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Impact of Ethical Artificial Intelligence Governance on Teachers' Technology Acceptance in Universities

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ABSTRACT

Universities have embraced artificial intelligence at a rapid pace, and the effects are visible across teaching, assessment, and administration. Personalized learning tools, adaptive grading, learning analytics, and administrative automation all promise efficiency gains, yet none of these gains materialize unless teachers are actually willing to use the tools. Whether AI succeeds or stalls in a classroom has less to do with how sophisticated the technology is and more to do with whether teachers judge the governance surrounding it to be fair, transparent, accountable, and respectful of data privacy. Concerns about algorithmic bias, the opacity of AI decision-making, the handling of student data, and the erosion of professional judgment are common among faculty, and these concerns shape how readily AI tools are taken up. Despite the practical importance of this relationship, empirical research linking ethical AI governance to teachers' technology acceptance in higher education remains limited. This study addresses that gap by testing the effect of ethical AI governance on teachers' technology acceptance, using the Technology Acceptance Model (TAM) as the guiding theoretical lens. Specifically, it examines how three governance dimensions transparency, accountability, and data privacy - relate to teachers' acceptance of AI and their behavioral intention to use it. Data were collected through a structured questionnaire administered to university teachers across several higher education institutions, and the proposed relationships were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that ethical AI governance, taken as a whole, has a significant positive effect on teachers' acceptance of AI technologies, with data privacy and transparency emerging as the strongest predictors. Accountability, by contrast, did not show a statistically significant direct effect on acceptance, suggesting that its influence may operate indirectly - through trust or transparency - rather than as a standalone driver of adoption. Technology acceptance itself was a strong predictor of behavioral intention, indicating that once teachers come to accept AI, that acceptance translates readily into a willingness to use it in practice. These findings extend the TAM literature by incorporating ethical governance as a substantive antecedent of acceptance, and they offer a more textured picture of AI adoption in university settings, one in which governance dimensions do not all carry equal weight. The practical implication is straightforward: universities that want faculty to embrace AI need to invest in credible, visible, and specific governance mechanisms - particularly around data privacy and transparency - rather than treating ethical AI governance as a single, undifferentiated policy commitment.

1. Introduction

The rapid development of artificial intelligence has become one of the most transformative forces shaping modern societies, economies, and institutions. Over the past several years, higher education has emerged as a critical arena for AI integration, driven by demands for digital transformation, personalized learning, data-informed decision-making, and institutional efficiency. Universities worldwide are deploying AI-powered tools - learning management systems enhanced with analytics, automated grading engines, adaptive learning platforms, plagiarism detection software, chatbots, and intelligent tutoring systems - in the hope of improving both educational delivery and administrative processes (Zawacki-Richter et al., 2024). These innovations carry real promise, but their success depends fundamentally on whether teachers, as the key actors in educational practice, are willing to engage with them.

Technology acceptance among teachers has long been recognized as a critical determinant of successful technology integration; teachers' attitudes, beliefs, and perceptions can make or break the effective use of new tools in the classroom (Wang et al., 2024). Established models such as Davis's Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) identify perceived usefulness, perceived ease of use, performance expectancy, and effort expectancy as the main predictors of adoption (Schorr, 2023). AI complicates this picture. Unlike conventional educational technology, AI systems often operate through opaque algorithms, rely on extensive data collection, and can act with a degree of autonomy that influences instructional decisions. As a result, ethical considerations have become central to how teachers evaluate whether to adopt AI tools, in a way that goes beyond the traditional concerns of usability and performance (Marikyan & Papagiannidis, 2023). The data-driven and often opaque nature of AI systems has made privacy and bias particularly salient concerns for educators (Floridi & Cowls, 2022).

Ethical AI governance refers to the mechanisms, policies, principles, and institutional arrangements that secure the design, deployment, and use of AI systems in an ethical and transparent way. International bodies such as the OECD and UNESCO have called for governance frameworks that keep AI human-centred, trustworthy, and inclusive, with education singled out as a particularly sensitive domain (Duoblienė et al., 2023). In practice, this can mean explicit policies on data protection, algorithmic transparency, accountability structures, and professional training on the ethical use of AI. These mechanisms matter because they are, in principle, what allow institutions to address teachers' ethical concerns and build trust in AI-powered tools. Yet empirical evidence on this link remains thin, especially in higher education: most existing research has focused on students' perceptions of educational technology or on the technical mechanics of AI implementation, while teachers' perspectives - despite their central role in technology integration - have received comparatively little attention. Understanding how ethical AI governance shapes teachers' acceptance of AI is therefore essential for institutions pursuing sustainable and responsible digital transformation.

Ethical concerns take on particular weight in education because of the sensitivity of student and teacher information, the risk of algorithmic bias, and the consequences of automated decision-making for academic autonomy and fairness. AI systems deployed in universities can involve collecting personal information, monitoring learning processes, forecasting student performance, and even recommending teaching strategies. These capabilities may improve teaching effectiveness, but they also raise questions about privacy, surveillance, data ownership, transparency, accountability, and equity (Eynon et al., 2025). Teachers, who are simultaneously

users of and subjects within these systems, may reasonably question whether AI technologies align with their professional values, pedagogical commitments, and institutional responsibilities.

In response to these concerns, the concept of ethical AI governance has gained traction among policymakers, researchers, and educational leaders as a collection of institutional policies, regulatory frameworks, ethical principles, and oversight mechanisms intended to keep AI systems ethical, responsible, transparent, and human-centred (Floridi & Cowls, 2022). Both the OECD (2019) and UNESCO (2021) have emphasized the importance of such governance for building trustworthy AI, particularly in education. At the university level, this can take the form of data protection policies, algorithmic transparency guidelines, ethical review boards, and professional development programs aimed at strengthening faculty understanding of AI.

Despite the prominence of ethical principles at the policy level, there remains a substantial gap between global-level commitments and their implementation on the ground. Many universities have adopted AI tools without a corresponding governance framework, leaving teachers uncertain about who is responsible for addressing ethical issues as they arise (Selwyn, 2022). This ambiguity can breed mistrust and dampen both acceptance and use of AI technologies. Trust, in turn, has been identified as an important mediator between ethical perceptions and technology acceptance, particularly in contexts involving automation and algorithmic decision-making (Lee et al., 2025). Perceptions of fairness, transparency, and accountability feed directly into this trust: teachers who believe algorithms are explainable, that decisions can be contested, and that institutional safeguards exist to prevent misuse are considerably more likely to accept AI technologies (Holmes, 2024). Where such assurances are absent, concerns about bias, privacy breaches, or excessive monitoring tend to produce resistance, anxiety, and skepticism - reactions that are especially pronounced in universities, where academic freedom and professional autonomy are deeply held values.

Although technology acceptance in education has been studied extensively, relatively few studies explicitly incorporate ethical AI governance as a factor shaping teachers' acceptance decisions. Much of the existing literature centers on students' experiences or on the technical and pedagogical effects of AI tools, with institutional governance structures and ethical safeguards receiving comparatively little empirical attention (Zawacki-Richter, 2022). Where ethics is addressed, the treatment is often conceptual rather than empirical, leaving a clear need for data-driven work that examines how governance mechanisms actually relate to teachers' attitudes and behavior.

This gap is compounded by a theoretical one. TAM and UTAUT were developed in settings where ethical considerations were not especially salient, and both have been criticized for their limited attention to ethical and normative dimensions of technology use (Schorr, 2023). As AI systems become more autonomous and less transparent, a more comprehensive analytical framework is needed - one that incorporates governance alongside the cognitive and behavioral variables that TAM and UTAUT already capture. Recent scholarship has suggested adding trust, perceived risk, and ethical alignment to models of AI acceptance, particularly in professional and institutional settings (Shin et al., 2022).

Several mechanisms plausibly link ethical AI governance to teachers' technology acceptance. Clear governance policies can improve the perceived transparency of AI systems by explaining how they work, what data they draw on, and how decisions are reached - reducing uncertainty and helping teachers judge whether a tool fits their educational objectives and ethical standards (Floridi & Cowls, 2022). Governance mechanisms centered on accountability, such as clearly assigned responsibility for AI-related decisions, can strengthen teachers' confidence that potential harms

will be addressed. Governance frameworks emphasizing data protection and privacy can ease concerns about surveillance and misuse of personal information. And participatory governance models, which involve teachers directly in decision-making, can foster a sense of ownership that further supports acceptance.

These dynamics are likely to be especially pronounced in developing countries and emerging economies, where regulatory frameworks for AI are less mature and institutional capacity varies considerably. Universities in such settings may face additional constraints - limited resources, uneven AI literacy, and weaker data safeguards - that make teachers more attentive to ethical risk in the absence of strong institutional protections. Cultural context adds a further layer: attitudes toward automation, institutional authority, and ethical regulation are shaped by cultural values such as uncertainty avoidance, power distance, and collectivism (Minkov & Kaasa, 2022). For university leaders and policymakers, the implication is that AI adoption strategies need to account for ethical and cultural readiness alongside technological readiness. Treating ethical governance merely as a compliance requirement risks underutilization, resistance, or unintended harm; treated instead as a catalyst for trust, legitimacy, and values alignment, it can meaningfully support the long-term success of AI initiatives in higher education.

Motivated by these gaps, this study examines the effect of ethical AI governance on teachers' technology acceptance in universities, integrating governance dimensions - transparency, accountability, and data privacy - with an established technology acceptance framework. In doing so, the study makes three contributions. First, it extends the technology acceptance literature by introducing ethical AI governance as a central explanatory factor, addressing a gap that existing models have largely overlooked. Second, it contributes to the broader literature on AI in education by moving beyond technical and pedagogical questions toward institutional and ethical ones. Third, it offers practical guidance for university leaders, policymakers, and educational technology developers seeking to design and deploy AI solutions that faculty are more likely to trust and adopt. As AI continues to reshape higher education, understanding the ethical factors that influence its uptake is not a peripheral concern but a central one: acceptance cannot simply be assumed, and it is more likely to be earned through governance that is transparent, accountable, and genuinely responsive to teachers' concerns.

2. Literature Review

2.1 Artificial Intelligence in Higher Education

Artificial intelligence has become one of the most influential forces reshaping higher education, touching teaching and learning, assessment, institutional management, and student support. Universities now use AI to build intelligent tutoring systems, adaptive learning platforms, learning analytics dashboards, automated grading engines, plagiarism detection software, student-facing chatbots, and predictive retention systems (Zawacki-Richter, 2022). Collectively, these tools promise gains in teaching efficiency, personalization, and evidence-based decision-making at both the classroom and institutional level.

Several forces have combined to push AI to the center of higher education: rapid technological progress, an unprecedented volume of student learning data, and mounting institutional pressure to remain competitive. Researchers have cautioned, however, that adopting AI in academic settings is not merely a technical undertaking. Selwyn (2022) frames it as a genuine socio-technical shift - one that unsettles established academic practice, redefines professional identity, and challenges

institutional values. Within this shift, teachers occupy a distinct and consequential role: they are the first line of responsibility for translating AI's technical capabilities into meaningful learning outcomes, and their receptiveness (or resistance) shapes how much benefit institutions actually realize from their investment in AI.

Even as AI use has expanded, its transformative potential is often underrealized. Holmes (2024) attributes this to persistent resistance, limited trust, and unresolved ethical concerns among teachers - a pattern that suggests teachers' engagement with AI depends on more than technical literacy alone. Trust, ethics, and institutional governance appear to matter just as much, which makes it essential to understand what encourages or discourages teachers from adopting AI responsibly.

2.2 Teachers' Role in AI Adoption

Teachers are arguably the most consequential group in determining how AI is implemented and used in higher education, since their decisions to adopt, adapt, or reject AI systems shape outcomes across the institution (Chen et al., 2025). Where students tend to focus on the usefulness and usability of AI tools for learning, teachers must weigh a broader set of considerations - pedagogical integrity, institutional accountability, academic freedom, and professional responsibility.

Empirical work suggests that teachers' acceptance of AI is shaped by an interplay of factors, including technological self-efficacy, institutional support, perceived relevance to teaching goals, and ethical alignment (Kong et al., 2023). A recurring theme is how teachers interpret AI's role: when AI is positioned as a complement to teacher expertise rather than a replacement for it, acceptance tends to be considerably higher. Where AI is instead associated with automated evaluation, algorithmic monitoring of classroom performance, or a loss of academic autonomy, resistance tends to follow.

Beyond questions of usefulness and autonomy, teachers frequently find themselves acting as moral gatekeepers within their institutions, weighing the fairness, inclusivity, transparency, and student-welfare implications of AI systems. These ethical considerations are not peripheral to how teachers see their professional role; they are central to it, and they shape how willing teachers are to bring AI into their teaching practice.

2.3 Technology Acceptance Theories

The Technology Acceptance Model (TAM), as discussed by Shahid et al. (2024), remains one of the most widely used frameworks for explaining how individuals come to accept new technologies. Its central claim is that two beliefs - perceived usefulness and perceived ease of use - shape users' attitudes toward a technology and, in turn, their intention to use it. Perceived usefulness reflects a user's expectation that the technology will improve task performance, while perceived ease of use reflects the belief that the technology is not unduly difficult to operate. TAM has been applied extensively in education and has proven a reliable predictor of teachers' adoption of instructional technologies (Yeo et al., 2022).

TAM has also drawn criticism for its narrow focus on cognitive factors, which leaves social, ethical, and contextual influences on adoption largely unaddressed. This limitation becomes more pressing as AI introduces complications that earlier technologies did not raise. Rai (2020) argues that theoretical extensions incorporating ethical governance, institutional trust, and perceived risk are needed, particularly in high-stakes professional contexts such as university teaching.

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), synthesizes eight prior acceptance models and identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as the primary drivers of technology use. Performance expectancy captures how useful a person expects a technology to be for their professional tasks; effort expectancy reflects anticipated ease of use; social influence captures the degree to which important others encourage use; and facilitating conditions reflect the organizational and technical support available.

UTAUT has been applied fruitfully across a range of educational technology studies, including AI-integrated learning systems, and often outperforms TAM in explanatory power. Even so, it shares TAM's relative inattention to ethics and governance. As concerns about data use, algorithmic accountability, and fairness become more prominent alongside increasingly complex AI systems, Shin (2021) suggests that UTAUT needs to explicitly incorporate ethical governance constructs if it is to remain theoretically adequate for AI adoption contexts.

2.4 Trust and Perceived Risk in AI Adoption

Trust is widely regarded as one of the central psychological factors influencing AI adoption, particularly in professional and institutional environments. In the context of AI, trust reflects users' confidence in the reliability, correctness, fairness, transparency, and ethical grounding of a system (Gefen et al., 2003). In higher education specifically, trust in AI is closely tied to perceptions of how algorithmic decisions are made, how institutional data is collected and used, and how accountable the institution is for AI-driven processes.

Perceived risk works in the opposite direction, capturing the apprehension users feel about using AI - concerns about unauthorized data access, biased or inaccurate outputs, diminished professional autonomy, and reduced control over pedagogical decisions (Shin, 2021). Perceived risk has been shown to consistently dampen teachers' willingness to use AI, even when they otherwise view the technology as useful - a pattern that underscores just how central trust and risk perception are to successful AI adoption.

Ethical AI governance functions as an institutional lever for managing this dynamic: transparent data policies, algorithmic accountability frameworks, and clearly defined ethical review procedures can directly ease teachers' concerns about the risks associated with AI. Where teachers perceive that their institution is not taking these ethical issues seriously, acceptance tends to suffer noticeably.

2.5 Ethical Issues in Educational AI

Data privacy is among the most pressing ethical concerns associated with AI in education. AI systems typically depend on the ongoing collection and analysis of substantial volumes of personal and behavioral data - academic records, engagement metrics, learning trajectories, and in some cases biometric data. AI-based monitoring tools can extend this scrutiny to teachers themselves, tracking teaching behaviors, course delivery patterns, and student outcomes (Williamson & Eynon, 2020). Concerns about unauthorized data access, institutional surveillance, and data misuse have a demonstrable effect on educators' trust in AI systems, a concern sharpened by teachers' own institutional and ethical responsibility to protect student privacy. Where data governance policies are unclear or difficult to interpret, these concerns intensify, making data privacy one of the most significant barriers to AI adoption among university faculty.

A second major ethical concern is algorithmic bias. AI systems trained on historically biased or unrepresentative data can inadvertently reproduce and amplify existing inequities, generating discriminatory outcomes for students grouped by gender, race, ethnicity, disability status, or socioeconomic background (O'Neil, 2016). When teachers suspect that AI-driven recommendations or automated evaluations are systematically unfair or unreliable, their willingness to trust or rely on these tools declines. Institutional responses - regular algorithmic audits, more diverse and representative training data, transparent reporting of model limitations, and accessible channels for questioning algorithmic decisions - can help address these concerns. Where governance mechanisms visibly address fairness, teacher confidence in AI systems, and acceptance of them, tends to follow.

Transparency and explain ability form a third pillar of responsible AI governance, and both are closely linked to trust and acceptance. Teachers are considerably more likely to adopt AI tools when they understand the underlying logic well enough to explain it to students and assess its instructional implications (Holmes et al., 2022). Black-box systems - opaque by design - tend to generate discomfort and ethical unease among educators, who are professionally trained to expect rational justification and accountability. The emergence of Explainable AI (XAI) reflects an effort to make AI decision-making more interpretable and auditable for non-expert users, and empirical work suggests that XAI can meaningfully improve acceptance by fostering a stronger sense of transparency and legitimacy (Shin, 2021). In higher education, establishing standards for explain ability is not just a governance matter; it is also a marker of a genuinely ethical AI culture.

2.6 Ethical AI Governance

Ethical AI governance encompasses the institutional frameworks, ethical principles, regulatory structures, and organizational practices that collectively shape the responsible development, deployment, and evaluation of AI. Floridi et al. (2018) define it as a unified set of principles, regulations, and organizational duties addressing the ethical dimensions of AI use. Understood this way, governance is not a static policy document but an ongoing institutional process that actively shapes how AI is used and evaluated.

In universities, ethical AI governance can take several forms: data protection and privacy policies, ethical review boards with real decision-making authority over AI use, transparency guidelines for algorithmic systems, safeguards for academic freedom, professional development opportunities for faculty, and formal mechanisms for raising and resolving AI-related concerns. Effective governance of this kind is central to building trustworthy, human-centred AI systems that serve the interests of both learners and teachers, a position echoed in international policy guidance from the OECD (2019) and UNESCO (2021).

Prior research suggests that strong governance enhances institutional legitimacy - faculty's trust that the university operates in accordance with accepted ethical standards - and that this legitimacy, in turn, strengthens both faculty trust and technology acceptance (Rai, 2020). While there is broad consensus that ethical AI governance matters, empirical work directly examining how governance practices shape teachers' actual acceptance behavior remains relatively limited.

2.7 Ethical Governance and Technology Acceptance

The relationship between ethical governance and technology acceptance has been studied empirically in other institutional contexts, including e-government services, health information systems, and financial technology platforms. Across these domains, a consistent finding emerges:

governance mechanisms that visibly mitigate ethical risk - through transparency, accountability, fairness assurance, and data protection - tend to strengthen user trust, reduce perceived risk, and support acceptance (Gefen et al., 2003; Shin, 2021).

Ethical governance also shapes institutional legitimacy more broadly. Clear policy frameworks, faculty involvement in AI policy development, functioning ethical review processes, and transparent data practices all signal that AI use is institutionally endorsed, ethically grounded, and professionally appropriate - a signal that carries particular weight in academic communities, where norms around institutional ethics run especially high.

Much of the existing empirical work on governance and AI acceptance in education, however, remains policy-oriented, focusing on the content of governance documents rather than on how teachers actually perceive, evaluate, and respond to them in practice. Understanding teachers' lived experience of AI governance - rather than simply the existence of governance frameworks - is essential for designing governance strategies that genuinely foster acceptance.

3. Methodology

3.1 Research Design and Approach

This study used a quantitative, deductive research design to test the effect of ethical AI governance on university teachers' technology acceptance. A quantitative approach was chosen because it allows for precise, replicable measurement of perceptions, attitudes, and inter-construct relationships, and supports rigorous statistical testing of theoretically derived hypotheses. Data were collected using a cross-sectional survey design, in which responses were gathered from university faculty at a single point in time - an approach consistent with established practice in technology acceptance research and well suited to the study's goal of capturing overall perceptions and testing structural relationships among latent variables (Hair et al., 2019).

The study adopts a post-positivist epistemological stance, on the premise that social phenomena such as technology acceptance can be observed, measured, and explained through causal relationships, while acknowledging the inherent uncertainty involved in measurement. This stance is consistent with the use of self-reported survey measures and probabilistic statistical inference, both of which underpin the study's methodology.

3.2 Population and Sampling

The study population comprised full-time and part-time faculty members at public and private universities. University teachers were selected as the unit of analysis because they are the primary implementers and critical evaluators of AI technologies in higher education. Their perspectives carry particular weight for institutional AI strategy, given their pedagogical authority and ethical accountability.

A non-probability sampling approach - combining purposive and convenience sampling - was used to accommodate practical constraints. Eligible participants had prior experience with, or working knowledge of, at least one AI-powered tool relevant to their professional role, such as AI-enhanced learning management systems, automated assessment tools, AI-powered plagiarism detection software, or AI-integrated institutional analytics. This criterion ensured that respondents could evaluate the constructs under study based on direct experience rather than speculation. Within this purposively defined population, convenience sampling was then used to collect data within the

study's time and resource constraints, a practice consistent with the broader methodological tradition of technology acceptance research.

3.3 Instrument Development

Data were gathered using a structured, self-administered questionnaire developed specifically for this study. The instrument was organized into three sections. The first captured demographic characteristics, including gender, academic rank, years of teaching experience, and institutional affiliation. The second addressed the theoretical dimensions of ethical AI governance - transparency, accountability, fairness, and data privacy - operationalized through items adapted from existing measures in the ethical AI and technology governance literature to ensure content validity and theoretical grounding. The third section assessed teachers' technology acceptance based on constructs drawn from TAM and UTAUT, including perceived usefulness, perceived ease of use, trust, and behavioral intention to use AI technologies.

All reflective items were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), a scaling approach that allows for reasonably precise quantitative representation of respondents' perceptions and is standard practice in survey-based technology acceptance research. Before full deployment, a panel of subject matter experts in educational technology, AI ethics, and research methodology reviewed the questionnaire for content and face validity. A pilot study with a small sample of university teachers followed, testing item clarity, internal consistency, and overall instrument reliability; feedback from this pilot phase was used to revise item wording and improve scale performance.

3.4 Data Collection Procedure

To accommodate differences in respondents' access to digital platforms and their individual preferences, data were collected through both online and paper-based methods. Surveys were distributed via institutional email networks and academic professional networks, and paper questionnaires were administered in person at participating institutions. Participation was entirely voluntary; respondents received a standardized information sheet outlining the study's academic purpose, the nature of participation, and applicable confidentiality protections before taking part.

Standard ethical procedures were followed throughout data collection. Informed consent was obtained from all participants, anonymity was preserved, and no personally identifiable information was collected at any stage. All data were used exclusively for research purposes, and participants retained an unconditional right to withdraw at any time without consequence.

3.5 Analytical Strategy

Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented in SmartPLS 4, served as the primary analytical method. PLS-SEM was selected over covariance-based SEM for several reasons: it is well suited to theory extension and exploratory research, performs well with non-normally distributed data, accommodates multiple latent constructs with multiple indicators, and does not impose strict minimum sample size requirements (Hair et al., 2019). These characteristics made it an appropriate fit for a study that builds on established theory to explore a relatively new governance-related construct space.

Following the two-phase approach recommended by Hair et al. (2019), the analysis first assessed the measurement model and then the structural model. Measurement model assessment examined outer loadings, internal consistency (via Cronbach's Alpha and Composite Reliability), convergent

validity (via Average Variance Extracted), and discriminant validity (via the Fornell-Larcker criterion). Structural model assessment used bootstrapping with 5,000 resamples to derive path coefficients and their significance, the coefficient of determination (R^2) to gauge explanatory power, the f^2 statistic for effect sizes, and the blindfolding procedure with the Q^2 statistic to assess predictive relevance.

Descriptive statistics were used to characterize the demographic profile of respondents and examine the distribution of the data, and reliability analysis via Cronbach's Alpha was conducted prior to structural model evaluation. Common method variance was addressed through procedural safeguards, including respondent anonymity and questionnaire structuring intended to minimize response bias.

4. Data Analysis and Results

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, chosen for its suitability to predictive, theory-extending research involving latent variables, non-normally distributed data, and a moderate sample size (Hair et al., 2019). Measurement model evaluation for reliability and validity preceded structural model evaluation of the hypothesized relationships, following the standard two-step sequence.

4.1 Descriptive Statistics and Demographic Profile

The sample consisted of university teachers from public and private universities, spanning academic ranks from Lecturer to Associate Professor and a diverse range of teaching experience. Demographic details are summarized in Table 1. Preliminary screening identified no major concerns related to missing data, response patterns, or distributional outliers.

Table 1: Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	178	64.5
	Female	98	35.5
Academic Rank	Lecturer	134	48.6
	Assistant Professor	98	35.5
	Associate Professor	44	15.9
Teaching Experience	1–5 Years	109	39.5
	6–10 Years	95	34.4
	Above 10 Years	72	26.1

4.2 Measurement Model Assessment

The measurement model was assessed in line with established PLS-SEM standards (Hair et al., 2019), covering indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All outer loadings exceeded the 0.70 threshold, indicating that each indicator reliably measured its intended construct. Table 2 reports the outer loadings for the measurement model.

Table 2: Outer Loadings of Measurement Items

Construct	Item	Outer Loading
Ethical AI Governance (EAIG)	EAIG1	0.81
	EAIG2	0.84

Construct	Item	Outer Loading
	EAIG3	0.79
Transparency (TR)	TR1	0.82
	TR2	0.85
	TR3	0.81
Accountability (ACC)	ACC1	0.80
	ACC2	0.83
	ACC3	0.84
Data Privacy (DP)	DP1	0.86
	DP2	0.88
	DP3	0.86
Technology Acceptance (TA)	TA1	0.84
	TA2	0.87
	TA3	0.82
Behavioral Intention (BI)	BI1	0.89
	BI2	0.91

4.2.2 Internal Consistency Reliability

Cronbach's Alpha (α) and Composite Reliability (CR) were used to assess internal consistency. All constructs exceeded the established 0.70 threshold on both measures, indicating good internal consistency across the scales. Reliability and convergent validity statistics are reported in Table 3.

Table 3: Reliability and Convergent Validity Statistics

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE
Ethical AI Governance	0.88	0.91	0.67
Transparency	0.85	0.89	0.72
Accountability	0.83	0.88	0.70
Data Privacy	0.87	0.92	0.75
Technology Acceptance	0.89	0.93	0.76
Behavioural Intention	0.90	0.94	0.81

4.2.3 Convergent Validity

Convergent validity was assessed using Average Variance Extracted (AVE) for each construct. All AVE values exceeded the 0.50 cut-off recommended by Hair et al. (2019), ranging from 0.67 (Ethical AI Governance) to 0.81 (Behavioral Intention). This indicates that each construct accounted for more than half the variance in its associated indicators, confirming convergent validity.

4.2.4 Discriminant Validity

Discriminant validity was examined using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceed its correlations with other constructs. As shown in Table 4, the square roots of AVE (reported along the diagonal) exceeded the corresponding inter-construct correlations for every construct, confirming discriminant validity.

Table 4: Fornell–Larcker Criterion Matrix

Construct	EAIG	TR	ACC	DP	TA	BI
EAIG	0.82					

Construct	EAIG	TR	ACC	DP	TA	BI
TR	0.61	0.85				
ACC	0.58	0.62	0.84			
DP	0.65	0.59	0.60	0.87		
TA	0.69	0.64	0.63	0.66	0.87	
BI	0.72	0.67	0.65	0.68	0.74	0.90

4.3 Structural Model Assessment

With the measurement model's reliability and validity established, the analysis proceeded to the structural model to test the proposed relationships among constructs, including assessment of collinearity, path coefficients, coefficients of determination, effect sizes, and predictive relevance.

4.3.1 Collinearity Assessment

Variance Inflation Factors (VIF) were calculated for all predictor constructs to assess multicollinearity. All VIF values fell below the conservative threshold of 3.0 (Hair et al., 2019), indicating no multicollinearity concerns and supporting reliable interpretation of the path coefficients.

4.3.2 Path Coefficients and Hypothesis Testing

Path coefficients (β), t-statistics, and p-values were derived using a bootstrapping procedure with 5,000 iterations. Table 5 presents the results of the structural model. Four of the five hypothesized paths were statistically significant at the $p < 0.001$ level and were therefore supported. The path from Accountability to Technology Acceptance (H3), however, did not reach statistical significance ($\beta = 0.09$, $t = 1.42$, $p = 0.156$) and was not supported.

Table 5: Structural Model Results – Path Coefficients and Hypothesis Testing

Hyp.	Path	β	t-value	p-value	Decision
H1	EAIG → TA	0.42	7.36	< 0.001	Supported
H2	TR → TA	0.28	4.91	< 0.001	Supported
H3	ACC → TA	0.09	1.42	0.156	Not Supported
H4	DP → TA	0.31	5.42	< 0.001	Supported
H5	TA → BI	0.56	9.11	< 0.001	Supported

Note: EAIG = Ethical AI Governance; TR = Transparency; ACC = Accountability; DP = Data Privacy; TA = Technology Acceptance; BI = Behavioral Intention.

The strongest predictor in the model was the path from overall Ethical AI Governance to Technology Acceptance ($\beta = 0.42$, $t = 7.36$, $p < 0.001$), indicating that a broad, well-rounded perception of ethical governance has a meaningful effect on teachers' acceptance of AI. Among the individual governance dimensions, Data Privacy showed the strongest effect ($\beta = 0.31$, $p < 0.001$), followed by Transparency ($\beta = 0.28$, $p < 0.001$). Accountability, by contrast, showed only a weak and statistically non-significant direct effect ($\beta = 0.09$, $p = 0.156$). The path from Technology Acceptance to Behavioral Intention ($\beta = 0.56$, $t = 9.11$, $p < 0.001$) was the strongest relationship in the entire model, indicating that acceptance is a powerful and direct predictor of teachers' intention to use AI technologies in their professional practice.

The non-significant result for H3 is worth pausing on rather than treating as a simple null finding. One plausible explanation is conceptual overlap: teachers may not clearly distinguish "accountability" from "transparency" in their day-to-day experience of AI systems, since both are

typically communicated to end users through the same institutional channels - policy statements, training sessions, and help documentation - rather than through separate, identifiable mechanisms. A second possibility is that accountability operates on acceptance indirectly rather than directly, for instance by first shaping trust or perceived risk, which then influence acceptance; a direct path from accountability to acceptance may therefore understate its actual role in the model. A third possibility is more practical: accountability structures in the participating institutions - lines of responsibility for AI-related decisions, escalation procedures, and the like - may be genuinely underdeveloped or poorly communicated relative to data privacy and transparency measures, making it difficult for teachers to form a strong opinion about them one way or the other. Each of these explanations points toward a useful direction for future research and, from a practical standpoint, suggests that institutions should not assume that improving accountability structures alone will move the needle on acceptance in the same way that data privacy and transparency measures appear to.

4.4 Summary of Results

The PLS-SEM analysis conducted in SmartPLS 4 provides a reasonably thorough and internally consistent empirical basis for the study's theoretical framework. The measurement model demonstrated good reliability and validity across all constructs, and the structural model showed that four of the five hypothesized relationships were statistically significant, with Accountability's direct effect on Technology Acceptance being the exception. Among the significant paths, Data Privacy and Transparency stood out as the governance dimensions most strongly associated with teachers' acceptance of AI technologies, while Technology Acceptance itself proved to be a strong and direct predictor of teachers' behavioral intention to use AI. Taken together, the model offers reasonably strong empirical support for the study's conclusions and recommendations, underpinned by acceptable R^2 values and positive Q^2 statistics, while also pointing to a more nuanced picture of governance than a uniformly significant model would suggest.

5. Conclusion

5.1 Summary of Findings

This study was motivated by a clear gap in the literature: empirical research in higher education has rarely examined, in a rigorous way, how ethical AI governance shapes technology acceptance among university teachers. Drawing on the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the ethical AI governance literature, the study developed and tested an integrated framework in which ethical governance - operationalized through transparency, accountability, and data privacy - serves as a multi-dimensional predictor of teachers' acceptance and behavioral intention.

The empirical results, based on survey data from university faculty analyzed via PLS-SEM, largely support the study's central premise, with one notable qualification. Ethical AI governance, considered broadly, has a strong and practically meaningful effect on teachers' technology acceptance. Data privacy emerged as the most influential governance dimension, reflecting educators' particular sensitivity to surveillance, student data privacy, and questions around data rights in AI-enabled systems. Transparency also had a clear positive effect, reaffirming that teachers value institutional assurances around explainability and fairness in how AI is used. Accountability, however, did not show a significant direct effect on acceptance in this sample - a finding that, as discussed above, is more likely to reflect the complexity of how accountability is

experienced and communicated than to suggest that accountability is unimportant to teachers. Technology acceptance, in turn, was a strong predictor of behavioral intention, with a substantial effect size indicating that teachers who genuinely accept AI technologies are highly motivated to use them in practice.

5.2 Theoretical Contributions

This study makes several theoretical contributions to the literature on technology acceptance and ethical AI in education. First, it offers one of the earlier multi-dimensional, empirically grounded attempts to examine the relationship between ethical AI governance and technology acceptance in a university teaching context, responding to calls for further research in this area from prior systematic reviews (Zawacki-Richter et al., 2019; Kong et al., 2022). Second, it extends TAM and UTAUT by incorporating ethical governance dimensions as explanatory antecedents, demonstrating that these established acceptance models can be meaningfully enhanced with constructs drawn from the AI ethics literature - while also showing, through the non-significant accountability path, that this extension is not simply a matter of adding more predictors and expecting all of them to matter equally. Third, the study builds on existing work on trust and perceived risk in AI adoption by showing that institutional governance - not only individual-level trust - is a meaningful determinant of acceptance, raising a genuinely open question about whether AI acceptance should be understood primarily as a psychological phenomenon, an organizational one, or some combination of the two. Fourth, because much of the existing literature draws on well-resourced academic environments in developed countries, this study contributes evidence from a developing-country university context, where governance capacity and institutional maturity may differ in ways that matter for how these relationships play out.

5.3 Practical Implications

These findings carry direct relevance for university administrators, AI policymakers, and educational technologists. Most importantly, they suggest that ethical governance functions as a practical lever for AI adoption, not merely a moral or compliance obligation - though the findings also caution against treating "governance" as a single, undifferentiated policy commitment. Visible, credible governance appears likely to support greater faculty acceptance and stronger behavioral intention to use AI in education, which in turn should improve the return on institutional investment in AI tools - but the specific governance dimension being strengthened seems to matter.

Given that data privacy emerged as the most influential governance dimension, institutions should prioritize clear data protection frameworks, meaningful consent processes, explicit guidelines on data collection for educational purposes, and faculty education on how their data - and their students' data - is used. Transparency should be treated with similar priority: universities should require vendors to provide accessible, genuinely comprehensible explanations of how AI systems generate their recommendations and decisions, rather than technical documentation aimed primarily at specialists.

The non-significant finding for accountability points to a different kind of implication. Rather than assuming that formal accountability policies will automatically translate into greater acceptance, institutions may need to make accountability structures more visible and concrete to faculty - for instance, by clearly communicating who is responsible when an AI system produces a questionable outcome, and by creating accessible channels through which teachers can raise concerns and expect a response. Simply having an accountability policy on file appears to be less effective than

data privacy and transparency measures at moving teachers toward acceptance, at least as far as this study can tell.

More broadly, the results suggest that university AI training programs should extend beyond technical skills to include ethical literacy as part of professional development. Teachers who understand the governance frameworks behind the AI tools they use are better positioned to assess, critique, and engage constructively with those tools - what might be called ethical AI literacy, which this study suggests is close to a prerequisite for meaningful acceptance rather than a nice-to-have addition. For AI system designers and developers, the implication is that governance mechanisms need to be designed into products from the outset rather than added on as an afterthought.

5.4 Limitations and Future Directions

This study has several limitations worth noting, each pointing toward directions for future research. The cross-sectional design, while common in technology acceptance research, does not support causal claims and limits insight into how teachers' acceptance of AI evolves over time as governance practices mature and AI systems become more deeply embedded in institutional life. Longitudinal designs would offer a more complete picture of how the relationship between governance and acceptance develops.

The non-significant finding for the accountability path also warrants further investigation. Future studies might examine accountability as a moderator or mediator rather than a direct predictor, test whether it operates through trust or perceived risk, or use qualitative methods to explore how teachers actually experience and interpret institutional accountability mechanisms - something a structured questionnaire alone struggles to capture in full. Finally, given the study's non-probability sampling approach and its focus on a single national context, future research would benefit from probability-based sampling and cross-national comparisons to test whether these patterns, including the accountability finding, generalize beyond the present sample.

5.5 Concluding Remarks

This study offers an empirically grounded and timely contribution to understanding AI adoption in higher education, at a moment when institutions worldwide are navigating both the opportunities and the challenges that AI presents. Its central message is both theoretically meaningful and practically useful: ethical governance of AI is not an afterthought but a genuine precondition for acceptance - though, as the findings show, not every governance dimension carries the same weight in teachers' eyes. Teachers who believe their institutions are genuinely committed to transparency, accountability, and data privacy in their use of AI are considerably more likely to accept AI technologies and to form real intentions to use them in their professional practice, even if accountability's role in this study appears less direct than transparency's or data privacy's. As AI technologies continue to proliferate across academic settings, the case for ethical governance only grows stronger. This study suggests that just as the practical case for adopting AI can be a powerful enabler of adoption, so too can ethical governance - provided institutions invest in governance that is specific, visible, and credible rather than aspirational. Universities that take this seriously, and that build genuinely robust governance frameworks for AI, will be better positioned to realize AI's potential in education while preserving the trust, independence, and ethical commitments of the academic staff who remain central to that mission.

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