive statistics were used to examine overall adoption patterns and satisfaction levels, consistent with prior AI perception studies [25], [28]. Second, a logistic regression model was estimated to identify the determinants of AI training participation. Third, ordinal regression was applied to analyze satisfaction levels, following established approaches for ordinal outcome modeling in educational research [30]. To examine the structural relationships among training, perceptions, usage, and satisfaction, a path analysis framework was employed. This approach aligns with prior work demonstrating the importance of perceptual constructs and training as mediating variables in AI adoption processes [24], [29].

Machine learning analysis using k-means clustering was then applied to identify distinct AI user segments. This segmentation method has been shown to provide valuable insights into heterogeneous technology adoption behavior in higher education contexts [16], [23]. The resulting clusters were interpreted as AI Skeptics, AI Learners, and AI Champions, reflecting different adoption readiness profiles.

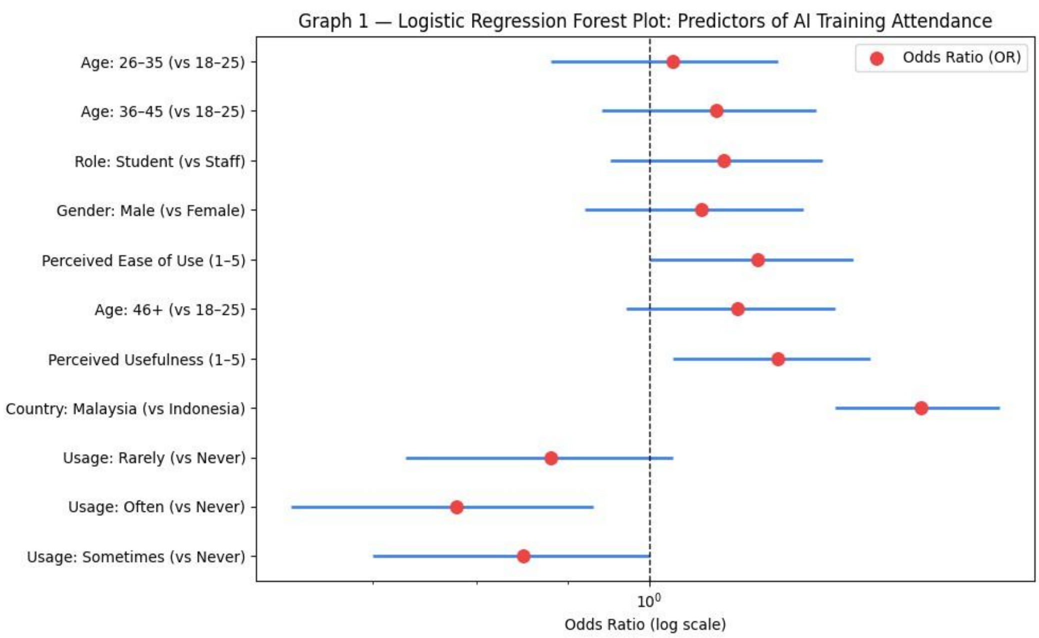
Finally, a composite AI Adoption Index was developed by integrating normalized measures of usage frequency, training participation, perceived usefulness, and perceived ease of use. This index provided an overall measure of institutional AI readiness, consistent with multidimensional adoption assessment approaches reported in the literature [26], [27].

RESULTS AND DISCUSSION

A total of 748 valid responses were obtained from Malaysian and Indonesian universities in 2025, representing a response rate of approximately 34%. The dataset provides a balanced cross-national representation of AI adoption patterns across academic roles, age groups, and institutional contexts.

Preliminary inspection of the data suggests that AI adoption within higher education in both countries is at a developmental stage, characterized by moderate usage levels and predominantly neutral-to-positive user satisfaction.

In order to identify the factors influencing participation in AI training programs, a multivariate logistic regression model was estimated. The results are summarized in **Graph 1**.



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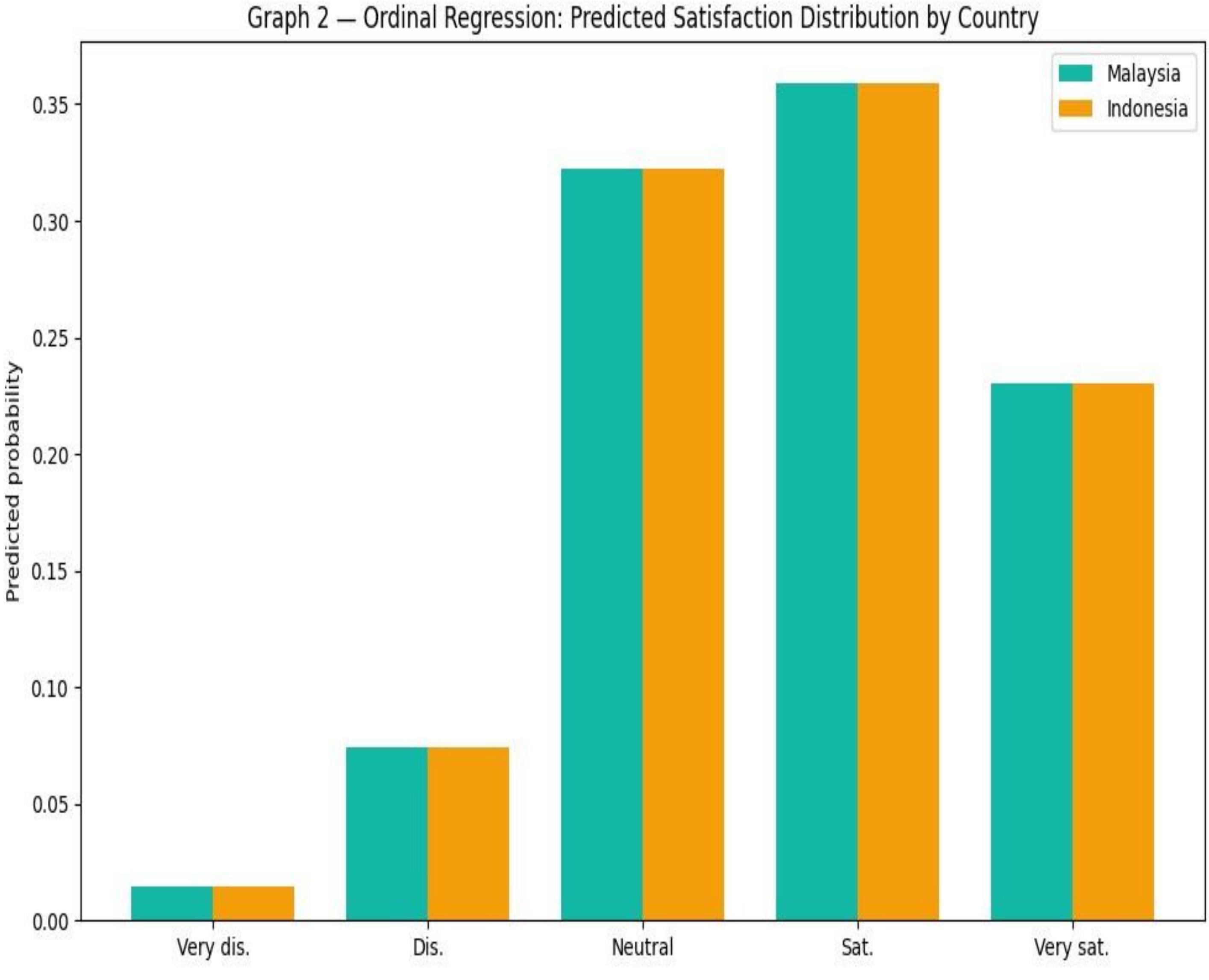
As illustrated in **Graph 1**, respondents from Malaysia exhibit significantly higher odds of participating in AI training compared to those from Indonesia, even after controlling for demographic, behavioral, and perceptual factors. This finding suggests stronger institutional support structures and more mature AI capacity-building frameworks in Malaysian universities.

Perceived usefulness and perceived ease of use emerge as the most influential predictors of training uptake. Individuals who regard AI systems as beneficial and manageable are substantially more likely to pursue formal training. Furthermore, frequent AI tool usage significantly increases the likelihood of training participation, indicating a mutually reinforcing relationship between experiential exposure and structured learning. Demographic characteristics such as age and gender display comparatively weaker and less stable effects, implying that AI adoption decisions are primarily driven by cognitive evaluations and usage behavior rather than inherent demographic attributes.

The determinants of satisfaction with AI integration were examined using an ordinal regression model. Predicted satisfaction distributions are presented in **Graph 2**.



As shown in **Graph 2**, satisfaction levels in both Malaysia and Indonesia are heavily concentrated within the *Neutral* and *Satisfied* categories. This distribution indicates that AI integration in higher education remains in a transitional phase, where foundational adoption has been achieved but institutional assimilation is not yet fully mature. Despite Malaysia's higher training participation rate, satisfaction levels remain comparable across countries. This pattern suggests that increasing training volume alone is insufficient to maximize user satisfaction. Instead, sustainable improvements in satisfaction likely require deeper integration of AI technologies into academic workflows, curriculum design, and institutional governance.

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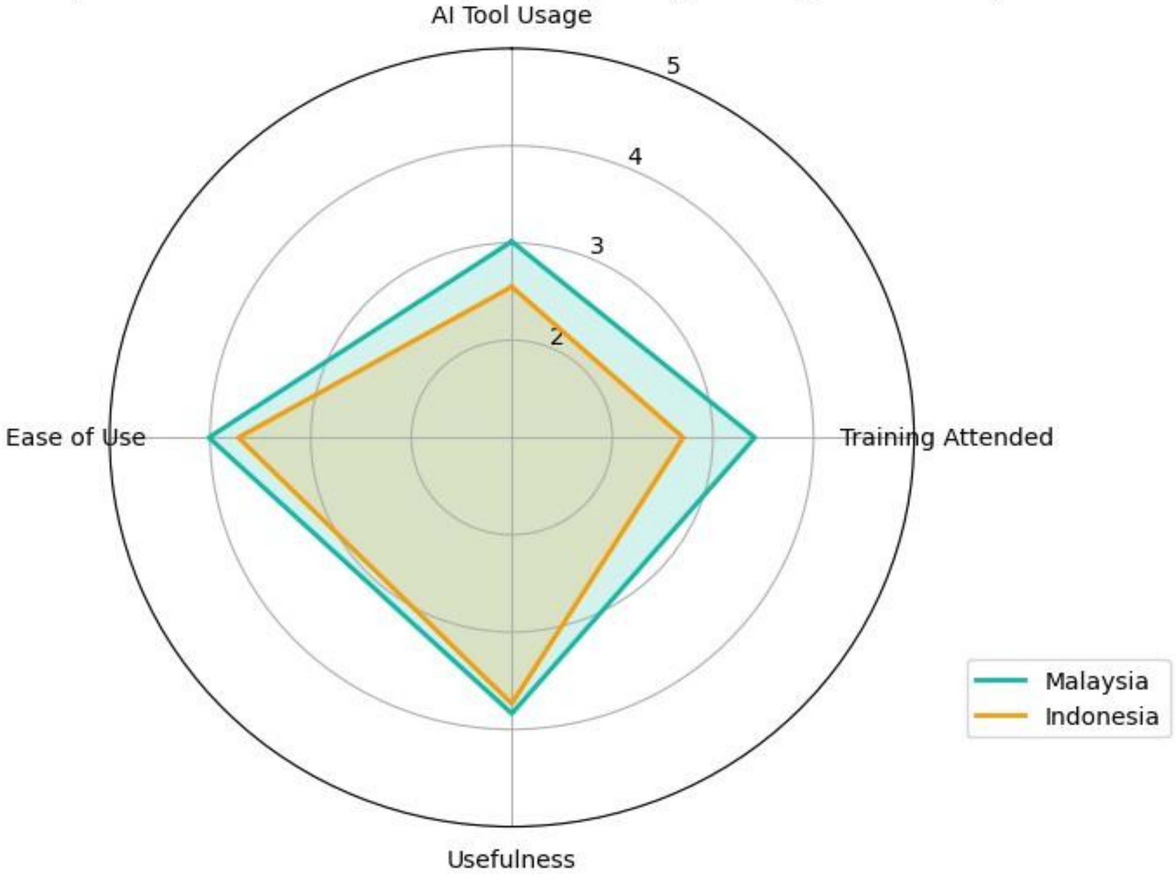
A composite AI adoption capability profile was constructed based on AI tool usage, training participation, perceived usefulness, and perceived ease of use. The comparative results are visualized in **Graph 3**.

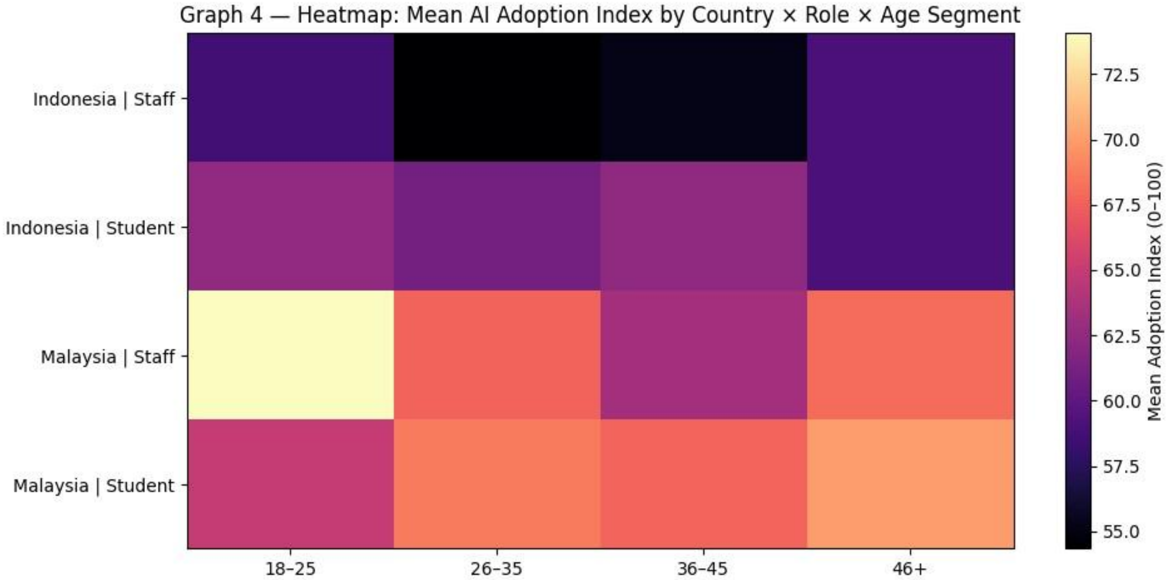
Graph 3 — Radar Chart: AI Adoption Capability Profile (Mean Scores)



The radar chart in **Graph 3** reveals that Malaysia consistently outperforms Indonesia across all four capability dimensions. The most pronounced differences are observed in training participation and perceptual measures, indicating that Malaysia currently possesses a more robust AI adoption ecosystem. These results suggest that institutional readiness, policy alignment, and sustained professional development initiatives play a critical role in accelerating national AI capacity within higher education systems.

In addition, exploring interaction effects among demographic and institutional variables, an AI Adoption Index was computed and analyzed across country, role, and age segments. The resulting patterns are displayed in **Graph 4**.

Graph 4 — Heatmap: Mean AI Adoption Index by Country × Role × Age Segment



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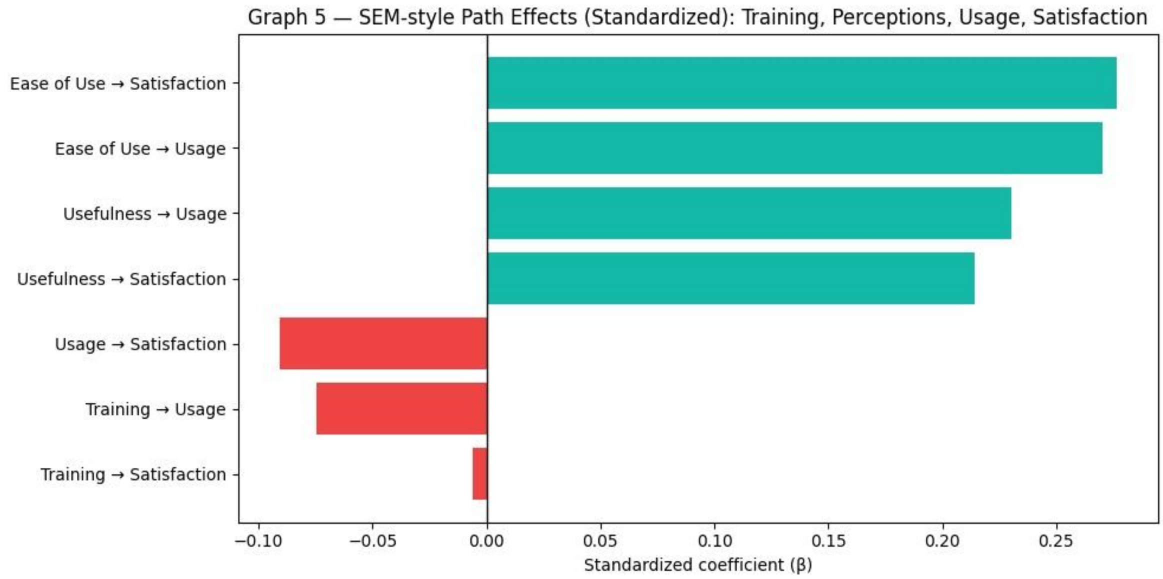
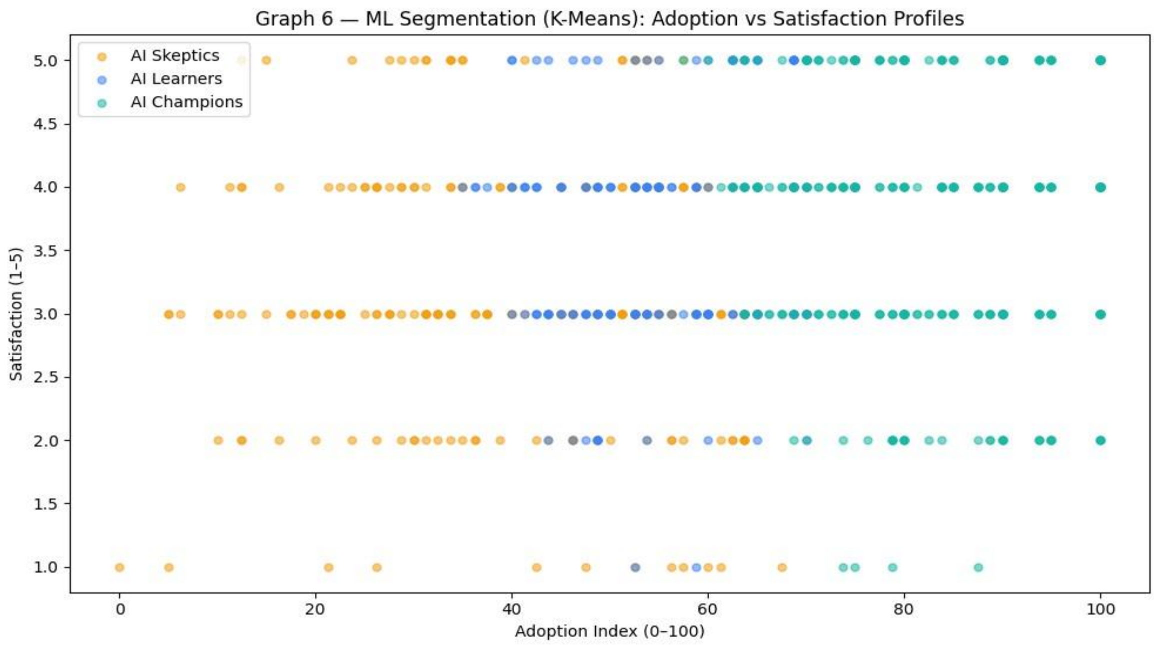
The heatmap in **Graph 4** demonstrates that students consistently exhibit higher adoption intensity than academic staff across both countries, highlighting the generational and pedagogical dynamics of technology diffusion. Notably, Indonesian academic staff display the lowest adoption levels across multiple age groups, identifying this cohort as a strategic target for institutional intervention. These findings emphasize the necessity of differentiated AI adoption strategies that address the unique needs of specific professional and demographic segments.

A SEM-style path analysis was conducted to examine the interrelationships among training, perceptions, AI usage, and satisfaction. Standardized path coefficients are reported in **Graph 5**.



As shown in **Graph 5**, perceived ease of use is the strongest predictor of both AI usage and user satisfaction, followed closely by perceived usefulness. This result strongly corroborates established technology acceptance models such as TAM and UTAUT. AI training exerts an indirect positive effect on satisfaction by increasing AI usage, confirming the mediating role of experiential engagement. The modest direct relationship between usage and satisfaction suggests that as users gain experience, they may develop more nuanced and critical evaluations of AI systems.

In this section we capture latent adoption patterns, a k-means clustering algorithm was applied, producing three distinct AI user profiles: *AI Skeptics*, *AI Learners*, and *AI Champions*. The segmentation outcomes are illustrated in **Graph 6**.



As presented in **Graph 6**, AI Champions demonstrate the highest adoption intensity and universal training participation, positioning them as potential internal change agents. AI Learners represent a transitional group requiring structured developmental support, while AI Skeptics display limited engagement and lower satisfaction, necessitating awareness-driven and low-barrier intervention strategies. This segmentation framework provides actionable insights for designing differentiated AI policies and targeted professional development programs.

Collectively, the results reveal that AI adoption in higher education is primarily shaped by perceptual and experiential factors rather than demographic characteristics. Ease of use and perceived usefulness serve as the central levers of adoption, while training functions as a catalytic mechanism that strengthens the usage–satisfaction relationship.

From a policy perspective, institutions should prioritize usability-centered AI deployment, experiential learning opportunities, and segmented capacity-building strategies to accelerate sustainable AI transformation in higher education.

CONCLUSION AND FUTURE WORKS

This study provides a comprehensive empirical examination of AI adoption dynamics in higher education institutions in Malaysia and Indonesia using advanced analytical techniques including logistic regression, ordinal modeling, structural path analysis, heatmap segmentation, and machine learning clustering. The findings demonstrate that AI adoption is primarily driven by perceptual and experiential determinants—particularly perceived ease of use and perceived usefulness—rather than demographic characteristics.

Although Malaysia exhibits higher AI training participation and stronger overall adoption capability, both countries remain within a transitional phase of AI integration, as evidenced by the predominance of neutral-tomoderate satisfaction levels. AI training serves as a catalytic mechanism that strengthens AI usage and indirectly enhances satisfaction; however, training alone is insufficient to achieve sustained institutional transformation without complementary improvements in usability, workflow integration, and organizational support.

Future studies should employ longitudinal designs to examine the dynamic progression of AI adoption over time and to validate causal mechanisms identified in this analysis. Multi-level modeling incorporating institutional variables would further enhance explanatory power. Qualitative investigations could complement quantitative findings by uncovering contextual and cultural nuances influencing AI integration.

Moreover, subsequent research should explore the pedagogical impact of AI adoption on learning outcomes, academic productivity, and institutional competitiveness, thereby expanding the analytical scope beyond adoption determinants toward educational effectiveness and innovation performance.

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