Vol 7 No 1 (2026) E-ISSN: 2735-1009

International Journal of Management, Finance and Accounting

Cultivating Responsible Artificial Intelligence Practices in Malaysian Higher Education

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Abstract

The integration of Artificial Intelligence (AI) in higher education presents both opportunities and ethical challenges. In Malaysia, private universities are adopting AI at a pace that often outshines the development of governance frameworks, raising concerns over transparency, data privacy, and ethical literacy. This research examines the influence of three predictors (AI Transparency, Data Privacy Awareness, and Ethical AI Literacy) on the ethical use of AI among 221 academicians. Guided by Deontological Ethical Theory and employing a quantitative correlational design, the analysis revealed strong and significant relationships among all variables. Data Privacy Awareness emerged as the most consistent and positive predictor of ethical AI usage. Interestingly, AI Transparency and Ethical AI Literacy showed suppressor effects, meaning their predictive power became clearer when accounting for the influence of other variables. The model achieved an R^2 value of 0.653, indicating that the predictors explained 65.3% of the variance in ethical AI behaviours. The research makes three key contributions. Firstly, it addresses a gap in AI ethics research within Malaysian private universities, integrating philosophical and empirical perspectives to inform governance. Lastly, it provides actionable insights for policy and training. By emphasising the need for transparent practices, robust data protection, and ethical literacy programmes, the findings directly support SDG 4 (Quality Education) by promoting responsible digital

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competencies and SDG 16 (Peace, Justice and Strong Institutions) by encouraging ethical governance in AI adoption.

Keywords: Artificial Intelligence Literacy, Artificial Intelligence Transparency, Data Privacy, Ethical Artificial Intelligence, Higher Education.

Received on 31 July 2025; Accepted on 31 October 2025; Published on 28 February 2026.

To cite this article: Raime, S., Abd. Rahman, N., Abdullah Hashim, R. & Shamsudin, M. F. (2026). Cultivating responsible artificial intelligence practices in Malaysian higher education. *International Journal of Management, Finance and Accounting, 7*(1), 448–474. https://doi.org/10.33093/ijomfa.2026.7.1.16

1.0 Introduction

Artificial Intelligence (AI) is changing higher education around the world, allowing universities to provide more personalised learning, optimising administrative pathways, and enhancing strategic decision-making using AI chatbots, predictive analytics, and adaptive learning platforms (Gomathinayagam et al., 2024; Vieriu & Petrea, 2025). Artificial intelligence in education is part of a period of global transition towards education heavily reliant on AI. Although the global excitement surrounding the possibilities offered by AI promises increased efficiencies, scalability and responsiveness to both student and faculty staff, it has nonetheless prompted discussions about transparency, algorithmic bias and fairness, and data governance (Giannakos et al., 2025). Examples relevant to global discussions surrounding AI in education include cases in the UK involving the problematic interference of AI in grading students and the proliferation of algorithmic surveillance in US universities (Balash et al., 2021). These developments compel the researchers to consider what it means to deploy AI in the absence of sufficient ethical safeguards. Subsequently, global policy initiatives, such as UNESCO's 2021 recommendation on the Ethics of Artificial Intelligence, have emphasised the importance of ensuring that AI implementation in education possesses human-centred and responsible principles prioritised at every stage of deployment.

The adoption of AI in Malaysian higher education has gained traction alongside the Malaysian Education Blueprint 2015-2025, which indicates innovation and digitalisation as the means to enhance institutional competitiveness (Mat Yusoff et al., 2025). Adoption of AI within higher education institutions, particularly within private universities, has seen implementations in automated admissions processing, forms of learning management systems, and predictions regarding student performance. However, recent evidence points to the institutional speed of technology adoption outpacing established sound governance (Mohd et al., 2024). In their assessments of institutional capabilities in adopting AI ethics policies within private universities, Mohd et al. (2024) highlighted evidence of inconsistent governance mechanisms leading to unclear policy communication, little ethical training for academic staff, and a lack of adequate infrastructural safeguards for data protection, contributing to unclear AI governance practices. For example, research by Wan Mokhtar et al. (2024) reported that less than

40% of private universities in Malaysia had a published formal AI ethics policy in place despite their use of AI-driven decision-support tools. This has led to challenges like data misuse, biased decisions, and a lack of accountability within AI-enabled decisions, contradicting the Blueprint's aspirations to provide equitable and quality education.

Even though there has been a substantial global growth in scholarship on AI ethics, the amount of empirical research into this area of interest, particularly concerning the distinctive Malaysian higher education context, is lacking (Ming et al., 2025; Wan Mokhtar et al., 2024). The current research focus in Malaysia is similarly limited concerning empirical work, not just in scholarship. There is a dearth of literature in Malaysian higher education that considers AI transparency, awareness of using data, and ethical literacy about AI, all of which can fundamentally influence AI usage (Mohamad et al., 2025). To address this knowledge gap, this research investigates the relationship between AI transparency, data privacy awareness, and ethical AI literacy on ethical AI usage in the context of academicians in private Malaysian universities. Underpinned by the deontological ethical theory and drawing upon the primary data of academic staff, this research seeks to provide evidence-based knowledge to inform policy implementation, targeted professional learning, and ethically inclusive practices surrounding AI in Malaysia's higher education sector.

2.0 Literature Review and Hypotheses Development

This research is based on deontological ethical theory, first developed by Kant (1975), which states that ethical behaviour must be based on a universal moral duty rather than the consequences of an action (Korsgaard, 2012). Deontology offers a robust normative base for thinking through AI ethics, as it draws attention to institutional action that involves AI and must recognise fairness, autonomy, and human dignity rather than mere efficiency or convenience. In higher education, when grounded by deontological ethics, the institutions will be obligated to ensure that any AI adoption does not violate stakeholders' rights and interests. As for the present research, deontological ethics are aligned with AI Transparency, Data Privacy Awareness, and Ethical AI Literacy since together they capture universities' ethical obligations toward individuals and communities, including students, staff, and the public. These ethical duties are not simply "best practices" when viewed through the deontological lens, but instead, are ethical commitments that should inform a responsible adoption of AI in educational contexts.

AI transparency is defined as the extent to which stakeholders are able to comprehend, interpret, and ultimately challenge AI-based decision-making (Liangru & Yi, 2022). AI transparency is essential in areas such as automated grading, plagiarism detection, and predictive analytics in higher education (Thelwall & Kousha, 2025). Transparency helps build trust, legitimacy, and user agency, ultimately leveraging the opportunity for users to react to biases or unfavourable outcomes that surface (Thelwall & Kousha, 2025). In reality, while there is an assertion associating transparency with accountability (e.g., Hellmann et al., 2022), there is also an argument stating that complete disclosure of algorithms may not be possible, as it may give away intellectual property or may even invite system manipulation (Radanliev, 2025). Besides, transparency does not always entail understanding. Users who do not have a technical background may be overwhelmed by the complexity of an AI model, giving rise to an "explainability gap" (Radanliev, 2025). In Malaysia, transparency issues are made worse by the few institutional policies requiring AI to disclose to students and staff. There may also be some cultural issues related to hierarchical decision-making, as there is open scrutiny of AI outputs (particularly in private institutions), which are typically "siloed" and based on bureaucracy, which is very common among private institutions (Leong & Zhang, 2025; Miskam et al., 2023). Nonetheless, irrespective of what the reasons are, when the institutions are grounded with deontological ethics, transparency is always expected to be present since being transparent (honest) is deemed as an ethical duty to ensure stakeholders can understand how and why decisions that affect them are made. Hence, the study hypothesis is proposed below:

H1: There is a significant relationship between AI Transparency and Ethical AI Usage among academicians in Malaysian private universities.

Meanwhile, data privacy awareness is defined as the level to which institutional actors understand the ethical use of personal and academic data that is processed using AI systems (Oji & Alordiah, 2024). AI is mostly reliant on student data, which is often sensitive in nature, creating complex questions about consent, security, and the potential for surveillance of students (Mahusin et al., 2024). Therefore, greater awareness of privacy can better equip institutions to manage their data appropriately, but it may not be without drawbacks. For instance, if institutions are more aware of privacy issues, they will handle and manage their data in a more proper and responsible way.

Nevertheless, the downsides of adopting stringent privacy policies might limit the types of data that can be utilised, thus reducing the accuracy or predictive power of AI systems, because AI often performs better with larger and diverse datasets (Alzoubi & Mishra, 2025). On top of that, research shows that there are often gaps or contradictions between what organisations say in their privacy policies and what they actually do in practice (Jeeyeon & Sangmin, 2024). Although, with the 2010 Personal Data Protection Act (PDPA), compliance among providers of higher education is inconsistent (Miskam et al., 2023). Since there is no guidance related to privacy and AI, it is possible for these institutions that have meaningful policies of general data use to breach ethical obligations intended to govern the use of AI. Cultural norms, such as dependence and trust in the institution and authority, may shape expectations of privacy law, thus reducing the possibility of questioning privacy practices (Miskam et al., 2023). Nevertheless, from a deontological perspective, the researchers highly believed that protecting personal data is not just a regulatory obligation but also a moral obligation (a right thing to do). This has driven the researchers to the second hypothesis:

H2: There is a significant relationship between Data Privacy Awareness and Ethical AI Usage among academicians in Malaysian private universities.

Ethical AI literacy refers to the knowledge, skills, and dispositions required to evaluate the ethical issues of AI and Act (Carolus et al., 2023). In higher education, strong literacy enables educators to identify bias, question unethical use, and implement AI responsibly. Although literacy can be improved through training, some researchers have identified that developing literacy is better when participants experience practice-oriented training rather than theoretical training (Yunjo et al., 2025). Besides, it is important to note that global frameworks of AI literacy may not entirely capture culturally specific or unique ethical priorities, like collective responsibility good in

Malaysian institutions. Digital literacy training at Malaysian universities is almost never contextualised with an ethics module in AI (Oji & Alordiah, 2024), and even in modules where it may have existed, tends to focus on operational, but not on ethical competencies (Oji & Alordiah, 2024). Hierarchical structures within an institution and an exam-centric academic culture should mean there are fewer opportunities to grapple with AI ethics. Deontological ethics support that literacy is a duty and a responsibility; hence, educators and administrators are expected to be able to demonstrate their capacity for upholding and advocating fairness, accountability, and respect in the utilisation of AI. With that, the third hypothesis is justified as follows.

H3: There is a significant relationship between Ethical AI Literacy and Ethical AI Usage among academicians in Malaysian private universities.

2.1 Research Framework

The proposed research framework in Figure 1 identifies AI Transparency, Data Privacy Awareness, and Ethical AI Literacy as the indicators of Ethical AI Usage based on Deontological Ethical Theory. This framework identifies the constructs as interrelated, while singular contributory constructs relate to ethical decision-making on AI adoption as follows.

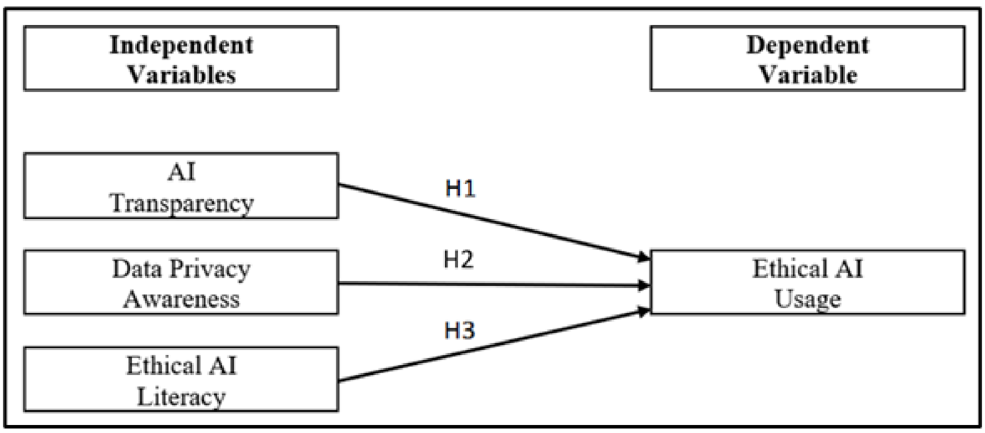

Figure 1: Research Framework

Source: Authors' Own Work

3.0 Methodology

This research used a quantitative correlational design to assess the relationships among three independent variables and the dependent variable. A correlational design was chosen because it provides means to identify and quantify the degree of statistical relationships among variables without changing the research environment. The researchers considered it to be appropriate because behaviour naturally occurs and is uncontrollable in the context of higher education institutions, with a consideration of education in the "real world" of higher education. While more advanced designs, such as structural equation modelling (SEM) or path analysis, might allow deeper inferences of causality in relationships (Li et al., 2025), the objective of this research was not to establish causality but to assess the strength and direction of the relationships. Thus, we deemed a correlational analysis to be the most practical and relatively simple method to quantify the relationships.

All measurement instruments were adapted from validated scales in prior research to ensure content relevance and reliability in the academic context. AI Transparency was measured using the scale developed by Hellmann et al. (2022) (Cronbach's $\alpha = 0.847$), Data Privacy Awareness from Jeeyeon and Sangmin (2024) ($\alpha = 0.880$), and Ethical AI Literacy from Carolus et al. (2023) ($\alpha = 0.770$). Ethical AI Usage was measured using the scale by Maharmah et al. (2025) ($\alpha = 0.707$). A number of preliminary steps were conducted to ensure the appropriateness of the instruments for the context of Malaysian private universities. This includes undergoing the face validity procedure via two experts from the field of educational technology and AI ethics. Upon receiving the replies from the two field experts, minor changes to wording were made as recommended for clarity and cultural suitability. Following this, a pilot test with 34 respondents was conducted to assess internal consistency and to measure construct validity. Cronbach's Alpha results for all of the constructs were above the minimum 0.70 threshold (Sekaran & Bougie, 2016) as reported in Table 1. Hence, the reliability of the factors was confirmed, and each factor loading matched our theoretical expectations, confirming construct validity.

Table 1: Pilot Test Results (Internal Consistency)

	Number of Items	Cronbach's Alpha (α)
AI Transparency	6	0.829
Data Privacy Awareness	8	0.881
Ethical AI Literacy	7	0.854
Ethical AI Usage	5	0.798

The population of interest included 30,572 lecturers at Malaysian higher education institutions (Kementerian Pendidikan Tinggi, 2024), with the final respondents being lecturers working for private universities. Therefore, the suitability was restricted to lecturers currently working in Malaysian private universities. The voluntary, web-based distribution also served as a natural exclusion mechanism for those outside the target group. Using the Krejcie and Morgan (1970) table, the sample size recommended was 380. However, under time pressure and because of administrative limitations, convenience sampling was used. Convenience sampling was utilised because the target population was located throughout the country across multiple institutions, and obtaining full lists of academic staff was not feasible due to the institutions' privacy policies.

No formal stratification was used by institution type or academic discipline; however, researchers sought to get the questionnaire to different private universities with the aim of capturing a range of perspectives. By the end of four months of data collection, the researchers received 230 complete responses, which is approximately 61% of the targeted sample size. Following Sekaran and Bougie (2016), researchers determined that equal distribution would not negatively affect analysis, as the sample size already exceeded 40% of the original population for the purposes of statistical inference. The survey was a web-based survey and, therefore, was anonymous and voluntary. Data screening, descriptive statistics and correlational analysis testing the hypothesis of this research were performed using SPSS version 26. Preliminary data checks included addressing missing data, testing for normality, and checking for multicollinearity.

4.0 Results and Discussion

4.1 Box Plot

For data screening, the researchers initially used the boxplot method to identify potential outliers that could warp or bias the results. As shown in Figure 2, numerous cases were identified as outliers and extreme outliers.

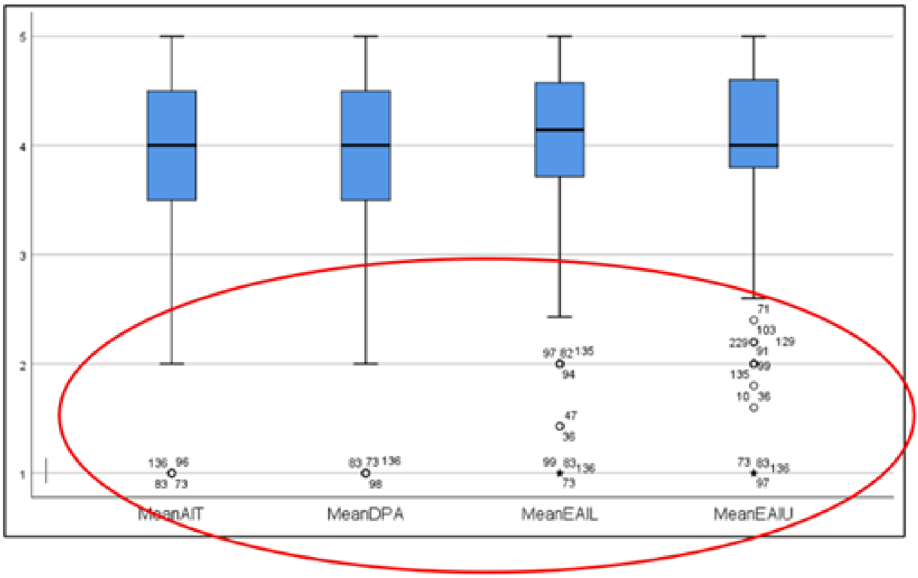

Figure 2: Boxplot (Outliers)

Consequently, the researchers ultimately opted to implement the Mahalanobis Distance procedure and compute the p-value to determine and eliminate the most extreme cases from their dataset. Nine cases with p-values below 0.001 are indicated in Figure 3; these are extreme cases that could bias the overall results and should be excluded (Barnett & Lewis, 1994). After calculating the p-values, the researchers agreed to exclude cases 99, 98, 119, 94, 97, 93, 95, 91, and 96. This leaves a total of 221 cases for comparatively adequate statistical validity going forward in the analysis.

	RESPONDENT	MAH_1	Pvalue
1	99	37.178	.000
2	98	34.530	.000
3	119	22.769	.000
4	94	21.611	.000
5	97	21.602	.000
6	93	19.623	.000
7	95	19.623	.000
8	91	18.938	.000
9	96	18.619	.000
10	73	15.746	.001
11	83	15.746	.001
12	136	15.746	.001

Figure 3: P-value (Mahalanobis Distance)

4.2 Normality Test

The researchers, in addition to performing boxplots and Mahalanobis Distance analysis, also performed a normality test to check for skewness and kurtosis. Normality is crucial; many statistical analyses assume normality with the data, and the assumption of normality helps to prevent erroneously concluding and making decisions (Kline, 2011). Skewness reflects the symmetry of the data distribution, and kurtosis reflects the height of the peak or flatness of the tails. A skewness score between -2 and plus 2 indicates symmetry without left or right skew (Kline, 2011). Kurtosis demonstrates that the data has either more or fewer outliers than would be expected with a normal distribution. A kurtosis score between -3 and plus 3 suggests no excessive flatness or no excessive peak (Kline, 2011). As noted in Table 2, the skewness and kurtosis values are within the ranges noted, supporting that the normality of the data is not concerning.

Table 2: Normality Testing

Variables	Mean	Skewness	Kurtosis
Ethical AI Literacy	4.0084	-1.480	2.976
Data Privacy Awareness	4.0084	-1.480	2.976
Ethical AI Usage	3.9792	-1.274	1.942
AI Transparency	3.9291	-1.239	1.883

4.3 Measurement Model Analysis

4.3.1 Internal Consistency

Table 3 presents the results of internal consistency, assessed using the Cronbach's alpha (α). All variables exhibit strong reliability results, with α-values ranging from 0.824 to 0.885. These values exceed the minimum acceptable threshold of 0.70, indicating strong internal consistency (Sekaran & Bougie, 2016). In another words, the results suggest that the items within each variable consistently and reliably measure the same construct (Nunnally, 1978). Therefore, it can be confirmed that the scales or measuring model used in this research are internally consistent and can be confidently employed to measure the relevant variables.

Table 3: Internal Consistency

Variables	No. of Items	Cronbach's Alpha (α)
AI Transparency	6	0.841
Data Privacy Awareness	8	0.885
Ethical AI Literacy	7	0.861
Ethical AI Usage	5	0.824

4.4 Structural Model Analyses

4.4.1 Linearity Analysis

The structural model analysis began with a linearity analysis procedure. The purpose of checking for linearity is to determine whether there is a straight-line relationship between the independent and dependent variables (Kline, 2011). This is crucial because the model's accuracy relies on the assumption of linearity. If the relationship is not linear, the model's predictions may be inaccurate. Moreover, a linear relationship also allows for easier interpretation of the model's coefficients (Kline, 2011). As reported in Table 4, it can be confirmed that there are no linearity issues between each independent variable and the dependent variable, as all have significance values below 0.05 (Kline, 2011).

Table 4: Results of Linearity Test (ANOVA)

Variables	Sig.	Linearity
DV EAIU * IV_AIT	<0.001	Yes
DV EAIU * IV DPA	<0.001	Yes
DV EAIU * IV_EAIL	<0.001	Yes

*EAIU = Ethical AI Usage, AIT = AI Transparency, DPA = Data Privacy Awareness, EAIL = Ethical AI Literacy

4.4.2 Correlation Analysis

The next analysis performed was the correlation analysis to evaluate the significance of relationships within the structural model, thus testing the research hypotheses. A satisfactory p-value less than 0.01 signifies a significant relationship between variables (Cesana, 2018). Table 5 summarises the correlation results between the variables. The results indicate there is a significant relationship between all the independent variables (AI Transparency, Data Privacy Awareness, and Ethical AI Literacy) and the dependent variable (Ethical AI Usage). This simultaneously confirms the proposed hypotheses for this research, where all hypotheses, H1, H2, and H3, are supported.

Table 5: Correlation Analysis

		EAIU	AIT	DPA	EAIL
EAIU	Pearson Correlation, r	1.000	0.796**	0.735**	0.701**
	Sig. (2-tailed)		0.000	0.000	0.000
	N	221	221	221	221

**Correlation is significant at the 0.01 level (2-tailed)
*EAIU = Ethical AI Usage, AIT = AI Transparency, DPA = Data Privacy Awareness, EAIL = Ethical AI Literacy

The correlation analysis presented in Table 4 reveals strong and statistically significant positive relationships between Ethical AI Usage (EAIU) and the three independent variables: AI Transparency (AIT), Data Privacy Awareness (DPA), and Ethical AI Literacy (EAIL). The strongest relationship is observed between EAIU and AIT, with a Pearson correlation coefficient of 0.796 ($p < 0.01$), indicating that higher levels of AI transparency are closely associated with increased ethical usage of AI. Similarly, the correlation between EAIU and DPA is 0.735 ($p < 0.01$), suggesting that individuals who are more aware of data privacy issues tend to engage more in ethical AI usage. Additionally, EAIU is strongly correlated with EAIL, with a coefficient of 0.701 ($p < 0.01$), implying that enhanced literacy regarding ethical AI contributes strongly to its ethical application. These findings highlight the importance of promoting transparency, privacy awareness, and AI literacy (with correlation strength, r higher than 0.50) to foster responsible and ethical use of artificial intelligence technologies (Cohen, 1988).

4.4.3 Regression Analysis

In addition to the correlation analysis, the researchers also conducted a multiple regression to see the unique contributions of all three independent variables (AI transparency, data privacy awareness, and ethical AI literacy) to Ethical AI Usage while they were all present at the same time. While the correlation analysis (Table 4) showed positive and significant relationships between each predictor (AI Transparency, Data Privacy Awareness and Ethical AI Literacy) and Ethical AI Usage, correlation alone cannot tell how much of the variance in Ethical AI Usage can be accounted for because of the relative contribution of each variable when they all exist together (Field, 2018; Tabachnick & Fidell, 2019). Thus, multiple regression was done to assess these relationships while accounting for shared variance in the independent variables.

The multiple regression analysis is shown in Table 6, indicating that the three independent variables productively accounted for the dependent variable (Ethical AI Usage) at a significant level ($p < 0.05$). Data Privacy Awareness ($\beta = 0.164$, $p = 0.029$) continued as positive to Ethical AI Usage as expected, as higher Data Privacy Awareness has a positive relationship with higher Ethical AI usage. The other two predictors, AI Transparency ($\beta = -0.181$, $p = 0.015$) and Ethical AI Literacy ($\beta = -0.134$, $p = 0.033$), resulted in negative coefficients despite being positively correlated with Ethical AI Usage, because of how they were incorporated in the regression with respect to the other predictors. This suggests that, when controlling for other factors, particularly data privacy awareness, higher levels of transparency and literacy may not necessarily lead to more ethical behaviour in practice.

One potential explanation for such an unexpected finding is contextual substitution effects wherein transparency and literacy are likely to raise awareness of ethical risks, but do not provide individuals with the dispositional authority, resources or supportive culture necessary to take ethical action (do the right things). In some situations, higher or greater literacy or transparency of AI processes may promote scepticism and resistance, or disengagement, particularly if staff view governing structures as insufficient or counterproductive. This relationship parallels publications in the field of technology adoption that use the term "awareness–action gaps," indicating that awareness/knowledge do not in themselves ensure an ethical application (Deisenrieder et al., 2020), particularly where a workplace has structural assumptions concerning hierarchy and accountability.

Yet another explanation is behavioural prioritisation. In an environment of limited resources or target-driven activity, staff may still succumb to efficiency or compliance pressures, even when the workplace or institutional culture may promote a greater literacy in AI ethics or some transparency. Assumptions about cultural norms in

Malaysia, such as deference to institutional authority (Ma'rof et al., 2024), likely reduced action on ethical concerns even if those concerns were acknowledged.

Table 6: Coefficient Analysis

Model	Unstandardized Coefficients		Standardized Coefficients	t-value	Sig. Tolerance
	Std. Error	Beta			
(Constant)	0.059	0.136			
AI Transparency	0.083	-0.193	-0.181	-2.445	0.015
Data Privacy Awareness	0.074	0.163	0.164	2.896	0.029
Ethical AI Literacy	0.066	-0.141	-0.134	-2.135	0.033

Dependent Variable: Ethical AI Usage

4.4.3.1 Multicollinearity Analysis

Multicollinearity statistics (Table 7) indicate Tolerance values above 0.2 and VIF values below 5 for all variables (AIT = 2.426; DPA = 2.511; EAIL = 2.149), confirming that multicollinearity is not distorting the regression model (Nakarmi, 2024). Thus, it seems improbable that the reversal of coefficients' signs is a statistical object of overlapping variables and instead suggests potentially more complicated underlying behavioural dynamics. While hierarchical regression or SEM methods could have formed a more in-depth examination of these predictive relationships, the researchers wished to pursue an objective of simply identifying predictors of significance as opposed to forming models of latent constructs or causal pathways. These predictive dynamics still do highlight that future research should examine some mediating or moderating factors, such as organisational culture, leadership support and/or perceived behavioural control, that might account for findings where AI transparency and AI literacy individually suggest a positive influence on AI ethical usage, but when considering data awareness privacy simultaneously, they emerge as less influential.

Table 7: Multicollinearity Analysis

Model		Standardized Coefficients	t-value	Sig.	Collinearity Statistics	
		Beta			Tolerance	VIF
1	(Constant)					
	IV AIT	0.562	-2.445	0.015	0.412	2.426
	IV DPA	0.228	2.896	0.029	0.398	2.511
	IV EAIL	0.192	-2.135	0.033	0.465	2.149

AIT = AI Transparency, DPA = Data Privacy Awareness, EAIL = Ethical AI Literacy

The next analysis run by the researchers was the coefficient of determination analysis (R^2) to assess how much of the variance in the dependent variable is explained by the model. The R^2 value for this research is 0.653, as shown in Table 8, demonstrating that 65.3% of the variance in the Ethical AI Usage is described by the model. In other words, 65.3% of the differences in respondents' Ethical AI Usage are predicted by the independent variables, namely AI Transparency, Data Privacy Awareness, and Ethical AI Literacy. According to Hair et al. (2021), an R^2 value between 0.25 and 0.75 is considered moderate. The rationale for this moderate level of acceptance will be further discussed in the section following the findings and discussion section.

Table 8: Coefficient of Determination

Model	R Square	Adjusted R-squared
1	0.653	0.642

Predictors: AI Transparency, Data Privacy Awareness, Ethical AI Literacy
Dependent Variable: Ethical AI Usage

The final analysis conducted by the researchers was the model summary analysis (ANOVA) to assess the overall significance of the model. The results presented in Table 9, confirm that the model is statistically significant, with a p-value of less than 0.001 (Hair et al., 1998; Nakarmi, 2024). This indicates that the model is valid and could be adopted by future researchers in similar or different research settings.

Table 9: Model Summary (ANOVA)

Model		Mean Square	F	Significant
1	Regression	45.094	187.915	0.000
	Residual	0.240		

Predictors: AI Transparency, Data Privacy Awareness, Ethical AI Literacy
Dependent Variable: Ethical AI Usage

5.0 Findings and Discussion

The strongest association was found between AI Transparency and Ethical AI Usage (r = 0.796), signifying that when AIT is more transparent, enterprises participate in more ethical behaviours using AI, which aligns with previous findings (e.g., Hellmann et al. (2022); Thelwall & Kousha (2025)). When AI systems have more transparency, this builds trust in AI systems and allows for easier ethical oversight. Regarding the deontological ethical theory, morality is the duty to provide stakeholders with the opportunity to make sense of decisions driven by AI systems or to disagree with these decisions, as the lecturer is obliged to protect fair and engaged accountability behaviours. When lecturers are clearer about the process of AI, they are in a better position to act morally, not just because it is useful, but because it is their duty as professionals to protect fairness and accountability. Data Privacy Awareness also had a strong, positive association with Ethical AI Usage (r = 0.735), which is consistent with Jeeyeon and Sangmin (2024) and Mahusin et al. (2024), who classify the privacy-concerned individual as expected to demonstrate responsible AI behaviours. This supports the deontological duty that should help protect personal data and should be viewed as an ethical duty rather than a compliance formality.

Likewise, Ethical AI Literacy was strongly correlated to EAIU (r = 0.701), confirming the work by Carolus et al. (2023), which indicated that ethical knowledge helps to prepare educators for dilemmas for a more responsible use of AI. However, there are studies (e.g., Yunjo et al., 2025) which indicate that literacy can very well be without application or call to action, which would not necessarily still create the ethical action implication presented here. This is also raised in the regression findings. While bivariate correlations indicated uniformly strong positive relationships, the multiple regression analysis revealed more nuanced dynamics. Data Privacy Awareness remained positively related to EAIU (β = 0.164, p = 0.029); however, AI Transparency had negative coefficients with AI Transparency (β = -0.181, p = 0.015) and Ethical AI Literacy (β = -0.134, p = 0.033), adjusting for other variables. This phenomenon, termed suppressor effects, occurs when the correlated variance amongst predictors affects the apparent contribution of each (Kim, 2019). Respectively, AIT and EAIL are conceptually linked to and shown to be empirically related to DPA in this research. In essence, when controlling for DPA, the remaining variance in AIT and EAIL could represent factors, such as complexity in procedures or a certain emphasis on theoretical ideals, that would dampen immediate ethical conduct in practice.

From a behavioural perspective, private university lecturers in Malaysia may respond with privacy-oriented actions rather than adopting transparency or ethical theory when considering AI in their everyday professional decisions. This may partially represent a cultural influence, as data governance (e.g., by law, governed by the Personal Data Protection Act 2010) has a relatively greater prominence in Malaysia's academic context, thus heightened sensitivity to data breaches in recent years (Mat Yusoff et al., 2025). From a deontological perspective, this outcome suggests that even though transparency and literacy are moral goods, they must be activated in ways that result in actual impact on ethical practice in everyday circumstances. If transparency policies are merely processed or interpreted as symbolic, and if literacy remains at the theoretical level without consideration of what it means in practice, their influence on behaviour may fall away when there are immediate responsibilities like protecting data that come into action. Additionally, the finding that DPA was the most consistent positive predictor resonates with Mahusin et al. (2024), who established in Southeast Asian contexts that the tangible, real risks (such as data misuse) are mainly what drives and motivates ethical engagement, compared to abstract ethical ideals. In contrast to the negative betas for AIT and EAIL, there have been other studies from Western contexts (Hellmann et al., 2022; Carolus et al., 2023), which established that transparency and literacy led to ethical usage consistently. The difference in findings here possibly reinforces the notion of context, for example, actual policy maturity, institutional culture and legal context, in how ethical constructs materialise into behaviour.

The $R^2 = 0.653$ conveys that the three predictors explain 65.3% of the variance of EAIU, which indicates a moderate-to-strong effect size for behavioural research (Hair et al., 2021), with the adjusted $R^2 = 0.642$, confirming that the model is sufficiently stable and that overfitting is unlikely. The evidence suggests a good model quality since the R^2 reports a good level of predictive capacity. However, variations in 34.7% of the dependent variable EAIU remains unexplained, which suggests, as Radanliev (2025) argues there are other drivers that seem to also have be influential factors such as, the organisational ethical climate and the commitment of leaders to the ethical treatment of data, enforcement mechanisms and compliance processes, the realm in which the ethical, regulatory, contract and operational matters are operationalised through digital data governance; all of which seem to be important aspects to positive ethical AI use from the data governance perspective. Theoretically, these findings extend Deontological Ethical Theory by displaying that even when moral duties are acknowledged (e.g., transparency, literacy), their behavioural impact may vary depending on how they intersect with more immediate ethical imperatives like data protection. Practically, the results indicate that Malaysian private universities should implement, if any, the ethical practice interventions through policy or training that focus on applied ethical practice and not an amalgamation of transparency and literacy without a connection to actual behaviours rather than concept and understanding of the ethical concept.

6.0 Conclusion and Future Research

The research investigated how AI Transparency, Data Privacy Awareness, and Ethical AI Literacy impact the Ethical AI Use for academicians working in private universities in Malaysia. The research established a relationship for all three variables to Ethical AI Use, with Data Privacy Awareness being the most consistent predictor in the regression model. The regression model had moderate to strong explanatory power ($R^2 = 0.653$), establishing a good level of ethical behaviour around AI use in academia. Supporting the hypotheses in the current research, the research also provided evidence for essential ethical constructs in AI Integration. The contribution to knowledge is timely as it helps to inform ongoing discussions around the responsible implementation of AI in Higher Education in the Malaysian context.

The research also utilised Deontological Ethical Theory as a basis for the research and employed validated measures. The research represents a framework that higher education institutions can use to evaluate ethical AI practice. In addition to the above, the research findings complement the Malaysian Education Blueprint and Sustainable Development Goals (SDG 4 and SDG 16), which were called for as part of the digitisation of institutions. A highlight of the research is the encouragement for ethical governance around AI, transparency, and data protection. Regardless of these gains in the body of knowledge, this research is limited as it only includes private (non-profit) universities, which may limit the generalisability of the results. Future research could consider incorporating public universities and examining longitudinal or mixed-method approaches, as well as accounting for potentially relevant variables like institutional culture, policy enforcement, and digital readiness. Examining possible moderating factors, such as leadership ethics or technological self-efficacy, may enhance and extend the understanding of how ethical AI is moulded across different learning contexts.

Author Contributions Statement: Conceptualisation: S.R., N.A.R.; Methodology: S.R., N.A.R.; Data analysis: S.R., R.A.H., M.F.S.; Writing – original draft preparation: S.R., N.A.R.; Review and editing: R.A.H., M.F.S; Funding acquisition: None; Resources: City Graduate School, City University Malaysia; Supervision: R.A.H., M.F.S. All authors read and approved the final manuscript.

Funding Statement: This research received no specific grant or financial support from any funding agency, commercial entity, or not-for-profit organisation for the preparation of this manuscript.

Informed Consent Statement: Informed consent was obtained from all individual participants involved in this research, and they were fully briefed on the purpose, procedures, and their rights, including the option to not participate without consequence.

Data Availability Statement: The datasets generated and/or analysed during the current research are not publicly available in order to preserve the originality of the research and prevent

unauthorised use for publication. However, access may be considered on a case-by-case basis at the discretion of the corresponding author.

Acknowledgement: The authors express their sincere gratitude to City Graduate School (City University Malaysia) for their support, to all respondents who participated in this research, and to the editors and reviewers of the International Journal of Management, Finance and Accounting for their valuable feedback and guidance.

Conflict of Interest Statement: The authors declare no competing interests related to the content of this research.

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