SOCIAL PRISM
Volume 2 Issue 4, 2025

A Comparative Study of AI Tools Adoption and Its Impact on Educational Practices in Public and Private Universities

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Abstract

Artificial Intelligence (AI) is increasingly becoming and integral component of the future of higher education, that is transforming traditional approaches to teaching and learning, academic research, assessment practices, and institutional administration. The literature of empirical studies covering emergent and resource-constrained situations is scarce although the scope of its influence has been rapidly expanding on the international stage. As a result, this paper involves the comparative analysis of the use of AI tools and the perceived effect of the latter on both the public and the private universities in the Khyber Pakhtunkhwa (KP) province of Pakistan. The study assumes that adoption depends on the perceived usefulness, perceived ease of use, institutional compatibility, and structural support thus analyzing the hypothesis that adoption is the nexus between technological integration and salient educational outcomes. Using quantitative, comparative survey as the research methodology, data were gathered involving 460 respondents, including faculty members and postgraduate students who were recruited, in a distributive way, in a public university (Gomal University), and a non-governmental university (Qurtuba University) in the city of Dera Ismail Khan. The instrument that was rigorously validated measured five central dimensions namely the rate of adoption of the AI tool, perceived effectiveness, user satisfaction, perceived performance improvement, and motivation. To question disparities in sectors, descriptive statistics have been employed along with independent-sample t-tests. The empirical study demonstrates a significantly greater rate of AI-tool use in the case of the public university, compared to the one in the private one. However, the two institutions did not show any statistically significant difference as regards to perceived effectiveness, user satisfaction, performance, or motivational outcomes. These results indicate that, despite the role of institutional context in access, the delivery of infrastructure, and the adoption patterns, the perceived pedagogical importance of AI technologies overlaps in sectors when the process of meaningful integration becomes a reality. That is, the adoption gap seems to be organized, but not observational of the difference of education levels. The study advances the academic discourse on the adoption of artificial intelligence (AI) in higher education, and especially in developing countries, by explaining how institutional preparedness, digital infrastructure, transparency in governance, and capacity development in the professional sphere can play a central role in supporting sustainable adoption of AI. The results highlight the need to establish institutional policies, sound ethical frameworks, and policy interventions that are narrowly focused and with which together would help to make AI technologies in KP and similar emerging environments the subject matter of responsible, fair, and pedagogically significant integration.

Keywords: Artificial Intelligence; AI tools; higher education; technology adoption; educational practices; public and private universities; Khyber Pakhtunkhwa; Pakistan

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Introduction

Artificial Intelligence (AI) is a technological breakthrough of the twenty-first century, which significantly changes the economic activity, the way people provide and use these services, and the structure of knowledge work, i.e. the way universities teach, assess, and manage (Kaplan & Haenlein, 2019; OECD, 2021). In higher education, AI-driven applications find their way into the everyday academic processes, including automated and semi-automated assessment, intelligent tutoring systems, adaptive learning and feedback technology, generative content support, learning analytics, predictive modeling of student success, and data-driven academic planning (Chen et al., 2020; Holmes et al., 2019; UNESCO, 2021). On top of the efficiency benefits, these technologies are often being framed as facilitators of pedagogical tailoring, increased learner engagement, and evidence-based decision-making, thus serving not as an addition to existing instructional and organizational practices but as a catalyst of an overarching change (Luckin et al., 2016; Popenici & Kerr, 2017).

The use of AI in education is gaining pace throughout the whole world alongside the blistering development of machine learning and the growing access to digital platforms and data infrastructures (Chen et al., 2020; UNESCO, 2021). However, the patterns of adoption are still unequal across and within states which indicates the differences in the institutional capacity, policy readiness and trust in the stakeholder. Indications exist that the introduction of technology frequently surpasses the creation of governance structure, ethical leadership, and well-organized professional education of educators, thus leaving an implementation mismatch between innovation and institutional readiness (Holmes et al., 2019; UNESCO, 2021). As a result of this, the spread of AI and its long-term adoption in higher education is determined, in addition to technical capacity, by the organizational culture, the commitment of the leadership, the clarity of regulations, and the value-perception and perceived usability of AI among the users (Erdmann & Toro-Dupouy, 2025).

In a developing country like Pakistan, the use of AI in higher education is still nascent and due to the structural conditions of digital infrastructure, resource distribution, leadership, and the systematic training and support facilities (UNESCO, 2021). In Khyber Pakhtunkhwa (KP), there is a different governance structure and funding method in place in both public and private universities, potentially affecting access to digital infrastructure, institutional policy formulation, and the level of technology-enabled innovation. Such disparities bring a key empirical issue: does institutional type hold any meaningful influence on not only the pace of AI adoption but also the perception of the stakeholders of the educational outcomes after incorporating the AI tools into academic life?

Though the adoption of AI and its educational consequences has been extensively researched in international scholarship, it is concentrated to a large extent in resource-rich environments. There is a dearth of comparative, sector-based research in the same developing regional setting, especially longitudinal research that concurrently analyzes patterns of adoption and perceived results among the primary higher-education stakeholders (faculty and postgraduate students)

(Holmes et al., 2019; UNESCO, 2021). Such scarcity of locally based comparative evidence limits the policy formulation and institutional strategy making, particularly where regulators and university administrators need locally based and context sensitive data to inform responsible and fair integration.

It is against this background that the current research paper takes the form of a comparative research on the use of AI tools and its perceived influence on the education practices in one public and one KP-based private university in Pakistan. In particular, it analyzes the adoption rate, perceived effectiveness, user satisfaction, perceived performance improvement, and motivation in faculty members and postgraduate students. The argument on which the study is based is that access and adoption levels might be profoundly affected by the institutional context whilst the perceived educational value might be homogeneous across the sectors as long as meaningful integration is attained.

The research is based on the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) theory to combine the micro-level cognitive determinants and macro-level institutional conditions. TAM describes the use of technology in terms of perceived usefulness and ease of use (Mpanza, 2025), whereas DOI focuses on how relative advantage, compatibility, complexity, trialability, and observability influence the speed with which the technology diffusion may proceed or be slackened in social systems (Overbye-Thompson & Hamilton, 2025). This combined lens facilitates a multidimensional approach to analysis of AI adoption both as an individual-level decision and an institutional-mediated process of diffusion.

This research will fill the literature gap on AI in higher education in developing settings and provide policy-makers and institutional leaders with practical ideas on how to create equitable, ethically justified, and pedagogically significant AI solutions (OECD, 2021; UNESCO, 2021). To make AI promote inclusive educational transformation, other than structural inequalities that exist, it is also critical to understand how institutional environments influence adoption and can be used to perceived outcomes.

Literature Review

Artificial Intelligence in Higher Education: Educational Utility and Transformative Potential

Artificial Intelligence (AI) has transformed into a ubiquitous educational technology that profoundly changes the nature of the instruction process, evaluation models, research outputs, and institutional organization. In the enterprise of higher education, AI-powered applications, such as intelligent tutoring systems, adaptive learning platforms, automated grading tools, generative content assistants, and predictive analytics, are becoming part of educational processes (Chen et al., 2020; Holmes et al., 2019). The systems help to make data-driven decision-making, make the process of feedback more efficient, and scale personalization of teaching, thus transforming traditional ways of teaching and management.

There is a large amount of literature that emphasizes the ability of AI to foster differentiated and student-centered learning. Adaptive systems allow and actively change the content depending on

the performance of the learner, allowing personalized learning paths and formative feedback in real-time, which would have been much harder to scale in the past (Miao et al., 2021; UNESCO, 2021). Predictive analytics also enable the institutions to help students who are at risk academically, enhance retention policies, and improve resource distribution (Luckin et al., 2016). Taken together, these trends imply that AI does not only imply an added value instructional resource but a source of structural and pedagogical change in higher education (Popenici & Kerr, 2017).

However, when the transformative promise of AI is brought up, very significant ethical and procedural issues are at stake. There is a growing trend of the problems of academic integrity, algorithm bias, data privacy, and transparency in automated decision-making in the literature (Holmes et al., 2019; UNESCO, 2021). Specifically, generative AI tools have further heated the discussion on authorship, originality, and assessment validity. These two stories of innovation and ethical care place AI as the driver of better but a technology with governance-sensitivity and requiring institutional regulation and ethical oversight.

Institutional Adoption Patterns and Organizational Readiness

Despite the fact that AI has been found to be advantageous in regards to pedagogy, there is disproportionate uptake of AI by institutions. Introduced factors include the capacity of digital infrastructure, funding mechanisms, the manner of leadership, faculty competence, and institutional culture, which affects the adoption pathways (OECD, 2021; Vincent-Lancrin et al., 2021). Empirical research indicates that technological implementation usually surpasses the policymaking process and workforce training, which creates an implementation gap between technological capacity and governance preparation (Doss et al., 2025).

Institutional preparedness does not just rely on the hardware and software availability. It comprises of strategic vision, policy focus, ethics and future professional development. The lack of parallel investments in faculty and governance system training when AI tools are implemented results in the universities being characterized by a disjointed integration, intra-stakeholder resistance, and ambivalent pedagogical outcomes (Holmes et al., 2019).

It is also shown in the cross-national research that the impact of the determinants of technology adoption (perceived usefulness, effort expectancy, facilitating conditions, social influence and others) varies across the socio-cultural and organizational context (Chopra et al., 2025). This variability confirms the hypothesis that the implementation of AI is a socially-based and institutionally-mediated process and not a technological one. The issues concerning governance, including the problem of algorithmic bias, the insufficient ethical standards, and the lack of the principles of proper classroom integration have also become the priorities of the European policy analysis (European Commission Joint Research Centre, 2025). Altogether, these findings suggest that a stable AI incorporation requires the consistency of the policy, the creation of infrastructures and the organization of capacity-building work.

Equity, Capability Gaps, and Developing-Context Constraints

A new body of literature warns that adoption of AI is likely to lead to the increase of the educational inequalities unless structural disparities are eliminated. The institutional resources level, access to technologies, and clarity of policies cause disparities in the level of adoption and differences in meaningful use (College Board, 2025; Doss et al., 2025). The higher the financial and technological strength of the institutions, the more important the opportunity to institutionalize the effective use of AI, and resource-limited institutions might be oriented on limited or experimental implementation of AI.

In addition to the disparities in access, there are capability disparities that influence the outcomes. According to international surveys, despite the growing availability of AI tools, the degree of confidence in their application in a pedagogically significant way is uneven both between institutions and stake holder groups (Arockia et al., 2025). This implies a multidimensional digital divide that is not just based on variation in technological infrastructure but also on variations in digital competence, pedagogical literacy and ethical sensitivity.

The lack of proper infrastructure, lack of professional development opportunities, funding resources, and inconsistency of policies have become a further obstacle to the large-scale adoption of AI in developing settings (Almaiah et al., 2022; Rana et al., 2024). Unless we strategically plan our institutions and provide them with regulatory direction, there is a threat that rapid technological growth will be a further entrenchment of systemic inequalities, instead of inclusive innovation. As such, the adoption policies should be context sensitive to integrate technology programs with institutional truths and economic-social realities.

Research Gap and Contribution of the Present Study

In spite of the fact that the world of scholarship has conducted a large-scale study of the potential of AI in education and the issue of governance, there are few comparative studies on institutional sectors in the developing world. A lot of the empirical data is based on technologically sophisticated systems, thus limiting the applicability of the data to new higher education situations where digital transformation is yet to take shape (UNESCO, 2021).

In Khyber Pakhtunkhwa (KP) in Pakistan, there is little empirical research that investigates the impact of the institutional type, or whether it is a public or a private institution, on AI adoption patterns and perceived educational outcomes. Since the models of governance, funding arrangements, infrastructure level, and leadership focus vary among the public and private universities, there is a need to conduct a comparative analysis based on the sectors.

The gap that the current research fills is by investigating the adoption levels as well as the perceived impacts of AI tools in one public and one privatized university within a similar regional setting. The combination of adoption determinants with the educational outcome dimensions, including adoption rate, perceived effectiveness, user satisfaction, performance improvement, and motivation also enable the study to contribute to the international discussion of AI integration in higher education with a locally-grounded evidence.

By using this comparative method, the study can contribute to the existing knowledge on whether the noticed differences are mainly structural and access-based or the difference in experiences

continues to be experienced after AI tools become integrated into everyday academic practice. This difference has important consequences in the institutional strategy, policy development, and fair digital transformation in building higher education systems.

Theoretical Framework of the Study

The current research has a theoretical foundation on two opposing viewpoints of technology uptake in learning institutions, the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory. Combining these frameworks offers a multi-tiered explanatory framework of studying the adoption of Artificial Intelligence (AI) within the sphere of higher education by combining the impact of individual cognitive determinants with the institutional and systemic circumstances.

The use of AI in universities is not merely a technological phenomenon; it is a socially anchored and mediated by organizations process. Perception is shaped among individual users, which in this context are the faculty and postgraduate students, on usefulness and usability of AI tools and access, infrastructure, governance and pathways of diffusion are shaped by institutional environments. Using the product of TAM and DOI, the study conceptualizes AI adoption as the result of both micro level psychological assessment and macro level structural preparedness (Dodge, 2025).

Technology Acceptance Model (TAM)

One of the most empirically tested models of explaining the adoption of information systems by users entails the Technology Acceptance Model (Tarhini et al., 2015). TAM also suggests that the key determinants of technology use are two fundamental cognitive beliefs namely, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Such beliefs determine the attitudes of the users to the technology which determine behavioral intention and eventually the real use of the system.

- ✓ **Perceived Usefulness (PU):** This is the level of how people believe that using a specific technology can improve their performance.
- ✓ **Perceived Ease of Use (PEOU):** This is used to denote how people think that they need to apply minimal effort to use the system.

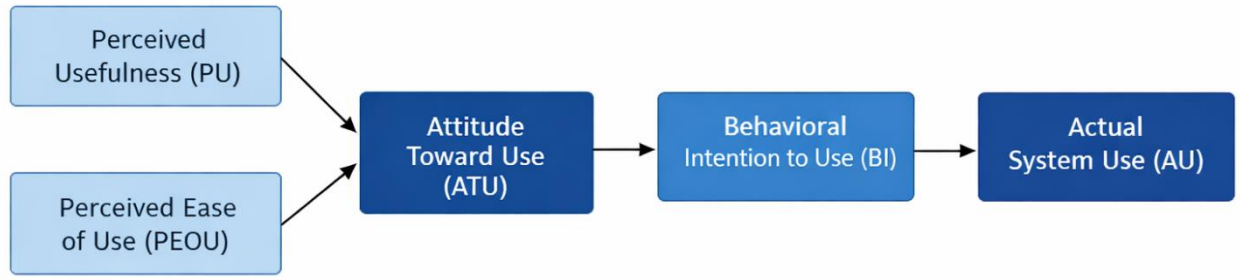

Figure 1. Technology Acceptance Model (TAM) Applied to AI Tool Adoption in Higher Education

Note. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward Use; BI = Behavioral Intention to Use; AU = Actual System Use. The model illustrates how user perceptions influence intention and actual AI tool usage.

In the higher education setting, the notion of perceived usefulness (PU) refers to the degree of perceived improvement in the quality of instruction, the productivity of research, efficiency of assessment, and effectiveness of administration due to the use of AI tools. Perceived ease of use (PEOU) is used to describe how AI tools are perceived to be accessible, manageable, and compatible with everyday academic processes. Empirical extensions of Technology Acceptance Model (TAM) including TAM2 and TAM3 are another way of showing that facilitating conditions and social influence together with prior experience are forces operating to strengthen or moderate the relationship between cognitive beliefs and usage behavior (Badda, 2025).

In the current paper, TAM presents a theoretical level of the micro-level of explaining the behavior of adoption of AI. It maintains the argument that stakeholders that perceive AI tools as effective and user-friendly are more likely to incorporate them into the academic practice and then report positive results in a form of improved performance, increased satisfaction, and motivation. Therefore, TAM supports the relationship between cognitive judgments and the adoption of AI behaviorally in the case of universities.

Diffusion of Innovations (DOI) Theory

Technology Acceptance Model (TAM) is focused on the individual decisions on acceptance, whereas the Diffusion of Innovations (DOI) theory by Rogers (2003) explains how innovations are diffused over social systems over time. DOI argues that there are five perceived attributes of an innovation that affect the adoption:

- ✓ Relative Advantage -The degree to which AI tools are thought to be better or worse than the current approaches.
- ✓ Cloneability - The extent to which AI is compatible with the institutional norms, pedagogical values and academic practices.
- ✓ Difficulty -The perceived challenge to learn and utilize AI tools.
- ✓ Trialability The chance to test AI on a small scale prior to a comprehensive use.
- ✓ Observability The perception of favorable results of AI utilization.

DOI, in institutional context, highlights the role of communication channels, leadership support, organizational culture and resource allocation in increasing or preventing the rate of diffusion of innovation. The more well-equipped universities with clear policy orientation and leadership support will have a better chance of institutionalizing the integration of AI successfully (Li et al., 2018).

DOI is especially relevant in explaining the variations in the rates of adoption in the sector in the context of the public and private universities in Khyber Pakhtunkhwa. The differences in funding and governance frameworks and policy articulateness can affect the pace of the diffusion of the AI tools within the institutional settings as well as the scope therein.

Integrated TAM-DOI Perspective

The combination of the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) model will provide the complete theoretical background to the current investigation. TAM clarifies the factors that influence the individual adoption of AI tools, and DOI clarifies how institutional conditions promote or inhibit diffusion. Such a dual-level construct will allow the study to conceptualize the adoption of AI in a three-part way:

- ✓ Cognitive process, determined by perceived usefulness, and perceived ease of use; a process mediated in the organization, through compatibility, leadership support, infrastructural adequacy, and policy preparedness;
- ✓ Systemic diffusion process - a process located in the broader institutional and socio cultural milieus.

Connecting the personal perception with the institutional preparedness, the integrated scheme would prove the main assumption of the research: the nature of institution could potentially impact the rate of adoption based on the structural factors, whereas the perceived learning outcomes may align as soon as AI tools become the staple of regular academic life.

Conceptual Framework of the Study

In continuation of the integrated Technology Acceptance Model (TAM) and Diffusion of innovations (DOI) model as it has been defined in the foregoing, the current conceptual framework, takes the theoretical propositions and converts them into empirically quantifiable variables in the Khyber Pakhtunkhwa (KP) Pakistani higher education system. TAM is used to explain the adoption of technology using those cognitive beliefs known as Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which are used to predict the behavioral intention and subsequent actual application (Nguyen et al., 2024). DOI builds on this view and adds the institutional level factors influencing diffusion of innovations, including compatibility, facilitating conditions, leadership support, and organizational readiness (Reis & Pinheiro, 2025).

With these views combined, the framework envisages the adoption of AI as the aggregate of micro-level mental appraisal and macro-level structural factors. When faculty members and postgraduate students determine that AI tools are useful and controllable in the context of the normal academic practice, they tend to embrace these tools (Mutanga et al., 2024). Meanwhile, institutional infrastructure, governance transparency and policy facilitation or inhibit diffusion processes.

In this model, the AI adoption rate is used as a mediating construct between two variables to bring individual perceptions and institutional readiness to perceived educational outcomes. As is consistent with TAM, the actual utilization precedes the experiential evaluations; consistent with DOI, the results of diffusion depend on structural context (Abulail et al., 2025). As a result, the process of adoption is placed as a mediating factor instead of an end goal.

The framework also includes institutional type (public/ private university) as a context variable that captures the variations in governance, funding system and infrastructural capacity. According to previous studies, these structural differences play a huge role in technological preparedness and

diffusion trends (OECD, 2021; Vincent-Lancrin et al., 2021). In line with this, institutional type is theorized to influence the level of adoption due to the structural preparedness, and level of perceived educational outcomes may converge after the meaningful integration of AI tools.

In general, the framework is capable of connecting the personal determinants (PU, PEOU), institutional preparedness variables, and outcome variables (effectiveness, satisfaction, performance, and motivation) into a rational empirical model. It allows testing the hypothesis of the existence of sectoral differences in AI integration that are either largely structural (access-driven) or whether differences in experiences remain post-adoption, thus simulating the TAM-DOI integration in a developing higher education environment.

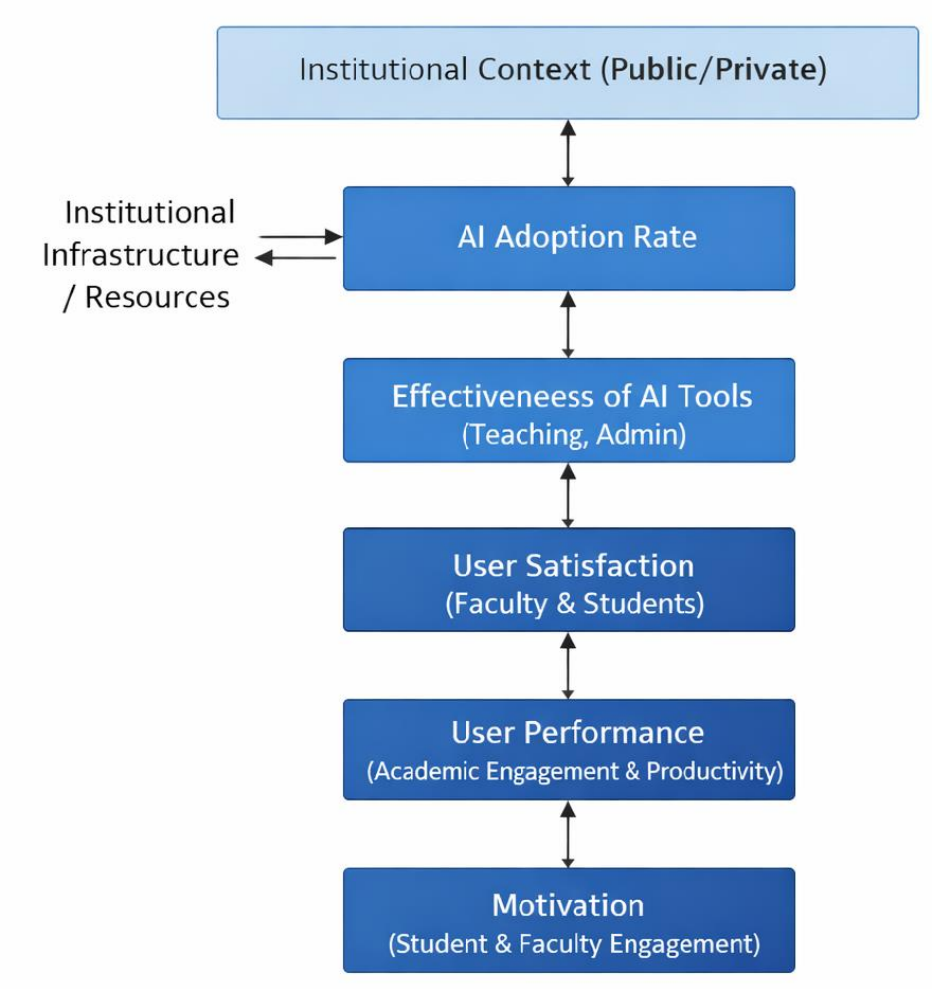

Figure 2. Conceptual Framework of AI Tool Adoption and Its Impact on Educational Practices

Note. The framework presents the relationship between institutional context (public/private), AI adoption rate, perceived effectiveness, user satisfaction, performance, and motivation, highlighting the proposed pathway from adoption determinants to educational outcomes.

Core Outcome Dimensions of AI Integration

The study operationalizes 5 outcome domains, which are interrelated, to capture the multidimensional effect of AI tools in higher education, in that, they collectively represent both behavioral integration and experiential evaluation.

1. **Adoption Rate of AI Tools**
   Adoption rate is the rate of AI use frequency, breadth, and depth of AI use in teaching, research, assessment, and administrative processes. In line with the technology acceptance theory, behavioral integration and not just access to the actual system use (Almaiah et al., 2022).

2. **Perceived Effectiveness**
   This construct is a measure of the assessment of the degree to which the AI tools can contribute to the quality of instruction, the learning process, the research process, and the efficiency of institutions. Evaluative judgment in respect of technology results has been found to be influenced by perceived usefulness (Hamzah et al., 2025).
3. **User Satisfaction**
   User satisfaction indicates the evaluative reaction of the faculty members and postgraduate students in their experience of using AI tools in academic context, which is consistent with post-adoption assessment viewpoints in information systems studies (Alyoussef et al., 2025).
4. **Perceived Performance Enhancement.**
   This dimension will examine how AI tools are perceived to enhance productivity, efficiency, academic output, and administrative effectiveness which are core elements of perceived usefulness in technology adoption models (Alkaabi et al., 2025).
5. **Motivation**
   Motivation represents the degree to which the integration of AI affects engagement, enthusiasm and desire to engage in academic and scholarly pursuits. According to prior acceptance research, a positive attitude towards usefulness and ease of use have a positive effect on attitudinal and motivational reactions (Guo et al., 2025).

These areas of outcomes combine behavioral (adoption) and perceptual-attitudinal (effectiveness, satisfaction, performance, and motivation) aspects of AI integration.

Determinants of AI Adoption

Based on the combined TAM DOI framework, the study detects five predictors that affect the AI adoption:

1. **Perceived Usefulness (TAM)**
   The extent to which the stakeholders feel that AI tools are increasing academic performance and institutional effectiveness (Rao et al., 2025).
2. **Perceived Ease of Use (TAM)**

How well the AI tools are seen to be under control and easily accessible in routine academic practice (Khalifa & Albadawy, 2024).

3. **Compatibility (DOI)**
   The perceived consistency between AI tools and already practiced approaches in pedagogy, institutional practices, and scholastic values (Pedro et al., 2019).
4. **Facilitating Conditions (Institutional Infrastructure)**
   The presence of technological infrastructure, training, and technical support, which make innovation diffusion in organizational systems easier (Tigabu et al., 2015).
5. **Policy and Leadership (Institutional Support)**
   Existence of official policies, top management support and elaborated integration plans that enhance organizational preparedness to innovation (Bernardo, 2014).

Such determinants are micro-level cognitive beliefs as well as macro-level structural conditions, which are in agreement with the TAM-DOI integration.

Proposed Relationship among Variables

The hypothetical model is a two-stage process:

Stage 1: Determinants → Adoption

The increased perceived usefulness, perceived ease of use, compatibility, facilitating conditions, and institutional support are likely to have a positive impact on the AI adoption rates. Favorable cognitive perceptions enhance behavioral intention and actual use in line with TAM. As stated in DOI, institutional readiness and organizational alignment facilitates the process of diffusion in the university system.

Stage 2: Adoption → Educational Outcomes

When adoption has been achieved, the increased AI integration levels are also predicted to impact positively:

- ✓ Perceived effectiveness
- ✓ User satisfaction
- ✓ Performance enhancement
- ✓ Motivation

Therefore, adoption is a mediating factor between institutional and perceptual determinants and educational outcomes.

Contextual Variable: Type of Institution (Public vs. Private)

Since the study is comparative in nature, institutional type is an imaginary conceptualized as a situational moderator of adoption patterns. Public and private universities might be different in:

- ✓ Capacity of digital infrastructure.
- ✓ Policies and governance systems.
- ✓ Funding models
- ✓ Faculty development programs.
- ✓ Innovation orientation of leadership.

Nevertheless, the framework gives the chance that even though the adoption differences can be present due to the structural conditions, perceived educational outcomes will be aligned after AI tools become an important part of the academic routine. This distinction will allow the study to distinguish between the access-based inequalities and experience-based similarities.

Conceptual Significance

The framework presents a model that can undergo empirical testing and which incorporates the behavioral adoption theory with the views of institutional diffusion. That is because it goes beyond only a technological understanding of AI integration and locates adoption in the context of wider structural, cultural, and governance.

The conceptual framework enhances the analytical consistency of the study by connecting institutional environment, adoption behavior, and educational outcomes to give a well-organized framework in which hypotheses will be tested and comparative research evaluated between the public and the private universities in Khyber Pakhtunkhwa.

Objectives of the Study

The proposed research is conducted based on the theoretical basis (TAM and DOI) and the suggested conceptual framework, i.e., the comparative analysis of the adoption of AI tools and its perceived educational effect in the context of public and private universities in Khyber Pakhtunkhwa. In particular, the research objectives of the study were:

1. To examine the level and patterns of AI tool adoption among faculty members and postgraduate students in public and private universities in KP.
2. To evaluate the perceived effectiveness of AI tools in enhancing teaching, learning, research, and administrative practices across institutional types.
3. To assess user satisfaction with AI tools among faculty members and postgraduate students in both sectors.
4. To determine the perceived impact of AI tools on performance, including productivity, efficiency, and academic outcomes.
5. To investigate the influence of AI tool usage on motivation, including engagement and enthusiasm towards academic activities.
6. To compare sector-based differences in adoption and perceived outcomes between public and private universities.

All these objectives make it possible to distinguish between differences in structural adoption and differences in experiential outcomes in different institutional settings.

Research Questions of the Study

On the basis of objectives and the conceptual framework, the study answered the following research questions:

1. What is the level of AI tool adoption among faculty members and postgraduate students in public and private universities in Khyber Pakhtunkhwa?
2. Are there significant differences in AI adoption rates between public and private universities?

3. How do stakeholders perceive the effectiveness of AI tools in improving educational and administrative practices across the institutional types?
4. Does user satisfaction with AI tools differ between public and private universities?
5. What is the perceived impact of AI tools on academic performance and institutional productivity in both sectors?
6. To what extent do AI tools influence the motivation of faculty members and postgraduate students in public and private universities?

The above research questions ensure conceptual alignment between institutional context, adoption behavior, and educational outcomes.

Hypotheses of the Study

The following hypotheses were formulated and tested, in order the achieve objectives of the study:

1. **H_{01}:** There is no statistically significant difference in AI tool adoption rates between public and private universities in Khyber-Pakhtunkhwa.
2. **H_{02}:** There is no statistically significant difference in perceived effectiveness of AI tools between public and private universities in Khyber-Pakhtunkhwa.
3. **H_{03}:** There is no statistically significant difference in user satisfaction with AI tools between faculty members and postgraduate students in public and private universities.
4. **H_{04}:** There is no statistically significant difference in perceived performance enhancement resulting from AI tool usage between public and private universities.
5. **H_{05}:** There is no statistically significant difference in motivation levels associated with AI tool usage between public and private universities.

Methodology

Research Design

The research utilized the quantitative, comparative and cross-sectional survey design to investigate the sector differences in the adoption of the Artificial Intelligence (AI) tools and its perceived educational use in both the public and private universities of Khyber Pakhtunkhwa (KP), Pakistan. To explore the hypothesis on whether the institutional type (public vs. private) plays an important role in adoptions and related educational outcomes, a comparative design was adopted. The cross-sectional methodology allowed gathering the empirical data at one moment, during which the stakeholders are actively involved in the academic processes.

The design also supports the hypothesis-testing orientation of the study and inferences by using statistical procedures to determine whether the institutional context moderates the two outcome perceptions and AI adoption. Since the conceptual framework is a combination of Technology Acceptance Model (TAM) and Diffusion of innovations (DOI) theory, the quantitative survey approach was suitable in operationalization of the perceptual constructs of perceived usefulness, perceived ease of use and institutional facilitating conditions (Soon et al., 2016).

Population and Sample

Population

The targeted population of the study was the faculty and postgraduate students (MPhil and PhD) of two universities in Dera Ismail Khan, KP, as they represented two different governance systems:

- ✓ **Public University: Gomal University.**
- ✓ **Private University: Qurtuba University.**

The two institutions were chosen to reflect two opposite models of funding, system structures and infrastructural backgrounds in the same geographical environment to limit extraneous geographical dispersion and maintain institutional contrast.

Sample

The proportionate purposive sampling strategy was used and it was done so as to have institutional representation that would be representative of difference in faculty distributions in the public and the private sector.

The sample consisted of:

- ✓ Teachers (Public University): 100
- ✓ Teachers (Private University): 30.
- ✓ Postgraduate Students (Public University): 100.
- ✓ Postgraduate Students (University of private): 30.

This gave a total sample of: **N = 260 respondents**

Table-1: Details of Demographic Variables along-with frequencies

Demographic Variable	Category	Frequency (n)	Percentage (%)
Institution	Public University	200	76.9%
	Private University	60	23.1%
Respondent Type	Faculty Members	130	50.0%
	Postgraduate Students	130	50.0%
Total		**260**	**100%**

The proportionate sampling provided realistic institutional representation without balancing the categories of stakeholders by the sector.

Sampling Technique

The current study used purposive proportionate sampling in the selection of the people who were in the practice of teaching, research, assessment, and academic administration. The faculty members and the postgraduate students were picked as the main users and evaluators of AI-added academic processes.

Although purposive sampling limits the possibility of statistical generalization, it enhances contextual validity, as data are obtained through participants with abundant data and direct experience on AI-enabled academic settings (McAllister, 2026). Gender was represented to make appropriate comparisons in case of sub groups.

Instrumentation

A structured and self-administered questionnaire was used to collect empirical data; this questionnaire was designed based on the integrated Technology Acceptance Model-Diffusion of Innovation (TAM -DOI) framework.

There are five fundamental dimensions that were operationalized in the instrument:

- ✓ AI Adoption Rate
- ✓ Perceived Effectiveness
- ✓ User Satisfaction
- ✓ Perceived Performance Enhancement.
- ✓ Motivation

Measures of items adopted determinants were conceptually based on:

- ✓ Perceived Usefulness (PU)
- ✓ Perceived Ease of Use (PEOU)
- ✓ There are three facilitation conditions and social influence
- ✓ Compatibility, Organizational Readiness

The responses were registered on a five-point Likert-type scale with strongly disagree (1) to strongly agree (5). Likert scaled items enabled the measurement of behavioral integration and perceptual assessments, which is consistent with what was done in previous research on technology acceptance (Scherer et al., 2019).

Validity

The instrument content validity was determined using the method of Item -Objective Congruence (IOC), and thus, a rigorous congruence between the research objectives, theoretical constructs and survey items was achieved. The conceptual clarity, relevance, and accurate reflection of the constructs were confirmed following the review of the experts.

Reliability

Cronbach's alpha coefficient was used to assess internal consistency reliability to determine that it was over 0.80 in all the main constructs. This implies that the degree of internal reliability is very high and the level of measurement precision is appropriate in the inferential analyses.

Data Collection Procedure

The data was gathered directly via the university faculty members and post graduate students in the chosen universities. The participants were completely informed about the reason why the study was being conducted and were assured of confidentiality and the possibility of voluntary participation.

The ethical consideration was noted by the following measures:

- ✓ Anonymity of respondents
- ✓ No divulging of identifiable information.
- ✓ Voluntary participation
- ✓ Academic use of data only

The administered survey was structured which guaranteed standardized data collection in the two institutional settings.

Data Analysis

Data analysis was a combination of descriptive and inferential statistics to gain a holistic insight into the research phenomenon.

1. Descriptive Statistics: The means and standard deviations were calculated to summarize the patterns of central tendencies and dispersion of each measured construct. This descriptive study provided a brief summary of the level of adoption and the perception of effects by the different categories of institutions.

2. Inferential Statistics: In order to test the null hypotheses, as well as to explore sector based differences, the following steps were used:

- ✓ Independent Samples t-tests were used to compare responses of the public and the private universities in regard to the adoption and outcome variables.
- ✓ When comparisons between subgroups of the study population (e.g. gender or type of stakeholders) had to be performed, Analysis of Variance (ANOVA) was used.
- ✓ The statistical significance was determined at $\alpha = .05$.

These statistical methods guaranteed that comparative and explanatory analyses were controlled in line with the research questions, and the research hypotheses and the general analytical plan.

Methodological Rigor

The study demonstrates methodological rigor through:

- Clear alignment between theoretical framework and operationalized constructs
- Proportionate institutional sampling
- Balanced stakeholder representation
- Valid and reliable measurement instruments
- Appropriate application of inferential statistics
- Transparent reporting of analytical procedures

Collectively, the revised methodological design supports a robust and context-sensitive sectoral comparison of AI adoption and its perceived educational impact within the higher education landscape of Khyber Pakhtunkhwa.

Results and Discussion

The findings are provided in compliance with the mentioned research objectives and hypotheses. Given the proportionate sample (Public=200; Private=60; N=260), to conclude whether the institutional type produced a strong impact on AI adoption and perceived educational outcomes, independent-samples t-tests were carried out.

1. Adoption Rate of AI Tools

The descriptive statistics used were that the means of adoption score were higher in the public university than in the private university. Educators and postgraduate students of the public institution stated they had more and more frequently and extensively integrated AI tools in their teaching, research, assessment, and administrative tasks.

Table-2: Independent Sample t-Test for Adoption Rate of Institutional Type

Variable	University Type	Mean	SD	t-value	p-value
Adoption Rate	Public (n=200)	4.28	0.76	9.84	< .001
	Private (n=60)	3.41	1.18		

The difference in adoption rate was statistically significant ($p<.001$). Therefore, H01 was rejected, indicating that AI tool adoption significantly differs between public and private universities.

Interpretations: The rate of adoption is higher with public universities, and this difference could be explained by the fact that such institutions are more exposed in terms of institutional aspects, due to the development of digital infrastructure, and because of the presence of organized academic activities. Although the existing assumptions suggest that a greater technological adaptability lies in the domain of the privately established organizations, the actual evidence shows that big-scale infrastructure and the state-imposed initiatives that are typical of the state have an overriding effect on the pace of the AI spread.

Applying diffusion of innovations (DOI) viewpoint, the facilitation conditions and institutional support seem to boost the diffusion of innovation in the public sector. At the same time, the technology acceptance model (TAM) proposes that the increased perceived usefulness and ease of use can be supported by the institutional familiarity and institutionalized usage patterns.

2. Perceived Effective of AI Tools

The descriptive analysis indicated comparable means scores for perceived effectiveness across both institutional types.

Table-3: Independent Sample t-Test for Perceived Effectiveness

Variable	University Type	Mean	SD	t-value	p-value
Effectiveness	Public (n=200)	3.81	1.02	0.42	.673
	Private (n=60)	3.76	1.08		

The differences between the two sectors for not statistically significant, therefore, H02 was not rejected.

Interpretation: The rate of adoption is higher with public universities, and this difference could be explained by the fact that such institutions are more exposed in terms of institutional aspects, due to the development of digital infrastructure, and because of the presence of organized academic

activities. Although the existing assumptions suggest that a greater technological adaptability lies in the domain of the privately established organizations, the actual evidence shows that big-scale infrastructure and the state-imposed initiatives that are typical of the state have an overriding effect on the pace of the AI spread. Applying diffusion of innovations (DOI) viewpoint, the facilitation conditions and institutional support seem to boost the diffusion of innovation in the public sector. At the same time, the technology acceptance model (TAM) proposes that the increased perceived usefulness and ease of use can be supported by the institutional familiarity and institutionalized usage patterns.

3. User Satisfaction

Table-3: User satisfaction scores across both Institutions

Variable	University Type	Mean	SD	t-value	p-value
Satisfaction	Public	3.74	0.97	0.58	.562
	Private	3.68	1.05		

The mean difference was not statistically significant, therefore H03 was not rejected.

Interpretation: The level of satisfaction of the stakeholders in the two institutional settings showed similarity in regards to AI tools. This justifies the hypothesis of TAM that the perceived usefulness and usability have a direct correlation to satisfaction after behavioral adoption.

4. Perceived Performance Enhancement

Table-4: Performance related Outcomes of Using AI

Variable	University Type	Mean	SD	t-value	p-value
Performance	Public	3.79	1.00	0.36	.718
	Private	3.75	1.07		

The above results showed that there was no significant difference found, therefore, H04 was rejected.

Interpretation: Respondents in both industries saw AI tools as increasing productivity, efficiency, and academic performance to the same degree. This implies that AI tools can have an educational utility that might be inherently technology based, but not institution specific at adoption levels that are reached.

5. Motivation

Table-5: Motivation of Stakeholders across Institutions

Variable	University Type	Mean	SD	t-value	p-value
Motivation	Public	3.83	0.95	0.49	.623
	Private	3.77	1.02		

The difference regarding motivation was not statistically significant ($p>.05$), therefore, H05 was not rejected.

Interpretation: The use of AI tools seems to have no significant effect on engagement and academic enthusiasm in an institutional context. It means that the motivational outcomes can be more related to the user interaction with the technology, rather than to the structural institutional differences.

Integrated Discussion

The findings indicate that the structural-experiential difference is noticeable:

- ✓ **Structural Difference:** Public universities were significantly more adoption.
- ✓ **Experiential Similarity:** The perceived performance, satisfaction, effectiveness, and motivation statistically did not differ across sectors.

The implication of this trend is that institutional infrastructure and policy orientation predominately factor in the levels of adoption, which also concurs with the theory of Diffusion of Innovations. However, as the AI tools are actively utilized, the perceived educational benefits become similar and thus reinforced the cognitive acceptance mechanisms of the technology acceptance model.

These results add to the overall discussion regarding the adoption of AI in developing situations by proving that:

These results add to the overall discussion regarding the adoption of AI in developing situations by proving that:

1. In institutional typology, access and diffusion are affected.
2. Technology is perceptions which are mostly technology-based in value once integrated.
3. The sector ownership does not play as much of a role as structural readiness in creating disparities in adoption.

Theoretical Implications

1. Supports the assertion of the Technology Acceptance Model that perceived usefulness and perceived ease of use bring positive results.
2. Support the focus on institutional readiness and facilitating conditions of the Diffusion of Innovations framework.
3. Hypothesizes that adoption is an intervening factor between institutional environment and educational achievement.

Practical Implications

1. Backs infrastructure development as a way of reducing inequalities in adoption.
2. Emphasizes the indispensable support of institutional policy and governance towards faster diffusion.
3. Refers to the fact that AI tools perceived to have an educational advantage in various industries are consistent when barriers to adoption are removed.

Conclusion

This paper offers empirical based findings on comparative adoption and perceived effects of Artificial Intelligence (AI) tools on the public and private universities in Khyber Pakhtunkhwa, Pakistan. The response based on the proportional sample of faculty members and postgraduate students (N = 260) shows that there is a clear difference between the structural adoption gaps and convergence of the outcomes of experience.

The findings indicate that the adoption rate of AI tools is much greater in public universities compared to the case of private universities. That implies that policy orientation, institutional infrastructure, and readiness of the organization determine access and diffusion of AI technologies decisively. These results can be explained by the Diffusion of Innovations (DOI) theory, which focuses on one of the essential roles of enabling conditions, supporting leadership, and compatibility in the rapid diffusion of the technology in the social system.

Nevertheless, even though the adoption rates varied greatly, there were no statistically significant differences on how well perceived was, level of user satisfaction, the impact of it on performance or the degree of motivation between public and private universities. These are signs that, when the AI tools are introduced to the academic practices, the stakeholders of the two types of institutions have similar benefits of education. The results are in line with the Technology Acceptance Model (TAM) that assumes that perceived usefulness and ease of use affect positive user experiences and results independent of institutional context.

Taken together, the results indicate that the institutional type is the key factor that determines the degree of AI adoption instead of the perceived education value of AI tools. Access and diffusion patterns seem to depend on structural preparedness, digital infrastructure, effective governance, and leadership orientation, whereas the outcomes in the field of experience become unified as soon as there is meaningful integration.

The present paper adds to the expanding research on AI in higher learning as it presents empirical evidence in a particular setting that is specific to a developing area. It contributes to the comprehension of mediating effects of technology adoption in institutional settings and also emphasizes that the pedagogical and motivation advantages of AI resources can be naturally transferred across industries once the adoption barriers are eliminated.

Finally, AI implementation in higher education cannot be considered only as a technological intervention but as an institutional change that would need to be implemented through the coordination of infrastructure investment, institutional strategy, ethics governance, and professional development. The problem of structural disparities in adoption will be critical to the achievement of the equitable and responsible AI integration in both public and private universities in Khyber Pakhtunkhwa and other emerging educational settings.

Recommendations

Based on the most significant result of the study, which is a greater AI adoption in the public university, yet the same perceived outcomes (efficiency, satisfaction, performance, motivation) are observed within the spheres, the following actionable recommendations can be offered:

A. Recommendations for Universities (Public and Private)

1. Establish a formal policy and AI usage policies and guidelines on acceptable use, assessment limits, and academic integrity.

2. Enhance the digital infrastructure (good internet, license access to AI, laboratories, campus Wi-Fi) to decrease the adoption disparities, especially in the corporate world where the adoption is lower.
3. Be institutionalized capacity building by teaching faculty and postgraduate students to use AI in teaching research and assessment design on a continuous basis.
4. Establish AI support systems (help-desk/IT support, faculty champions, brief tutorials, and troubleshooting options) to enhance continued usage.
5. It is recommended to incorporate AI in pedagogy through a deliberate restructuring of assessments (rubrics, reflective tasks, oral defenses, project-based learning) in order to protect originality and the quality of learning.
6. Adopt ethical governance (privacy protection, bias awareness, transparency, and responsible data handling) to create a level of trust, and ensure adoption.

B. Policy Recommendations (HEC / Provincial Higher Education Authorities)

1. Publication Standardize national or provincial AI integration policies in universities (ethical principles, evaluation regulations, governance policies).
2. Fund digitally equitable investments in AI infrastructure and training at resource-constrained institutions and departments.
3. Implement pilot, research and inter-university partnerships at the regional level by establishing AI-in-education innovation hubs in Khyber Pakhtunkhwa.
4. Implement monitoring and evaluation systems to monitor the adoption patterns, capacity-building achievements, and challenge of integrity.

C. Recommendations for Faculty and Postgraduate Students

1. AI is not a replacement, but rather a complimentary tool, and critical thinking, originality, and academic responsibility should be given priority.
2. Embracing AI literacy and verification procedures (fact-checking, source validation, plagiarism prevention, and citation discipline).
3. Do no harm through responsible research use, by recording AI assistance where needed and following institutional standards of ethics and integrity.

Strategic Implication

Since performance is similar regardless of the sector where AI is having its purposeful applications, it is now time to bridge adoption disparities by ensuring infrastructure and training and governance are in place, but not assuming that sector type dictates the value of AI in education.

Limitations and Directions for Future Research

Limitations

The research was also restricted to two universities in Dera Ismail Khan (Khyber Pakhtunkhwa) and this limits the generalization of the results.

The cross-sectional design will only capture perceptions of respondents at only one time and causation cannot be inferred.

All data were self-reported, this created the chance of bias in response.

The limited discussion of institutional type, and lack of deep analysis of the context of discipline, digital literacy and leadership, limits the breadth of the analysis.

Purposive sampling was used; therefore, restricting the representativeness of the statistical inferences.

Future Research Recommendations

1. Increase the sample size to include a variety of universities in different provinces to enhance the generalization.
2. Use longitudinal designs to monitor the change in AI adoption with time.
3. Use mixed-method designs wherein qualitative and quantitative methods are used to obtain a more comprehensive understanding.
4. Moderating and mediating variables to be examined include digital literacy, academic discipline, and leadership support.
5. Combine objective academic performance measures as well as perception based measures.
6. Become a better person by researching ethical governance, academic integrity, and policy preparedness to enable sustainable AI integration.

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