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Impact of Ethical AI Use on Learning Patterns of Pre-Service Teachers at a Public Sector University in Karachi

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ABSTRACT

This study investigated the impact of ethical Artificial Intelligence (AI) use on the learning patterns of pre-service teachers. A quantitative correlational research design was employed, and data was collected from pre-service teachers enrolled in a B.Ed. programme at a public sector university in Karachi. A survey questionnaire was used to measure ethical AI use and learning patterns, including deep learning, strategic learning, and surface learning, among participants. To analyse data, simple linear regression was performed using SPSS to examine relationships between dependent and independent variables. Results indicated that ethical AI use was positively associated with deep and strategic learning patterns. Low ethical AI use was linked with surface learning tendencies, such as over-reliance on AI for ready-made answers and reduced personal effort. The study concluded that ethical AI use is not merely a moral and policy requirement but also an emerging pedagogical approach that can promote higher-order thinking and reflective learning among pre-service teachers. Recommendations included integrating ethical AI education into teacher education curricula to develop responsible, reflective, and future-ready teaching professionals.

Keywords: *Ethical AI Use, Learning Patterns, Pre-Service Teachers, Teacher Education*

INTRODUCTION

Educational practices across the globe have been remarkably influenced by the rapid advancements in Artificial Intelligence (AI), especially Generative AI (Garzón et al., 2025). Studies report an increasing use of AI tools among students at various levels in different ways, such as educational content generation, problem-solving, and information retrieval (Kasneci et al., 2023; Garzón et al., 2025). While ChatGPT and other AI tools may improve accessibility and learning, they also raise some serious ethical concerns related to academic integrity, fairness, transparency, and data privacy (Zhai, 2022). The ethical use of AI in education, as also recently highlighted by UNESCO, calls for a responsible, open, and academically honest adoption of AI technology in teaching and learning processes (Holmes & Miao, 2023). Students must avoid plagiarism, acknowledge the assistance of AI, and consider AI as a tool rather than an alternative for human cognition (Chan & Hu, 2023).

According to recent studies in the global context, AI tools can have both beneficial and detrimental effects on students' learning patterns. While ethical and responsible AI use can support inquiry-based learning, personalisation, and feedback, over-dependence on AI can lead to procrastination, less cognitive effort, and poorer performance (Heung & Chiu, 2025; Abbas et al., 2024; Chen et al., 2023). This issue is particularly critical in teacher education, where students, termed as pre-service or prospective teachers, are in the process of developing both personal learning patterns as well as professional norms that they will later transmit to school students.

One way to conceptualize student learning pattern is through the Deep–Strategic–Surface Learning Framework introduced by Marton and Säljö (1976), elaborated further by Entwistle & Ramsden (1983) and later expanded by Biggs and Tang (2011). Deep learning involves critical thinking, conceptual understanding, and intrinsic motivation; strategic learning reflects organized, goal-oriented study behaviour; and surface learning is characterized by rote memorization, minimal engagement, and grade-focused task completion. These learning patterns are strongly associated with academic achievement, self-regulation, and long-term professional competence (Entwistle & Ramsden, 1983; Biggs & Tang, 2011).

Despite the growing empirical base on AI adoption into teaching and learning, no published Pakistani study has so far systematically examined how ethical AI use relates to pre-service teachers' learning patterns. Therefore, this study aims to examine the impact of ethical AI use on the learning patterns of pre-service teachers enrolled in a public sector university in Karachi, Pakistan. By integrating ethical AI scholarship with the Deep–Strategic–Surface Learning Framework, the study provides empirical evidence on whether responsible AI use supports meaningful learning or reinforces superficial academic behaviour among future teachers.

LITERATURE REVIEW

The concept of ethical AI use in education is based on the principles of fairness, accountability, data protection, and academic integrity (Holmes & Miao, 2023). Keeping in view the recent advancements and increased use of AI, especially generative AI, scholars now distinguish between productive AI use and misuse that results in academic misconduct or cognitive reliance. A large-scale study conducted by Chan and Hu (2023) revealed that university students usually perceive generative AI positively for support with writing, brainstorming, and research, but also worry about accuracy, privacy, and ethical risks. Researchers concluded that institutional guidelines and ethical framing are crucial for ensuring responsible use of AI.

Bittle and El-Gayar (2025) conducted a systematic review on generative AI and academic integrity in higher education and concluded that GenAI tools simultaneously create new opportunities for formative feedback and new risks of plagiarism. He argued that without explicit ethical training, students often normalize borderline behaviours such as undisclosed AI rewriting or idea generation, which may conflict with institutional policies of originality. Abbas et al. (2024) developed and validated a scale for ChatGPT usage among university students and reported that academic workload and time pressure significantly increase reliance on generative AI, while heavy use is associated with higher procrastination, memory problems, and lower academic performance. They concluded that ethical AI use cannot be separated from broader learning habits, motivation, and self-regulation. These studies collectively suggest that ethical AI use is not only about compliance with institutional rules; it is deeply tied to how students think, plan, and regulate their learning. For teacher education, this means that ethical AI literacy must be framed as both a moral and a pedagogical competency.

Marton and Säljö (1976) introduced the difference between the deep and surface approaches to learning and showed that students engaging deeply with meaning, structure, and argumentation achieved more rigorous understanding than those focusing only on reproducing facts. Entwistle and Ramsden (1983) further elaborated this work and then Biggs and Tang (2011) later expanded this learning framework by highlighting a third pattern, namely strategic learning. This pattern refers to an organized and goal-oriented study behaviour that aims at maximizing academic performance through effective time management and assessment-focused strategies.

Deep learners look for meaning, integrate ideas, and perform critical reflection. Strategic learners monitor demands, plan their work, and adapt their strategies to assessment expectations whereas surface learners focus on rote memorization, minimal effort, and narrow task completion without conceptual and critical engagement. Empirical studies show that deep and strategic learning approaches are positively associated with higher academic achievement, better retention, and stronger problem-solving skills, whereas surface approaches are associated with low motivation and minimal understanding (Diseth, 2007; Valadas et al., 2017; Tuononen et al., 2020).

Although research on associating ethical AI use with the deep–strategic–surface framework is still emerging, several evidence are relevant. Internationally, Chan and Hu (2023) report that students who use generative AI critically by checking accuracy, reflecting on AI output, and integrating it into their own thinking, tend to describe more active, self-regulated learning experiences, which align with deep and strategic approaches. On the other hand, students who perceive AI as a shortcut for completing tasks report concerns about reduced effort and increased reliance. Abbas et al. (2024) noted that heavier ChatGPT use under high workload and time pressure can encourage shortcut behaviours leading to procrastination and lower performance. This pattern is consistent with surface learning, which is often associated with time pressure, fear of failure, and extrinsic motivation.

Ashraf et al. (2025) conducted a study in the context of Pakistani higher education and found that ChatGPT use can improve students' academic performance when mediated by positive behavioural intentions and habits. They suggested that when AI is integrated as part of a broader technology acceptance process instead of a shortcut, it may enhance self-directed learning and academic performance. Balqees et al. (2024) surveyed educators and students in Pakistani universities and found that ChatGPT is increasingly used for teaching, learning, and administrative tasks. They reported that participants articulated the benefits of AI such as efficiency and personalization but also demanded clear policies to regulate its use.

Bano and Mehdi (2024) conducted a systematic review of AI use in Pakistani education and found that most local research focuses on general attitudes, perceived usefulness, or classroom applications, with very limited attention to ethical literacy. From an academic integrity perspective, Azeem et al. (2025) explored teachers' and students' perspectives on AI and academic integrity in a Pakistani public university. They found that both groups acknowledged AI's potential as a learning support but expressed concern about cheating, weak detection mechanisms, and students' confusion about ethical guidelines. They recommended that institution-wide AI literacy and explicit ethical guidelines should be devised. Specific to teacher education, Rasheed et al. (2025) investigated teacher educators' perspectives on integrating AI tools in pre-service teacher education programmes in Pakistan. The study reported that teacher educators perceive AI as a source of pedagogical innovation but are worried about authenticity, academic integrity, and the decline of traditional professional identities. They call for professional development and policy frameworks that help teacher educators model responsible AI practices.

Despite this growing body of literature, no Pakistani study has empirically linked ethical AI use to pre-service teachers' learning patterns. This study addresses that gap by operationalizing Ethical AI Use as a measurable construct, linking it empirically with established learning patterns and focusing specifically on pre-service teachers in a public sector university in Karachi, whose learning behaviours will shape future classroom practices and ethical norms.

Research Questions & Hypotheses

This study is guided by the following research questions:

1. Is there a significant and positive relationship between Ethical Artificial Intelligence (AI) Use and the Deep Learning Pattern among pre-service teachers?
2. Is there a significant and positive relationship between Ethical Artificial Intelligence (AI) Use and the Strategic Learning Pattern among pre-service teachers?
3. Is there a significant and negative relationship between Ethical Artificial Intelligence (AI) Use and the Surface Learning Pattern among pre-service teachers?

In this study, Ethical Artificial Intelligence Use is treated as the independent variable, while Deep Learning Pattern, Strategic Learning Pattern, and Surface Learning Pattern are treated as dependent variables. The hypothesized relationships assume that ethically grounded AI practices promote higher-order cognitive engagement and structured learning behaviours, and reduced rote, shortcut-based learning behaviours. The following three hypotheses were formulated:

1. H_1: Ethical Artificial Intelligence (AI) Use has a positive and significant effect on the Deep Learning Pattern of pre-service teachers.
2. H_2: Ethical Artificial Intelligence (AI) Use has a positive and significant effect on the Strategic Learning Pattern of pre-service teachers.
3. H_3: Ethical Artificial Intelligence (AI) Use has a negative and significant effect on the Surface Learning Pattern of pre-service teachers.

RESEARCH METHODOLOGY

Research Design

The present study used a quantitative, correlational research design. Simple linear regression models were employed to examine the impact of Ethical Artificial Intelligence Use (EAIU) on pre-service teachers' learning patterns namely Deep Learning Pattern (DLP), Strategic Learning Pattern (StLP), and Surface Learning Pattern (SuLP) at a public sector university in Karachi, Pakistan. Three simple linear regression models were specified, one for each learning pattern:

$$\text{Deep Learning Pattern} = \alpha + \beta 1(\text{Ethical AI Use}) + e$$

$$\text{Strategic Learning Pattern} = \alpha + \beta 1(\text{Ethical AI Use}) + e$$

$$\text{Surface Learning Pattern} = \alpha + \beta 1(\text{Ethical AI Use}) + e$$

Where α is the intercept (constant), $\beta 1$ is the regression coefficient of Ethical AI Use, and e is the error term.

Participants

The participants in this study were pre-service teachers enrolled in a B.Ed. programme at a public sector university in Karachi, Pakistan. Data from 116 students (12 males and 104 females) were used for analysis. The age and gender distribution is shown in Table 1. Most participants were female, reflecting the typical gender composition of teacher education programmes. In terms of age, the largest group was in the 18–25 bracket, followed by participants in the 26–30 and 31–35 brackets. Smaller numbers were in the 35–40 and 41 above brackets. This distribution shows s a sample that is predominantly young adult pre-service teachers, with some representation of mid-career entrants into teacher education.

Table 1: Demographics of Participants

		Age					Total
		18-25	26-30	31-35	35-40	41 & Above	
Gender	Male	3	3	2	2	2	12
	Female	41	18	20	17	8	104
Total		44	21	22	19	10	116

Instruments

Four self-report instruments were used for data collection, all developed by the researchers following an extensive review of literature on ethical AI use and learning patterns. Ethical AI Use (EAIU) scale, comprised of 10 items, measured pre-service teachers' awareness, attitudes, and self-reported practices regarding the ethical use of AI in academic tasks, for example, information search, content generation, assignments, and assessment support. Deep Learning Pattern (DLP) scale, comprised of 5 items, assessed meaningful and conceptually rich learning, including critical thinking, integration of ideas, and deep understanding of course content. Strategic Learning Pattern (StLP) scale, comprised of 5 items, assessed goal-oriented learning behaviours such as planning, time management, organisation of study activities, and exam-oriented strategies. Surface Learning Pattern (SuLP) scale, comprised of 5 items, measured rote learning, minimum-effort strategies, over-reliance on shortcuts, and a focus on merely completing tasks. All items were rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

The internal consistency of each instrument was checked using Cronbach's alpha (α) in SPSS. Content and face validity were ensured through expert review by specialists in teacher education, educational psychology, and educational technology. Minor phrasing revisions were made based on their feedback. Detailed reliability and factor analysis results are presented in the Data Analysis section.

DATA ANALYSIS AND RESEARCH FINDINGS

Data analysis and hypothesis testing were conducted using SPSS. After data entry and coding, exploratory factor analysis (EFA) and reliability analysis were performed to validate the measurement instruments. Composite scores for each construct – EAIU, DLP, StLP, and SuLP – were then computed, and simple linear regression analyses were performed to test the study hypotheses.

Kaiser–Meyer–Olkin (KMO) and Bartlett's Test

KMO test is performed to check collected sample sufficiency for running factor analysis and computing variables. Before running factor analysis, the values of KMO and Bartlett's test were checked. KMO test was performed for checking sampling adequacy. The KMO value, as shown in Table 2, was .866 which exceeded the minimum acceptable value of .50 (Kaiser & Rice, 1974, as cited in Siddiqui et al., 2018). It indicated that the sampling adequacy was high and the correlation patterns were compact enough to yield reliable factors. This suggested that the data were suitable for factor analysis. Bartlett's test of sphericity identifies that correlation matrix is not an identity matrix. The Bartlett's test of sphericity should be significant ($p < .05$) for factor analysis to be suitable (Bartlett, 1950, as cited in Siddiqui et al., 2018). As shown in Table 2, the Bartlett's Test of Sphericity was significant at $p < .001$, indicating that the correlation matrix was not an identity matrix. In other words, the items were found to be sufficiently interrelated to justify the application of factor analysis. Together, these results confirmed that factor analysis was appropriate for the 25 items used in this study.

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.866
Bartlett's Test of Sphericity	Approx. Chi-Square	1410.302
	df	300
	Sig.	.000

Factor Analysis

Principal Component Analysis (PCA) with Varimax rotation was used to examine the underlying structure of the 25 items corresponding to the four factors in the instrument. Table 3 presents the rotated factor loadings for the four main components corresponding to Ethical AI Use (EAIU), Deep Learning Pattern (DLP), Strategic Learning Pattern (StLP), and Surface Learning Pattern (SuLP). All 10 EAIU items loaded positively on the EAIU factor, with loadings ranging from .408 to .774. The 5 DLP items loaded on a distinct factor, with loadings between .508 and .804. The 5 StLP items loaded on a third factor, with loadings between .469 and .734. The 5 SuLP items loaded strongly on a fourth factor, with loadings between .581 and .864.

Table 3: Factor Loadings

Items	EAIU	DLP	StLP	SuLP
EAIU1	.774			
EAIU2	.627			
EAIU3	.553			
EAIU4	.503			
EAIU5	.597			
EAIU6	.455			
EAIU7	.494			
EAIU8	.616			
EAIU9	.454			
EAIU10	.408			
DLP1		.801		
DLP2		.804		
DLP3		.610		
DLP4		.508		
DLP5		.745		
StLP1			.575	
StLP2			.469	
StLP3			.579	
StLP4			.591	
StLP5			.734	
SuLP1				.792
SuLP2				.864
SuLP3				.812
SuLP4				.687
SuLP5				.581
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				

Factor loadings greater than .40 are generally considered acceptable indicators of a meaningful relationship between an item and its underlying factor (Hair et al., 2019). In this study, all items loaded at or above this threshold on their respective factors, and cross-loadings were minimal. This pattern supports the construct validity of the four-dimensional structure: one factor for Ethical AI Use and three distinct factors for the learning patterns: deep, strategic, and surface.

Total Variance Explained

The four components of the instrument together accounted for approximately 56.62% of the total variance in the items after extraction. After rotation, the variance was more evenly distributed across the four factors, with each factor contributing meaningfully to the explained variance. A total explained variance of around 50–60% is generally acceptable in social science research (Tabachnick & Fidell, 2019). The four-factor structure explains a substantial proportion of the variability in responses, indicating that the measurement model captures the core dimensions of Ethical AI Use and learning patterns among pre-service teachers.

Reliability Analysis

The instrument reliability was assessed using Cronbach's alpha (α). As shown in Table 4, Ethical AI Use (10 items) yielded α = .825, Deep Learning Pattern (5 items) yielded α = .838, Strategic Learning Pattern (5 items) yielded α = .837, and Surface Learning Pattern (5 items) yielded α = .831. In this way, all four scales demonstrated good internal consistency, with Cronbach's α values above .80. These values exceed the commonly accepted threshold of .50 (Cronbach, 1951, as cited in Siddiqui et al., 2018), indicating that the items within each scale measure the same underlying construct in a consistent manner. The Ethical AI Use scale and each learning pattern scale was therefore considered reliable for further analysis.

Table 4: Reliability Statistics

Variable	**Number of Items**	**Cronbach's alpha (α)**
Ethical AI Use	10	.825
Deep Learning	5	.838
Strategic Learning	5	.837
Surface Learning	5	.831

Regression Analysis

Simple linear regression was performed to examine the impact of Ethical AI Use (EAIU) on each learning pattern: Deep Learning Pattern (DLP), Strategic Learning Pattern (StLP), and Surface Learning Pattern (SuLP). As shown in Table 5, Ethical AI Use was found to be a significant positive predictor of the Deep Learning Pattern among pre-service teachers. The coefficient (B = 0.404) suggests that, on average, a one-unit increase in Ethical AI Use is associated with a 0.404-point increase in Deep Learning Pattern scores, holding other factors constant. The model explains about 48.1% of the variance in deep learning (R^2 = .481), which is a substantial proportion in educational research. The high F-value and its significance ($p < .001$) further confirm that the overall regression model is statistically significant. These results support H_1, indicating that higher ethical use of AI is associated with more pronounced deep learning behaviours, such as critical thinking and conceptual understanding.

Table 5: Regression Analysis on EAIU and DLP

Variables	B	T	T (Sig.)	F-Value	F (Sig.)	R	R Square	Adjusted R Square
(Constant)	4.72	3.097	0.002	105.576	.000[b]	.693[a]	0.481	0.476
Deep Learning Pattern	0.404	10.28	.000					

Ethical AI Use, as shown in Table 6, also significantly predicted the Strategic Learning Pattern. The coefficient (B = 0.446) indicates that a one-unit increase in Ethical AI Use corresponds to an average 0.446-point increase in Strategic Learning Pattern scores. This model explains 53.0% of the variance in strategic learning ($R^2 = .530$), which is slightly higher than that for deep learning and indicates a strong association. The F-statistic is large and highly significant, confirming that the model provides a good fit to the data. These findings support H_2, suggesting that when pre-service teachers use AI ethically, they are more likely to engage in strategic behaviours such as planning their studies, managing time, and adopting exam strategies.

Table 6: Regression Analysis on EAIU and StLP

Variables	B	T	T (Sig.)	F-Value	F (Sig.)	R	R Square	Adjusted R Square
(Constant)	2.751	1.802	.074	128.328	.000[b]	.728[a]	.530	.525
Strategic Learning Pattern	.446	11.328	.000					

As shown in Table 7, Ethical AI Use was found to be a significant negative predictor of Surface Learning Pattern. The coefficient (B = –0.153) indicates that, on average, a one-unit increase in Ethical AI Use is associated with a 0.153-point decrease in surface learning scores. However, the effect size is modest: Ethical AI Use explains about 4.2% of the variance in surface learning ($R^2 = .042$). While the relationship is statistically significant ($p = .028$), the relatively low R^2 suggests that surface learning is influenced by many other factors beyond ethical AI use, such as prior learning habits, assessment culture, or institutional expectations. These results support H_3, indicating that higher levels of ethical AI use are associated with lower tendencies toward surface learning, although the magnitude of this effect is small.

Table 7: Regression Analysis on EAIU and SuLP

Variables	B	T	T (Sig.)	F-Value	F (Sig.)	R	R Square	Adjusted R Square
(Constant)	18.900	7.098	.000	4.940	.028[b]	.204[a]	.042	.033
Surface Learning Pattern	-.153	-2.223	.028					

Overall, the findings suggest that promoting ethical use of AI among pre-service teachers is associated with more desirable learning patterns (deep and strategic) and reduced reliance on surface-level approaches.

DISCUSSION & CONCLUSION

This study sought to investigate the impact of Ethical Artificial Intelligence Use (EAIU) on the Deep Learning Pattern (DLP), Strategic Learning Pattern (StLP), and Surface Learning Pattern (SuLP) of pre-service teachers enrolled in a public sector university in Karachi, Pakistan. The regression results showed that ethical AI use significantly and positively predicted deep learning and strategic learning, while it negatively predicted surface learning. These findings provide strong empirical support for all three proposed hypotheses (H_1–H_3).

The first major finding showed that Ethical AI Use significantly and positively predicts Deep Learning Pattern, explaining a substantial proportion of the variance (R^2 = .481). This result suggests that when pre-service teachers use AI responsibly and ethically, they are more likely to adopt learning approaches like critical thinking, conceptual understanding, and intrinsic academic engagement. This finding is consistent with international studies indicating that ethically guided use of generative AI enhances reflective thinking and higher-order cognition (Kasneci et al., 2023; Chan & Hu, 2023).

The second key finding revealed that Ethical AI Use is an even stronger predictor of Strategic Learning Pattern (R^2 = .530). This indicates that ethically responsible AI users tend to demonstrate better planning, time management, goal-setting, and performance-oriented learning behaviours. This result supports the argument that ethical AI use functions as a self-regulatory learning scaffold, rather than merely a content-generation shortcut. Recent research similarly shows that controlled and reflective AI use enhances students' study efficiency and academic performance when embedded within goal-oriented learning routines (Ashraf et al., 2025). Within teacher education, this is particularly important because strategic learning skills are foundational to professional teaching competence, lesson planning, and classroom organization.

The third finding demonstrated that Ethical AI Use negatively predicts Surface Learning Pattern, although the effect size was modest (R^2 = .042). This indicates that as ethical AI use increases, tendencies toward rote memorization, minimal effort, and shortcut-based academic behaviour decline. However, the relatively low variance explained suggests that surface learning is influenced by multiple competing factors beyond AI use. However, the statistically significant negative relationship confirms that unethical AI practices such as blind copying, and over-reliance on auto-generated answers, are directly linked with surface-level learning behaviours, as also warned by Stokel-Walker and Van Noorden (2023).

From a Pakistani perspective, these findings are highly significant. While recent studies confirm that Pakistani university students increasingly use AI tools such as ChatGPT (Balqees et al., 2024; Ashraf et al., 2025), concerns about weak digital ethics, plagiarism, and lack of institutional AI governance remain widespread (Azeem et al., 2025). This study extends that body of work by showing that ethical readiness is not merely a moral issue, but it is directly linked to the quality of learning itself. Pre-service teachers who demonstrate ethical AI behaviour are not only more honest academically but also better learners cognitively and strategically. The findings also strongly support a recent UNESCO's position that ethical AI literacy should be treated as a core professional competency for teachers, not merely as a regulatory requirement (Holmes & Miao, 2023). Since pre-service teachers serve as future role models of digital behaviour, their current AI practices are likely to be replicated in school classrooms. If ethical AI use is not explicitly taught and assessed during teacher preparation, there is a serious risk of normalizing unethical digital shortcuts in future generations of learners.

The study recommends that Ethical Artificial Intelligence Use should be integrated as a compulsory component of all pre-service teacher education programmes to promote responsible digital learning practices. Teacher educators should receive regular professional development on ethical AI use to model responsible practices in teaching, assessment, and research supervision. Universities should establish clear institutional AI ethics policies defining acceptable use, disclosure requirements, and penalties for misuse. The Higher Education Commission of Pakistan should issue national ethical AI guidelines, link ethical AI literacy with accreditation standards, and support AI-ethics research across Pakistani universities.

Despite its contributions, this study has certain limitations. The data were collected from a single public sector university, which may limit generalizability. The study relied on self-reported measures, which may be influenced by social desirability bias. The relatively low R^2 value for surface learning indicates that additional psychological, institutional, and cultural predictors should be examined in future research. Future studies may use mixed-method designs to explore how students actually use AI during learning tasks, investigate discipline-wise differences in ethical AI use and learning patterns, and examine mediating variables such as self-regulated learning, assessment pressure, and digital anxiety. Longitudinal studies can also be conducted to track how ethical AI habits evolve across teacher education programmes.

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