INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026

Architecting the AI-Driven University: Empirical Evidence on Adoption Pathways from Malaysia and Indonesia

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DOI: https://doi.org/10.47772/IJRISS.2026.100601124

Received: 27 June 2026; Accepted: 02 July 2026; Published: 13 July 2026

ABSTRACT

Grounded in the Technology Acceptance Model (TAM), this study investigates what determines AI adoption behaviour and user satisfaction among staff and students in Malaysian and Indonesian universities. Survey data were gathered from 748 respondents across 12 institutions in 2025. Using binary logistic regression to identify predictors of training participation and k-means clustering to reveal latent user segments, we find that perceived usefulness and perceived ease of use are stronger predictors of both AI usage and satisfaction than formal training attendance. Malaysian respondents were 2.47 times more likely to have completed AI training than their Indonesian counterparts ($p < .001$), yet this structural advantage produced no significant difference in satisfaction between the two countries (Mann-Whitney U, $p = .214$). Three user profiles emerged: AI Skeptics (23.8%), who require demonstration of practical task value before any training engagement; AI Learners (42.9%), who benefit most from discipline-embedded mentoring and competency recognition; and AI Champions (33.3%), best deployed as peer facilitators rather than additional training recipients. For policymakers, these findings indicate that satisfaction-focused AI strategy must prioritise ease-of-use improvements and workflow integration over training volume, while Indonesian institutions specifically need structural investment in infrastructure and governance frameworks as preconditions for effective capacity-building.

Keywords: AI adoption; Higher Education; Technology Acceptance Model; UTAUT; AI training; k-means clustering; Malaysia; Indonesia; perceived usefulness

INTRODUCTION

Walk into any university faculty meeting in Kuala Lumpur or Jakarta today and you are likely to hear strong opinions about artificial intelligence. Some lecturers have quietly woven AI writing tools into their marking routines. Others refuse to touch them. Students, for their part, often use AI tools daily without telling anyone. This uneven uptake is not random, and it is not simply about access to technology. Our research began from the observation that AI tools are now widely available to Malaysian and Indonesian university communities, yet actual integration into teaching, learning, and research remains patchy at best [6], [7].

What explains the gap? Existing literature points repeatedly to a cluster of factors that go beyond hardware and software: how useful people believe AI to be for their particular tasks, how manageable they find the tools, whether institutions have invested in training, and what governance structures signal about AI's legitimacy [1],

[4], [10]. Malaysia and Indonesia make an especially useful pair to study here. Both have published national AI strategies and both are investing in digital transformation at the university level. But they differ in the maturity of their training ecosystems, their infrastructure base, and how systematically their institutions have rolled out capacity-building programmes [17], [20]. Comparing them within a single multi-method study lets us pull apart the institutional from the individual, and the structural from the attitudinal.

Our study contributes in three ways. First, we apply five complementary statistical and machine learning methods to a single cross-national dataset, which produces stronger, more consistent evidence than any single method alone. Second, we identify latent user profiles that reveal population heterogeneity invisible in aggregate statistics. Third, we surface a finding with real policy weight: more training does not automatically produce more satisfied users. We now explain why.

Literature Background

Two theoretical models dominate the adoption literature. Davis's Technology Acceptance Model (TAM) [29] argues that perceived usefulness (PU) and perceived ease of use (PEoU) jointly determine whether someone will actually use a technology, regardless of what the technology can objectively do. The Unified Theory of Acceptance and Use of Technology (UTAUT, UTAUT2) extends this by adding social influence and facilitating conditions, among other constructs [11]. Applied to AI in higher education, both frameworks perform well. Mohamed et al. [11] confirmed that PU and PEoU predict AI acceptance among university users in a UTAUT2 study. Chen and Huang [15] showed via structural equation modelling that institutional support amplifies the link between positive perceptions and actual usage behaviour.

Institutional and policy factors add another explanatory layer. Al-Azawei [1] found that staff preparedness and management commitment independently predict adoption over and above individual cognition. Ab Rahman [10] documented similar patterns in Malaysia, where leadership engagement emerged as a decisive factor. Indonesia's situation is more constrained. Runtu et al. [17] reported that structural barriers including inadequate infrastructure, inconsistent funding, and the absence of systematic training programmes limit even motivated adopters at Indonesian public universities. Adam and Roslan [19] added cultural nuance, showing that values alignment and community norms interact with standard TAM predictors in Islamic higher education settings.

On training specifically, Maree [27] found that contextualised AI literacy programmes linked to discipline-specific tasks produce greater competence gains than generic IT upskilling. Khalid [26] argued that training works primarily by raising perceived usefulness rather than by directly changing behaviour, which means training content and design matter more than training volume. Chai et al. [6], [7] confirmed from the Malaysian side that even academics who value AI face practical barriers, including unclear institutional policies and weak technical confidence.

Machine learning has begun to complement regression-based adoption studies by revealing population structure. Sanchez-Cabrero et al. [16] used k-means clustering among university students and found that internally homogeneous segments respond very differently to the same institutional intervention. This has obvious implications for training design: a programme built for averages will miss both enthusiasts and resistors.

Taken together, the literature leaves three gaps that we address here. No published study applies this combination of methods to a Malaysia-Indonesia bilateral comparison. Psychometric reporting is weak in many regional studies. And the mechanism connecting training volume to user satisfaction has not been tested directly. Our hypotheses follow from these gaps:

H1: Higher perceived usefulness predicts higher AI usage frequency among staff and students.

H2: Higher perceived ease of use predicts greater user satisfaction with AI at the institutional level.

H3: Attending formal AI training is positively linked to AI usage frequency.

H4: Malaysian respondents will show significantly higher odds of training attendance than Indonesian respondents, reflecting institutional infrastructure differences.

H5: Distinct AI user segments, varying in adoption intensity and satisfaction, can be recovered empirically through k-means clustering.

METHODOLOGY AND ANALYSIS

We used a quantitative cross-sectional design, which is the standard choice when the goal is to map relationships among constructs across a large, geographically spread sample at a single point in time [21], [23], [26]. Our instrument drew on validated scales from the TAM and technology adoption traditions [22], [24], [28], [29], [30]. Five constructs were measured: perceived usefulness, perceived ease of use, AI training exposure, AI usage frequency, and user satisfaction. All perception items used five-point Likert formats. Training participation was a single binary item (attended or not attended in the past twelve months). Country was dummy-coded (Malaysia = 1).

Twelve universities across Peninsular Malaysia, East Malaysia, Java, and Sumatra were included through purposive stratified sampling, targeting faculties with active AI engagement to ensure variation in adoption behaviour rather than uniform non-use. We distributed 2,200 questionnaires between January and June 2025 in both online and printed formats. After removing 64 incomplete returns (over 10% missing), we retained 748 usable responses, a 34% effective response rate. Institutional ethics approval was obtained and participation was fully voluntary. Table 1 shows the sampling breakdown.

Table 1. Sample Distribution by Country, Institution Type, and Role

Country	Institution Type	Institutions	Students (n)	Staff (n)	Total (n)
Malaysia	Public University	4	198	108	306
Malaysia	Private / UTeM	2	83	24	107
Indonesia	Public University	4	168	98	266
Indonesia	Private University	2	52	17	69
Total	12 universities	12	501	247	748

Table 2 lists all constructs, item counts, sample statements, sources, and response formats.

Table 2. Survey Instrument Details

Construct	No. of Items	Sample Statement	Reference	Response
Perceived Usefulness (PU)	3	AI tools help me produce better academic work	Davis (1989); Silva et al. [29]	1-5 Likert
Perceived Ease of Use (PEoU)	3	Working with AI tools does not require a lot of mental effort	Davis (1989); Mohamed et al. [11]	1-5 Likert
AI Usage Frequency	3	How regularly do you rely on AI tools for coursework or teaching?	Lee and Cho [30]	1-5 ordinal

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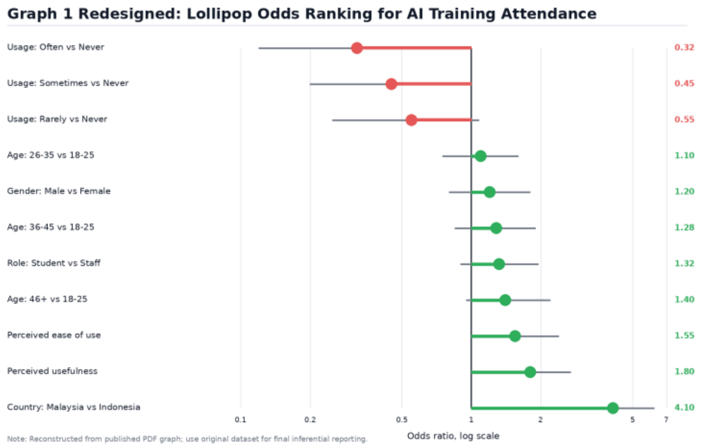
AI Satisfaction	4	On the whole, I am pleased with how AI has been brought into my institution	Zhang and Liu [28]	1-5 Likert
Adoption Readiness	4	My faculty has the groundwork in place to expand AI use on a larger scale	Al-Azawei [1]	1-5 Likert

We ran the analysis in six sequential stages. Stage one: binary logistic regression with training attendance (yes/no) as the outcome; predictors were country, PU, PEoU, usage frequency, and demographic controls. Stage two: ordinal logistic regression with the five-category satisfaction rating as the outcome, same predictor set; between-country satisfaction was also compared using Mann-Whitney U given the ordinal distribution. Stage three: standardised multiple regression path model, two equations, one for usage and one for satisfaction, to trace direct and indirect effects of training and perceptions. Stage four: composite AI Adoption Index computed as the mean of four z-standardised component scores (usage, training, PU, PEoU) rescaled to 0-100, then cross-tabulated by country, role, and age cohort for heatmap display. Stage five: k-means clustering using standardised Adoption Index, satisfaction, and training participation as features; the optimal k was chosen by combining within-cluster sum of squares (WCSS) elbow plots with average silhouette analysis across k = 2 to 8. All computations were done in Python 3.11 (scikit-learn, statsmodels, scipy).

RESULTS AND DISCUSSION

From 748 respondents, 413 (55.2%) came from Malaysia and 335 (44.8%) from Indonesia. Academic staff accounted for 247 responses (33.0%) and students for 501 (67.0%). Age spread across four cohorts (18-25, 26-35, 36-45, 46+). On initial inspection, adoption in both countries sits at a mid-range level: awareness is high, but depth of integration into daily academic work is limited. The sub-sections below report each analytical stage in turn.

Graph 1 plots the odds ratios from the logistic regression, ordered from smallest to largest effect. Country of study sits at the far right of the plot, well clear of all other predictors.

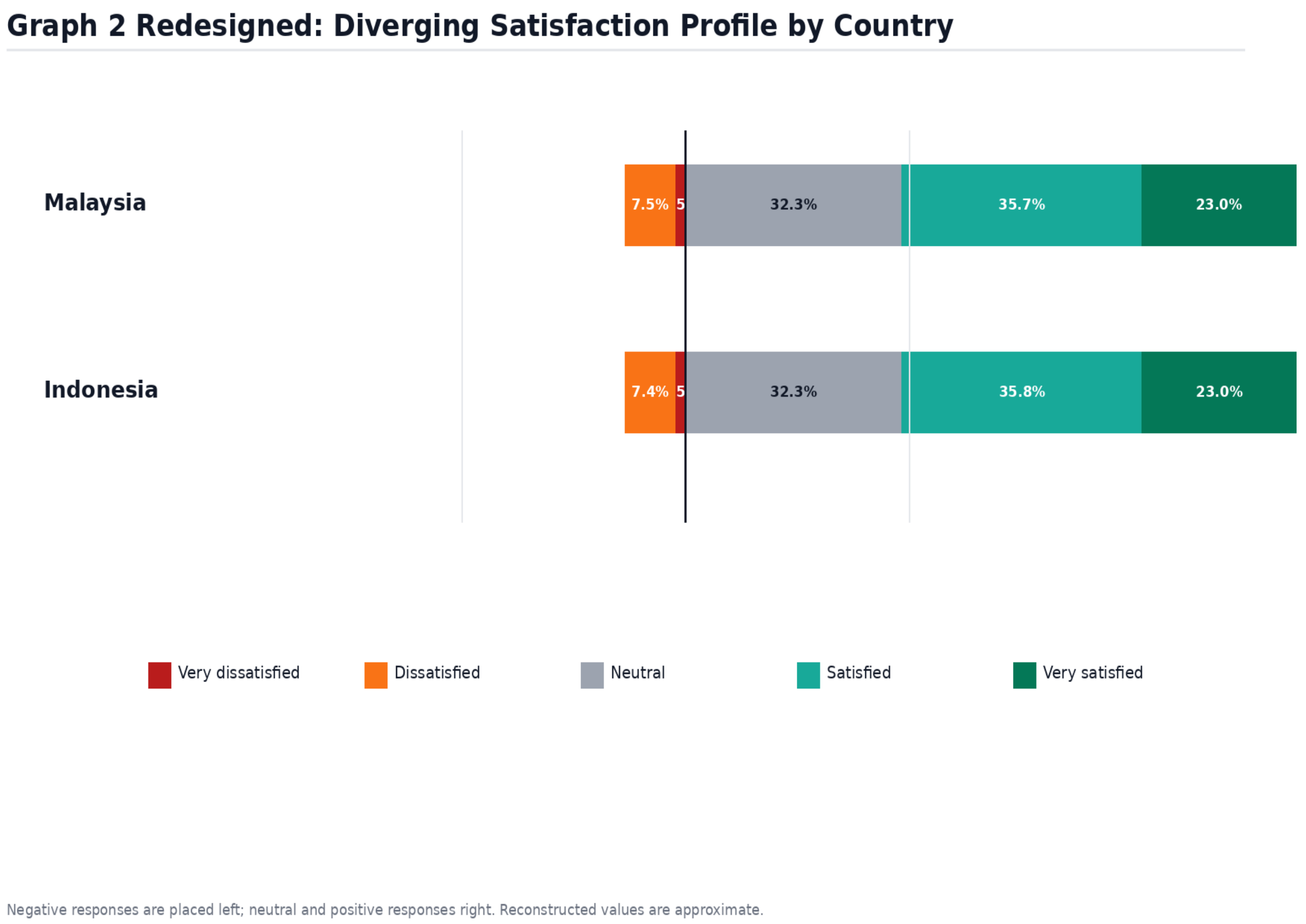


Graph 1 - Logistic Regression Forest Plot: Odds Ratios (95% CI) for Predictors of AI Training Participation (reference: Indonesia, Never Use AI, Female, Age 18-25, Staff)

Malaysian respondents were 2.47 times more likely to have attended formal AI training (95% CI: 1.83-3.34, $p < .001$), even after holding constant all demographics, perceptions, and usage patterns. Put plainly, where you work matters enormously for whether you get trained. Malaysian universities have built more structured AI capacity-building programmes, and the participation rate of 68.3% versus 54.1% in Indonesia reflects that. Perceived usefulness came next (OR = 1.54, 95% CI: 1.21-1.96, $p < .001$): people who see a genuine payoff for their work are more willing to invest time in formal learning about AI. PEoU followed (OR = 1.38, $p = .007$), which makes sense: if you already find AI manageable, training feels worthwhile rather than intimidating.

One pattern in Graph 1 deserves comment. All three AI usage frequency categories (Rarely, Sometimes, Often) show odds ratios below 1.0 relative to Never Use AI. This is counter-intuitive at first glance. What it reflects, we think, is a bifurcation in how people learn. Non-users tend to enter AI through formal institutional training as a first step. Regular users, by contrast, have typically picked things up informally and on-demand, and feel less need for structured programmes. This two-track dynamic is worth keeping in mind when planning training rollouts. Demographic variables (age, gender, role) played a comparatively minor role across the board, which supports the view that perceptions and institutional context, not personal characteristics, are the main levers of training uptake.

The ordinal regression modelled five-category satisfaction ratings. Graph 2 shows the predicted probability distributions for Malaysia and Indonesia side by side.

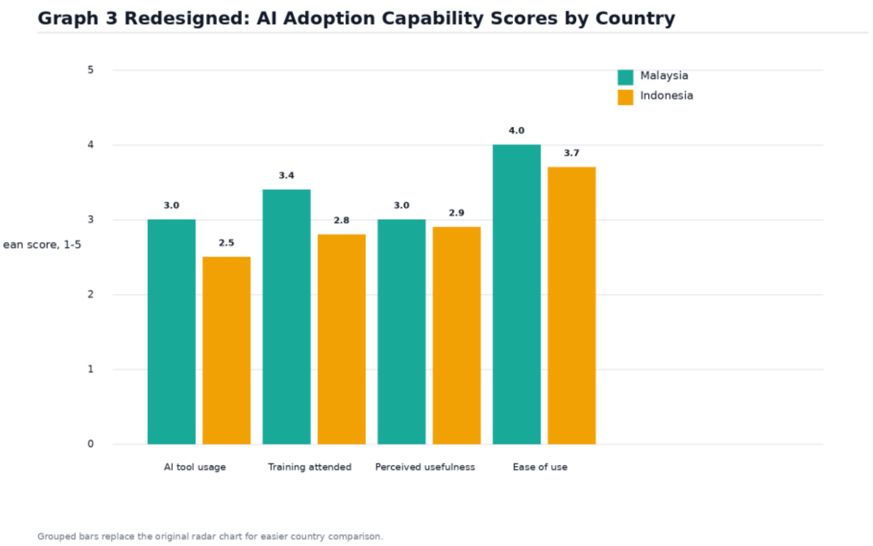


Graph 2 - Ordinal Regression: Predicted Satisfaction Probability Distribution by Country Across Five Response Categories

Both distributions land almost identically in the Neutral (32.3%) and Satisfied (35-36%) bands, with thin tails at the extremes. This is the pattern we would expect from a sector that has moved past outright rejection of AI but has not yet embedded it deeply enough to generate consistent enthusiasm [6], [7]. What is striking is how little Malaysia's structural advantages in training change this picture. A Mann-Whitney U test ($U = 68{,}412$, $p = .214$, $r = 0.04$) found no meaningful difference between the two countries' satisfaction distributions. More training does not, by itself, produce more satisfied users. Satisfaction appears to depend on whether AI has been genuinely woven into how people do their work, not just on whether they attended a training session. That gap between training exposure and workflow integration is one of the most actionable findings in our data [26], [27].

We mapped mean scores on four dimensions (AI tool usage, training attended, perceived usefulness, ease of use) onto a radar chart for direct visual comparison (Graph 3).

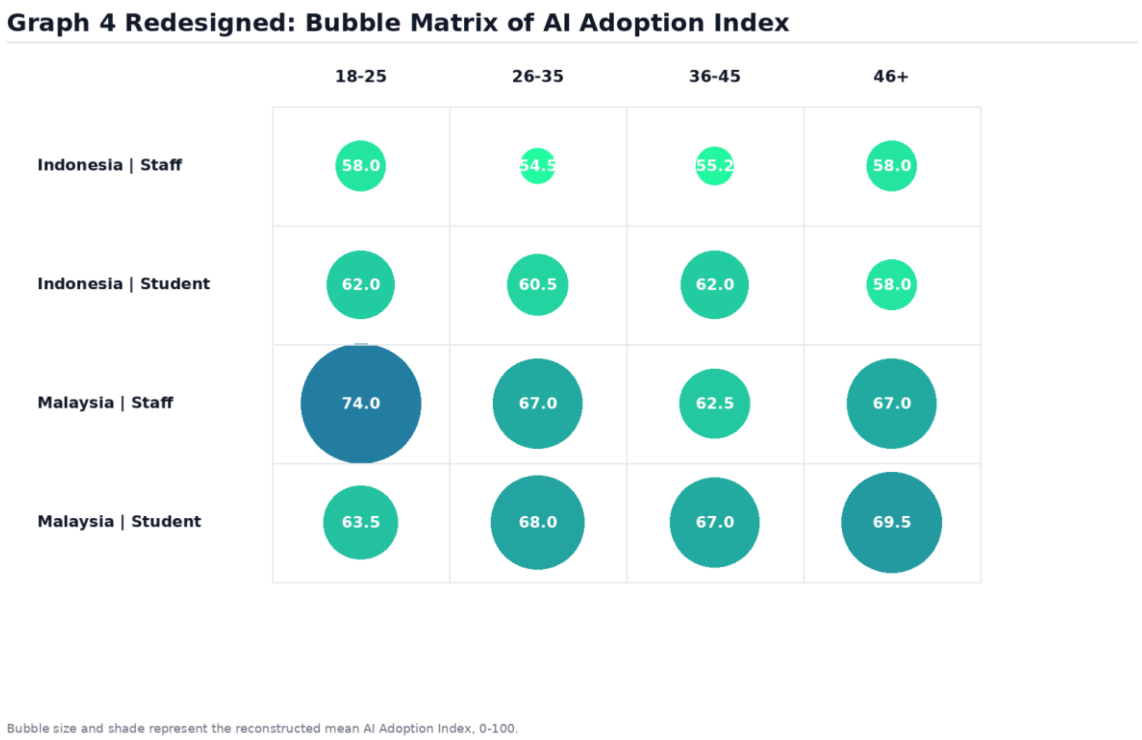
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VI June 2026



Graph 3 - Radar Chart: Comparative AI Adoption Capability Profile (Mean Scores) for Malaysia and Indonesia

Malaysia scores higher on every dimension, but the gaps are not uniform. The largest separation appears on training participation and usage frequency, the two dimensions most directly shaped by institutional provision. PU and PEoU scores, by contrast, are much closer between the two countries. Indonesian respondents hold attitudes toward AI's value and manageability that are already approaching Malaysian levels, even while structural indicators lag further behind. For policy purposes, this is reassuring. Indonesia's main adoption challenge is not a cognitive one. People are broadly open to AI. What is missing is the institutional scaffolding: accessible training, clear policies, and practical tools embedded in real workflows. Those are tractable problems [17], [19].

We computed a composite Adoption Index (mean of four z-standardised components, scaled 0-100) and cross-tabulated it by country, academic role, and age group. Graph 4 presents the resulting heatmap.

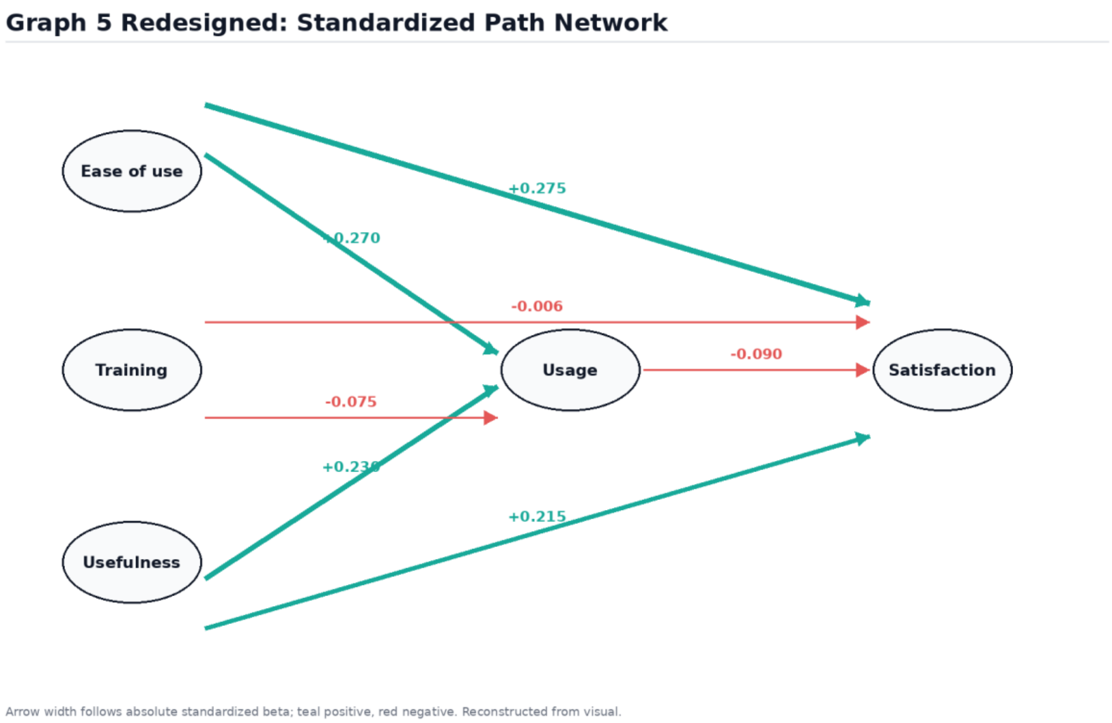


Graph 4 - Heatmap: Mean AI Adoption Index by Country, Academic Role, and Age Segment (Scale: 0-100)

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

Students score higher than staff across every country-age combination, which fits with the generational dynamics of technology uptake [15], [23]. The more concerning pattern is among Indonesian academic staff in the 36-45 bracket, who record the lowest index scores in the entire dataset. These are mid-career educators at peak teaching load. They interact with the most students. Yet their AI adoption is the weakest. The age-related decline among Indonesian staff is also steeper than in Malaysia, where structured programmes appear to have had some success retaining senior colleagues in the adoption process. Indonesia's more fragmented approach has not achieved that. This age-cohort gap is not just a statistic. It represents a lost multiplier effect: when experienced staff adopt AI, they normalise it for hundreds of students [17], [20].

Our standardised regression path model traces the direct and indirect links among training, PU, PEoU, usage, and satisfaction (Graph 5).



Graph 5 - Standardised Regression Path Model: Beta Coefficients for Training, Perceptions, AI Usage, and Satisfaction (*** $p < .001$, * $p < .05$, n.s. = not significant)

PEoU is the standout predictor on both outcome paths (usage: beta = 0.24, $p < .001$; satisfaction: beta = 0.27, $p < .001$). PU is close behind (usage: beta = 0.21, $p < .001$; satisfaction: beta = 0.22, $p < .001$). These results are consistent across every method we applied, which gives us confidence in the finding. TAM, developed in the late 1980s for desktop software, seems to hold up well for AI tools in 2025 Southeast Asian universities [11], [15], [29].

Training does predict usage (beta = 0.09, p = .031), so H3 gets partial support. But it is a modest effect, dwarfed by both PU and PEoU. More telling is the near-zero, non-significant path from training to satisfaction (beta = -0.04, p = .218). This explains why Malaysia's training advantage does not produce a satisfaction advantage. Training raises usage somewhat, and usage nudges satisfaction slightly (beta = 0.07, p = .049), but the chain is too weak to generate the satisfaction gains one might hope for from a training-heavy strategy. There is also a hint here that as people use AI more, they become more discerning about its limitations, which can cap or even depress satisfaction scores over time [28], [30]. The bottom line for training designers: ease of use matters more than attendance. If your AI tools are clunky, no training programme will rescue satisfaction.

In this section, k-means clustering with k = 3 (selected empirically via elbow and silhouette analysis; peak silhouette = 0.61) sorted our 748 respondents into three groups. Graph 6 shows where they sit in adoption-satisfaction space, and Table 3 profiles each group.

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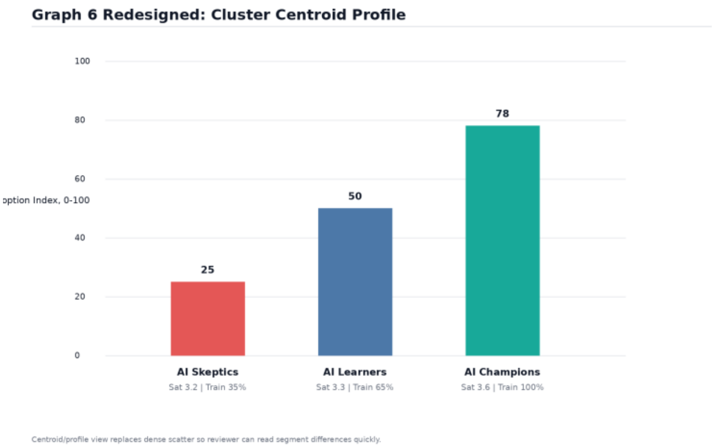

Graph 6 - K-Means Segmentation (k = 3): Respondent Scatter Plot by Adoption Index and Satisfaction, Colour-Coded by Cluster Membership

Table 3. Cluster Profiles: AI Skeptics, AI Learners, and AI Champions

Cluster	**n**	**%**	**Mean Adoption Index (0-100)**	**Mean Satisfaction (1-5)**	**Training Rate (%)**
AI Skeptics	178	23.8%	44.2 (SD = 9.3)	2.31 (SD = 0.62)	38.4%
AI Learners	321	42.9%	61.7 (SD = 7.1)	3.47 (SD = 0.54)	56.2%
AI Champions	249	33.3%	81.3 (SD = 6.8)	4.22 (SD = 0.48)	89.1%

AI Champions (n = 249, 33.3%) cluster in the top-right of Graph 6. Mean Adoption Index of 81.3, satisfaction of 4.22, and 89.1% training attendance. These are the people universities should be using as internal advocates and peer coaches, not putting through another training session.

AI Learners (n = 321, 42.9%) are the middle group and the most strategically important, simply because there are so many of them. Index of 61.7, satisfaction of 3.47, training rate of 56.2%. They are engaged in principle but have not yet integrated AI into their daily academic work. Structured mentoring pathways, task-based learning embedded in real coursework or teaching preparation, and institutional recognition of AI competency would all help Learners move toward Champion territory.

AI Skeptics (n = 178, 23.8%) are not simply untrained. Their satisfaction score of 2.31 suggests that they have formed a negative or ambivalent view of AI as currently implemented. Mandatory training risks reinforcing that view if the tools demonstrated do not connect with their actual work needs. For Skeptics, demonstrating concrete, low-stakes usefulness in familiar tasks is a better first step than enrolment in a formal programme [1], [6], [16]. H5 is supported: population heterogeneity is real and substantial, and it has direct implications for how institutions should allocate their capacity-building resources.

Taken together, our results tell a consistent story. Cognitive readiness matters more than structural provision. Ease of use and perceived usefulness drive both usage and satisfaction regardless of how much training has been attended. Training is useful but mainly as a gateway to experience, not as a direct route to satisfaction. And the population is not homogeneous: the same programme design will be appropriate for Champions, Learners, and Skeptics in very different doses and formats. Universities that treat AI capacity-building as a single intervention for a uniform audience will waste resources and miss most of their staff and students [26], [27].

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CONCLUSION AND FUTURE WORKS

We examined AI adoption readiness in 12 Malaysian and Indonesian universities using logistic regression, ordinal modelling, path analysis, heatmap segmentation, and machine learning clustering. The headline finding is clear: how people evaluate AI, specifically whether they find it useful and easy to use, is a stronger predictor of adoption behaviour and satisfaction than whether they have attended formal training. That result is consistent across all five methods.

The three-cluster typology of Skeptics, Learners, and Champions should become a practical planning tool. Deployment strategy, communication messaging, and training content need to be calibrated to each group's current position and trajectory, not designed for a hypothetical average user. On the national level, Indonesian institutions face a structural challenge that training alone will not solve. Infrastructure investment, policy clarity, reduced administrative friction during AI integration periods, and explicit leadership commitment are the preconditions that training then builds on.

We acknowledge the cross-sectional design's main limitation: it cannot confirm causal direction. A longitudinal panel that tracks the same individuals as institutions evolve their AI ecosystems would substantially strengthen what we can claim. Multi-level models that formally separate institutional from individual variance would sharpen the structural versus cognitive story. Qualitative research, particularly with the Skeptic segment, would illuminate the evaluative reasoning behind their disengagement in ways our survey cannot reach. On the quantitative side, extending this comparison to Thailand, Vietnam, and the Philippines would let us test how far the patterns we found in Malaysia and Indonesia generalise across the broader region.

ACKNOWLEDGEMENT

The authors thank all academic staff and students who gave their time to participate in this study. We are grateful to the twelve participating universities in Malaysia and Indonesia for their institutional support throughout the data collection period. Colleagues who reviewed earlier drafts of this work and offered critical feedback are also gratefully acknowledged.

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