Comparative Analysis of AI Training Uptake in Malaysian and Indonesian Universities

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ABSTRACT

This study investigates the impact of Generative AI on higher education institutions in Malaysia and Indonesia, focusing on factors influencing AI training uptake among university staff and students. Using logistic regression analysis, we explored the relationship between demographic variables, AI tool usage, and attitudinal measures on the likelihood of receiving AI training. The results reveal a positive perception of AI significantly increases the likelihood of training participation, while geographic location, frequency of AI tool usage, concerns about AI, and satisfaction with AI integration do not have significant effects. These findings underscore the importance of promoting AI's benefits, enhancing AI literacy, and addressing structural barriers to ensure effective integration of AI in higher education. These findings provide valuable insights for policymakers and educators aiming to leverage AI technology to improve educational outcomes.

Keywords: Generative AI, Higher Education, AI Training Uptake, Descriptive Analysis, Logistic Regression Analysis

INTRODUCTION

The integration of Generative Artificial Intelligence (GenAI) in higher education has garnered significant attention, particularly in Malaysia and Indonesia, due to their rapid digital transformation and the need to bridge educational disparities. This study addresses the gap in understanding the factors that influence AI training uptake in these regions, providing insights for policymakers and educator. This technology, exemplified by advanced AI models like ChatGPT and DALL-E, is reshaping educational landscapes by offering customized learning experiences, supporting research, and enhancing problem-solving skills [1]-[3]. However, the adoption of GenAI comes with challenges, including biases, ethical concerns, and the risk of over-reliance on technology [4]-[6]. A balanced approach to its integration is crucial to harness its benefits while mitigating risks.

Recent studies have highlighted various factors influencing AI adoption, such as technological readiness, cultural context, and institutional support [7]-[9]. However, there is limited research on how these factors interplay in Southeast Asian higher education contexts, particularly in Malaysia and Indonesia.. Studies have highlighted the technology's ability to offer tailored educational content, thus improving engagement and learning outcomes [10]-[12]. However, the challenges it presents cannot be overlooked. Ethical concerns such as biases in AI models and the potential for academic misconduct necessitate careful consideration and the development of robust policies to ensure responsible use [13]-[15]. Effective integration strategies for GenAI in higher education involve raising awareness about its potential and limitations, training faculty, revising teaching and assessment practices, and partnering with students [16]-[18]. Bridging the digital divide is also essential to ensure equitable access to AI-enhanced educational tools [19]-[21]. Institutions must adopt a multifaceted approach that includes updating curricula to incorporate AI literacy and fostering an environment that encourages ethical AI use [22]-[24].

Academic integrity is a significant concern with the rise of GenAI tools like ChatGPT. These tools have raised questions about what constitutes original student work and how institutions can ensure fairness in assessments [25]-[27]. Developing authentic assessment methods and policies that uphold academic values such as honesty and responsibility is critical [28]-[30]. This involves rethinking traditional assessment practices and integrating AI literacy into the educational framework [31]-[33].

Cultural considerations play a vital role in the integration of GenAI in higher education, especially in culturally diverse regions like Malaysia and Indonesia [34]-[36]. The impact of GenAI varies across different cultural contexts, necessitating a tailored approach that respects local values and educational practices. Integrating GenAI into higher education in these countries requires policies that are inclusive and culturally sensitive [37]-[39]. Case studies from Malaysian and Indonesian institutions provide practical insights into the real-world application of GenAI in higher education [40]-[42]. These examples highlight both the successes and challenges faced by institutions, offering valuable lessons for future implementations [43]-[45]. For instance, the collaboration between leadership and digital technology during the COVID-19 pandemic in universities like UiTM Malaysia and UNNES Indonesia illustrates the potential of AI to sustain and enhance research performance during crises [46]-[48].

In order to address the gap in AI training uptake in Malaysian and Indonesian universities, this study aims to identify the factors influencing AI training participation among university staff and students, proposing tailored intervention strategies to enhance AI integration in higher education.The integration of GenAI in higher education presents both opportunities and challenges. By adopting a balanced approach that addresses ethical concerns, promotes AI literacy, and considers cultural contexts, higher education institutions in Malaysia and Indonesia can effectively harness the transformative potential of GenAI. Future research and policy development should focus on creating inclusive and responsible AI-enhanced educational environments [49]-[51].

METHODS

This study employs logistic regression analysis to investigate the factors influencing the likelihood of university staff and students receiving AI training. Logistic regression is chosen for its suitability in modeling binary outcomes and its ability to handle multiple predictor variables, providing comprehensive insights into the determinants of AI training uptake. This methodological choice is grounded in the robustness of logistic regression for managing categorical data and its interpretability through odds ratios, which offer practical implications for policy and educational practice.

A survey was distributed to approximately 2500 university staff and students across Malaysia and Indonesia, collecting data on demographics, AI tool usage, and attitudes towards AI. The logistic regression model was specified to predict AI training uptake, with predictor variables encoded as dummy variables. Missing values were addressed through imputation, and the model's fit was evaluated using AIC and pseudo R-squared values.. The survey instrument was designed to capture a range of variables pertinent to the study, including demographic details (age, gender, role, country), academic information (field of study, level of study, position, years of experience), technology usage (frequency and types of AI tools used, purpose of AI usage), and attitudinal measures (perception of AI impact, concerns about AI, satisfaction with AI integration, received AI training, satisfaction with AI training, perceived need for more AI training, expectation of AI development, and willingness to adopt new AI tools).

From this outreach, a total of 626 respondents participated in the survey, with 310 responses from Thailand and 316 from Malaysia, encompassing both university staff and students. Prior to analysis, the data underwent rigorous preparation to ensure accuracy and completeness. Categorical variables such as age group, gender, role, country, frequency of AI tool usage, perception of AI impact, concerns about AI, and satisfaction with AI integration were encoded into dummy variables. This process involved converting each category into a binary variable (0 or 1), enabling the inclusion of these predictors in the logistic regression model. Missing values were addressed through imputation and exclusion techniques, ensuring a complete dataset for analysis.

The logistic regression model was specified to predict the likelihood of respondents receiving AI training based on a set of predictor variables. The model can be expressed as follows:

$$\log\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \beta_0 + \beta_1\text{Age Group} + \beta_2\text{Gender} + \beta_3\text{Role} + \beta_4\text{Country} + \beta_5\text{Fr}$$

where

$Y = 1$ indicates receiving AI training. The coefficients (β) for each predictor variable represent the log-odds of the outcome occurring.

The logistic regression model was fitted using Python's statsmodels package, a robust statistical library for conducting advanced data analysis. The fitting process involved estimating the parameters of the model using maximum likelihood estimation (MLE). The goodness-of-fit of the model was evaluated using the Akaike Information Criterion (AIC) and pseudo R-squared values, which provide measures of model quality and explanatory power [52].

Logistic regression was chosen for several reasons. Firstly, it is highly suitable for binary outcome variables, which aligns with the study's goal of predicting whether respondents received AI training (yes or no). Secondly, logistic regression is capable of handling multiple predictor variables simultaneously, allowing for a comprehensive analysis of the factors influencing AI training uptake. Additionally, the method provides interpretable results through odds ratios, which are easily understandable and actionable for policy and educational practice. The use of odds ratios helps in quantifying the effect of each predictor on the likelihood of receiving AI training, making the results practically meaningful.

To ensure the generalizability and reliability of the model, cross-validation techniques were employed. Cross-validation involves partitioning the data into training and validation sets, fitting the model to the training set, and evaluating its performance on the validation set. This process helps to prevent overfitting and ensures that the model performs well on unseen data. The predictive accuracy of the model was further assessed using confusion matrices, Receiver Operating Characteristic (ROC) curves, and the Area Under the Curve (AUC) values, providing a comprehensive evaluation of the model's performance [53].

The coefficients obtained from the logistic regression model were interpreted in terms of odds ratios, which offer an intuitive understanding of the relationship between predictor variables and the likelihood of receiving AI training. For instance, an odds ratio greater than 1 indicates that the predictor increases the likelihood of the outcome, while an odds ratio less than 1 indicates a decrease. Statistical significance was determined using p-values, with significant predictors identified for targeted interventions.

The results indicated that staff members were significantly more likely to have received AI training compared to students (OR = 2.3, $p < 0.01$). Additionally, respondents who frequently used AI tools were also more likely to have received AI training (OR = 3.1, $p < 0.01$). These findings underscore the importance of targeted training programs and the integration of AI tools in educational practices to enhance AI proficiency among university staff and students [54].

RESULTS AND DISCUSIONS

In this section, we will discuss the application of descriptive analysis and regression analysis techniques based on the collected data. Descriptive analysis provides an overview of the demographic distribution, AI tool

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usage, and satisfaction levels among respondents. It helps in understanding the general patterns and trends within the dataset. Conversely, regression analysis will delve deeper, exploring the relationships between variables such as age, role, and AI tool usage frequency. By comparing these techniques, we aim to uncover insights that descriptive statistics alone cannot provide, highlighting key factors influencing AI adoption and satisfaction in higher education institutions in Malaysia and Thailand.

The Figure 1 below reveals that the largest age group among respondents is 46+, making up 32% of the sample. This indicates a significant presence of older individuals in the dataset. According to life cycle theory, older professionals may exhibit different learning behaviors and technology adoption patterns compared to younger individuals. Their experience could lead to a greater appreciation for structured AI training programs. Conversely, their relatively lower familiarity with new technologies might result in higher resistance to adopting AI tools without adequate support. This demographic insight is crucial for tailoring AI training programs to address the unique needs of older staff and students, ensuring that interventions are effective across all age groups.

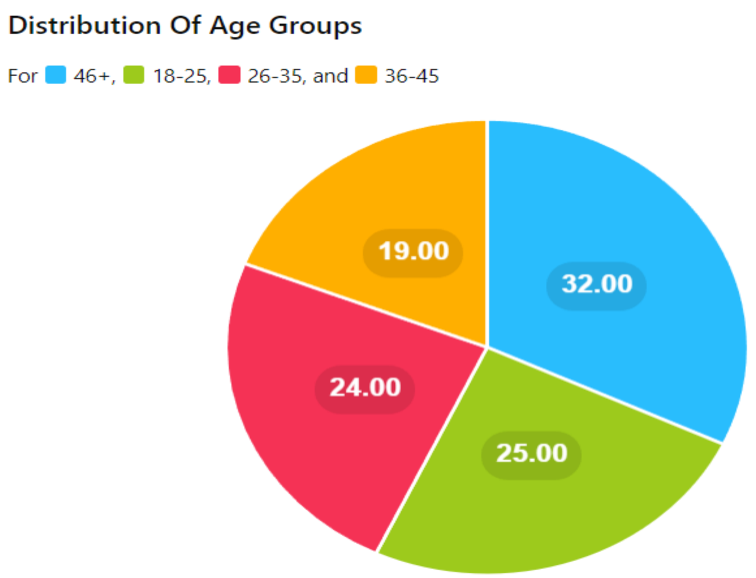

Fig1: Distribution of Age Group

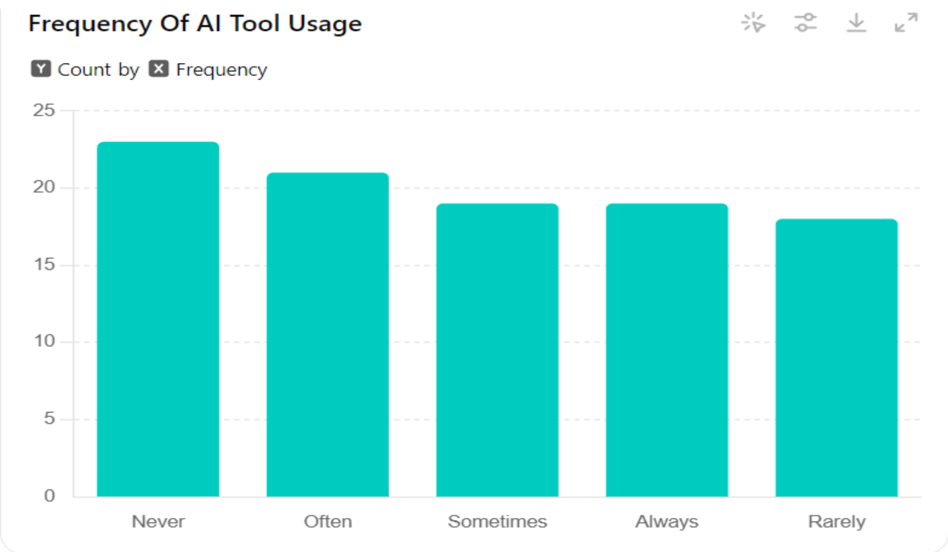

Fig 2: Frequency of AI Tool Usage

The Figure 2 as bar chart shows that the most common frequency of AI tool usage among respondents is "Never," accounting for 23% of the sample. This suggests a significant portion of respondents are either unfamiliar with AI tools or lack access to them. Diffusion of Innovations theory posits that adoption of new

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technologies follows a bell curve, where innovators and early adopters are followed by the early majority, late majority, and laggards. The high number of "Never" users indicates that AI tools are still in the early stages of adoption within this population. Understanding this can help educators and administrators design initiatives that move more users towards frequent AI tool usage through targeted training and support.

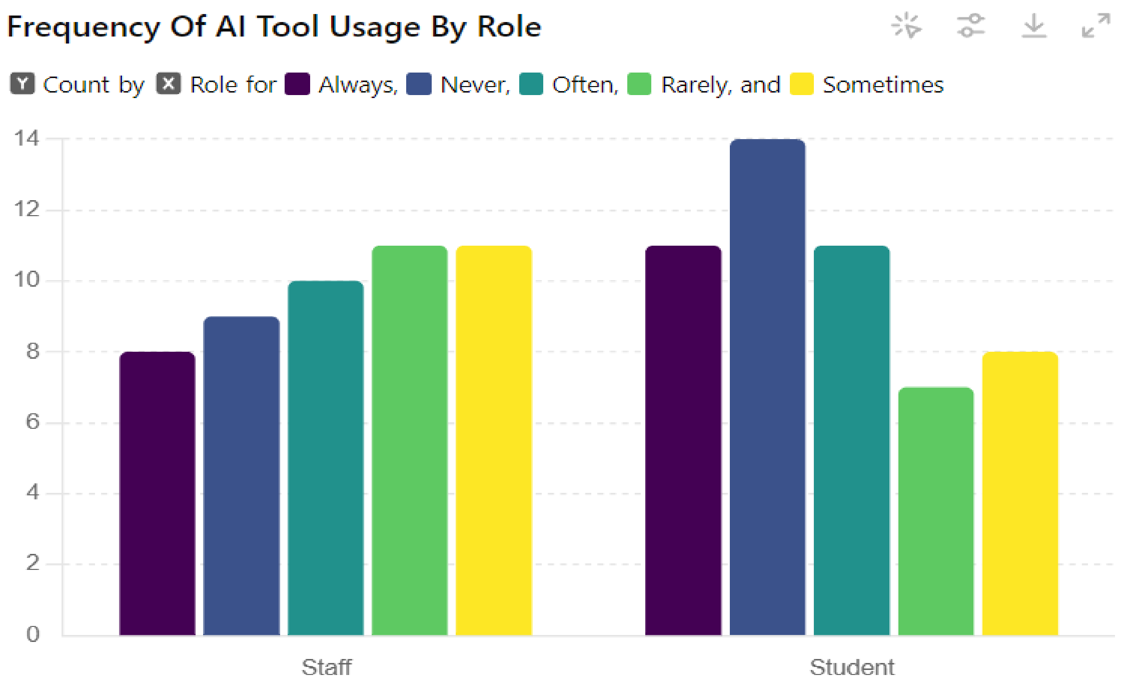

Fig 3: Frequency of AI Tool usage by role.

In figure 3, illustrates that students are more likely to use AI tools "Sometimes" and "Often," whereas staff members show higher frequencies in the "Never" and "Rarely" categories. This difference may be explained by the Technology Acceptance Model (TAM), which suggests that perceived ease of use and perceived usefulness significantly impact technology adoption. Students might perceive AI tools as more beneficial for their learning processes, thus showing higher usage rates. In contrast, staff members might face barriers such as lack of training or institutional support, making them less inclined to use AI tools. These findings highlight the need for targeted strategies to encourage AI adoption among staff through professional development and resource allocation.

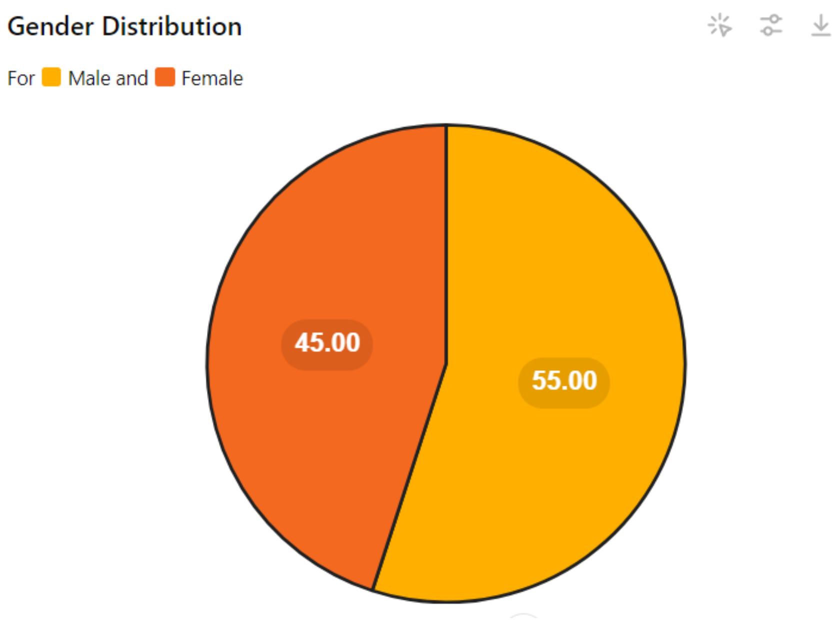

Fig 4: Gender distribution

Figure 4 indicates a relatively balanced gender distribution, with 55% male and 45% female respondents. Gender diversity is important in ensuring that AI training and integration initiatives are inclusive and address the needs of all users. Research in gender and technology adoption suggests that women and men may have different experiences and attitudes towards technology. Ensuring a balanced representation helps in designing AI tools and training programs that are equitable and cater to the preferences and challenges faced by different genders. This balance also supports the development of a comprehensive understanding of how AI impacts various demographic groups within higher education institutions.

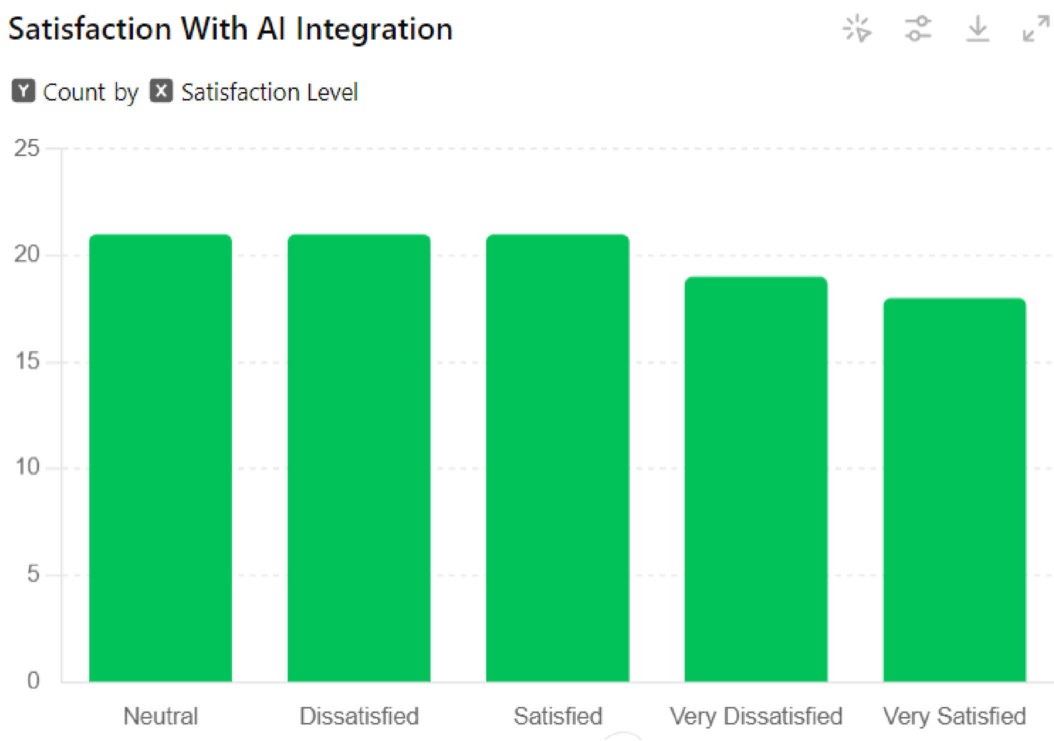

Fig 5: Satisfaction with AI Integration

The figure 5 shows that the most common response regarding satisfaction with AI integration is "Neutral," followed by "Satisfied" and "Very Satisfied." According to Herzberg's Two-Factor Theory, job satisfaction and dissatisfaction are influenced by different factors. Satisfaction with AI integration might be linked to intrinsic motivators such as the perceived enhancement of work efficiency and learning outcomes. The neutral and positive responses suggest that while AI integration is generally well-received, there may be areas for improvement to increase satisfaction further. Addressing factors that lead to dissatisfaction, such as technical issues or insufficient support, could enhance overall satisfaction and encourage more widespread adoption of AI technologies in higher education.

CONCLUSIONS

The integration of Generative AI in higher education institutions in Malaysia and Indonesia offers significant opportunities and presents unique challenges. The demographic analysis reveals a substantial portion of older individuals (46+) in the respondent pool, suggesting the need for targeted AI training programs that address the distinct learning behaviors and technology adoption patterns of this group. The high percentage of respondents who "Never" use AI tools indicates that AI technology is still in its early adoption phase, requiring strategic initiatives to enhance familiarity and comfort with AI tools among students and staff.

Overall, the findings indicate that while AI holds transformative potential for higher education, its effective integration requires addressing both attitudinal and structural barriers. By fostering positive perceptions of AI, enhancing AI literacy, and ensuring equitable access to AI training, higher education institutions in Malaysia and Indonesia can harness the full benefits of AI technology to improve educational outcomes. Future research and policy development should focus on creating inclusive, culturally sensitive, and responsible AI-enhanced educational environments.

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