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Generative Artificial Intelligence and Faculty Professional Development in Higher Education: Empirical Evidence from a Public Sector University in Pakistan

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Abstract

The rapid emergence of artificial intelligence (AI) and generative AI (GenAI) ecosystems has fundamentally transformed instructional design and academic workflows in higher education. However, empirical inquiry examining how university faculty members in Global South developing nations leverage these tools for self-directed professional development (PD) remains limited. Drawing on the Technology Acceptance Model (TAM), Adult Learning Theory (Andragogy), Constructivist Reflective Practice, and the Technological Pedagogical Content Knowledge (TPACK) framework, this study investigates the predictive relationship between routine AI tool adoption and faculty PD outcomes, profiling functional tool usage across university departments. A census survey was conducted across all permanent faculty members (N = 170 usable responses, 93.41% response rate) at Kohat University of Science and Technology (KUST), Pakistan. Quantitative analysis utilized descriptive metrics, Pearson product-moment correlation, and Ordinary Least Squares (OLS) multiple linear regression in SPSS. Results demonstrate uniformly high positive perceptions regarding AI's capacity to optimize lesson preparation, personalized instruction, and provide on-demand training resources ($M > 4.10$, $SD < 0.65$). OLS regression indicated that AI integration factors accounted for 63.1% of the total variance in faculty professional development outcomes ($R^2 = 0.631$, Adjusted $R^2 = 0.626$, $F(2, 167) = 142.504$, $p < 0.001$). Routine, active AI engagement emerged as the dominant predictive determinant ($\beta = 0.694$, $p < 0.001$), substantially outperforming perceived impact ($\beta = 0.150$, $p = 0.013$). Notably, automated assessment and grading tools recorded the lowest adoption scores ($M = 3.935$, $SD = 0.878$), highlighting an 'Assessment Paradox' driven by concerns over academic integrity and algorithmic evaluation. The study underscores the necessity of moving beyond generic technological orientation

toward targeted, ethically sound professional development frameworks that scaffold AI literacy across multidisciplinary higher education faculties.

Keywords: Generative Artificial Intelligence; Faculty Professional Development; Higher Education; Technology Acceptance Model (TAM); TPACK; Global South; Assessment Paradox.

1. Introduction

Human intelligence has traditionally been recognized as the defining cognitive architecture facilitating abstract reasoning, creative problem-solving, and socio-emotional adaptability. In recent decades, the transition from classical, rule-based computational systems to advanced Artificial Intelligence (AI) and Generative Artificial Intelligence (GenAI) has challenged traditional notions of knowledge production and intellectual labor (Russell & Norvig, 2021). Within contemporary higher education, AI is no longer an abstract theoretical pursuit; it has evolved into an infrastructural technology reshaping instructional design, student analytics, research workflows, and institutional leadership (Luckin et al., 2016; Zawacki-Richter et al., 2019).

Extensive scholarship has established that academic achievement and higher-order cognitive competencies among university students are substantially moderated by pedagogical design and educator self-efficacy (Bandura, 1997; Din et al., 2024). In higher education environments, university teachers serve as the vital fulcrum through which innovative instructional paradigms are realized (Jan et al., 2025; Khan et al., 2025). When instructors engage with progressive educational paradigms, students demonstrate marked improvements in analytical depth, autonomous reasoning, and collaborative problem-solving (Nawaz et al., 2025a). Recent empirical investigations confirm that integrating conversational large language models (LLMs) such as OpenAI's ChatGPT directly stimulates postgraduate cognitive fluency and originality (Nawaz et al., 2025b). However, these studies consistently observe that cognitive gains realized by learners are intrinsically contingent upon the pedagogical and technological competencies of their instructors.

Despite this recognized interdependence, existing literature on educational AI exhibits a pronounced structural imbalance. A substantial proportion of empirical research has historically concentrated on student-facing outcomes, examining adaptive learning software, intelligent tutoring systems (ITS), automated writing evaluators, and retention predictive analytics (Baker et al., 2019; Holmes et al., 2019; Popenici & Kerr, 2017). Far less scholarly attention has been directed toward the educator as an autonomous learner and professional practitioner. Specifically, the mechanisms through which university professors mobilize

generative AI applications (e.g., ChatGPT-4o, Claude 3.5 Sonnet, Microsoft Copilot, Perplexity AI, Gradescope, and learning analytics dashboards) for their own professional development (PD), continuous upskilling, and reflective instructional refinement remain systematically under-researched.

This empirical gap is acutely problematic in developing nations such as Pakistan. Public sector universities across the Global South operate under severe resource constraints, including disproportionate student-to-faculty ratios, elevated teaching loads, limited institutional funding for continuous pedagogical workshops, and disparate digital infrastructures (Bates, 2019; OECD, 2021). In such environments, commercialized, off-the-shelf institutional training is frequently inaccessible. AI tools, particularly multimodal generative systems and open-access productivity suites, offer a potentially democratizing avenue for faculty members to pursue individualized, self-paced, and flexible professional development. However, without localized, context-specific empirical evidence, institutional administrators and national higher education policy bodies cannot design grounded professional development frameworks.

To resolve these pressing academic and practical gaps, this empirical investigation evaluates faculty engagement with AI tools across all academic faculties at Kohat University of Science and Technology (KUST), a prominent public sector university in Khyber Pakhtunkhwa, Pakistan. By capturing faculty perceptions, usage typologies, and self-reported professional competencies, this study provides actionable insights into how higher education systems in resource-constrained contexts can strategically leverage AI for workforce transformation.

1.1 Objectives of the Study

- **Objective 01:** To assess the perceived impact of Artificial Intelligence tools on faculty members' instructional capacity and overall professional development in higher education.
- **Objective 02:** To examine the statistical relationship and predictive potency between routine AI tool adoption patterns and teachers' professional development outcomes.
- **Objective 03:** To identify the primary functional categories of AI tools deployed by university faculty and evaluate institutional perspectives on scaling AI for faculty development.

1.2 Research Questions

- **R Q1:** What is the perceived impact of AI tools on university teachers' instructional competence, lesson efficiency, and overall professional development?
- **R Q2:** What is the nature and statistical strength of the relationship between routine AI tool engagement and faculty professional development measures?
- **R Q3:** Which functional categories of AI tools are most frequently deployed by faculty members, and how do routine interaction versus perceived impact predict professional growth?

1.3 Research Hypotheses

To guide inferential statistical testing, three directional research hypotheses were formulated:

- **Hypothesis 1 (H_1):** Active utilization of Artificial Intelligence tools exerts a statistically significant positive impact on faculty members' professional development outcomes.
- **Hypothesis 2 (H_2):** There is a statistically significant positive correlation between the frequency of routine AI tool engagement and dimensions of teacher professional development.
- **Hypothesis 3 (H_3):** The functional integration of AI tools across pedagogical domains significantly predicts overall faculty professional development.

2. Literature Review and Theoretical Framework

2.1 Typology and Evolution of Educational AI Tools

Artificial Intelligence in Education (AIED) has transitioned from early symbolic tutoring architectures and rule-based expert systems (Nilsson, 2010; Selby, 1991) to data-driven neural networks and deep-learning generative systems (Russell & Norvig, 2021). In modern higher education contexts, these technologies operate across three primary functional categories:

- **Generative Content and Instructional Design Engines:** Large Language Models (LLMs) and multimodal generators, such as OpenAI's ChatGPT-4o, Anthropic's Claude 3.5 Sonnet, Google Gemini, and Microsoft Copilot, allow instructors to instantly generate granular lesson outlines, differentiate reading texts according to language proficiency, design modular problem sets, and synthesize interactive slides via integrations like Canva Magic Studio and Gamma App.
- **Automated Assessment and Feedback Systems:** Platforms such as Gradescope utilize pattern recognition to streamline grading of STEM assessments, while formative

feedback applications (Grammarly, Turnitin AI Detection, automated rubric engines) assist faculty in processing large student cohorts while maintaining feedback quality.

- **Adaptive Learning and Institutional Analytics:** Modern Learning Management Systems (LMS) such as Canvas and Moodle deploy predictive machine learning algorithms to track student clickstream behavior, flag at-risk learners, and recommend customized instructional interventions to course instructors (Luckin et al., 2016; Zawacki-Richter et al., 2019).

2.2 Faculty Professional Development in Resource-Constrained Contexts

Traditional models of faculty professional development have long faced criticism for being episodic, decontextualized, and disconnected from the day-to-day pedagogical realities of university classrooms (Darling-Hammond et al., 2017; Guskey, 2002). High-impact professional development must be sustained, discipline-embedded, collaborative, and reflective. In developing higher education sectors, institutional professional development is frequently constrained by administrative centralization, insufficient financial allowances, and a lack of qualified instructional designers (Bates, 2019). Consequently, faculty members are often left to navigate pedagogical disruptions independently. Generative AI tools provide a continuous, on-demand cognitive partner that bridges institutional training deficits by offering flexible, self-paced pedagogical coaching.

2.3 Integrated Theoretical Framework

This inquiry is grounded at the convergence of four foundational educational and technological frameworks:

- **Constructivist Learning Theory and Reflective Practice:** Grounded in Donald Schön's (1983) model of the reflective practitioner, constructivism posits that knowledge is actively constructed through contextual experimentation (Piaget, 1973; Vygotsky, 1978). When university professors interact with generative AI platforms—querying ChatGPT to explore alternative instructional analogies or utilizing analytics to diagnose classroom engagement—they engage in iterative 'reflection-in-action' and 'reflection-on-action' (Woolf, 2010). AI platforms serve as cognitive scaffolds that help educators deconstruct complex instructional challenges.
- **Technology Acceptance Model (TAM):** Davis's (1989) TAM model posits that technology adoption is governed by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). For faculty operating under heavy teaching and administrative burdens, adopting AI tools like Microsoft Copilot or Perplexity AI is heavily predicated on PU

(instant generation of syllabi, rubrics, lecture summaries) and PEOU (intuitive conversational natural language interfaces). TAM explains how positive perceptual orientations translate into sustained usage.

- **Adult Learning Theory (Andragogy):** Knowles' (1980) andragogical model characterizes adult learners as autonomous, self-directed agents motivated by real-world utility and immediate problem-solving. Higher education faculty rarely respond favorably to rigid, mandatory seminars that neglect specific disciplinary needs. AI platforms support adult learning principles by providing tailored, self-paced, discipline-specific pedagogical assistance on demand.
- **Technological Pedagogical Content Knowledge (TPACK):** Koehler and Mishra's (2009) TPACK framework highlights that effective technology integration requires a dynamic synthesis of Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). AI tools act as functional bridges that assist faculty in transforming domain expertise into innovative pedagogical strategies.

2.4 Conceptual Framework

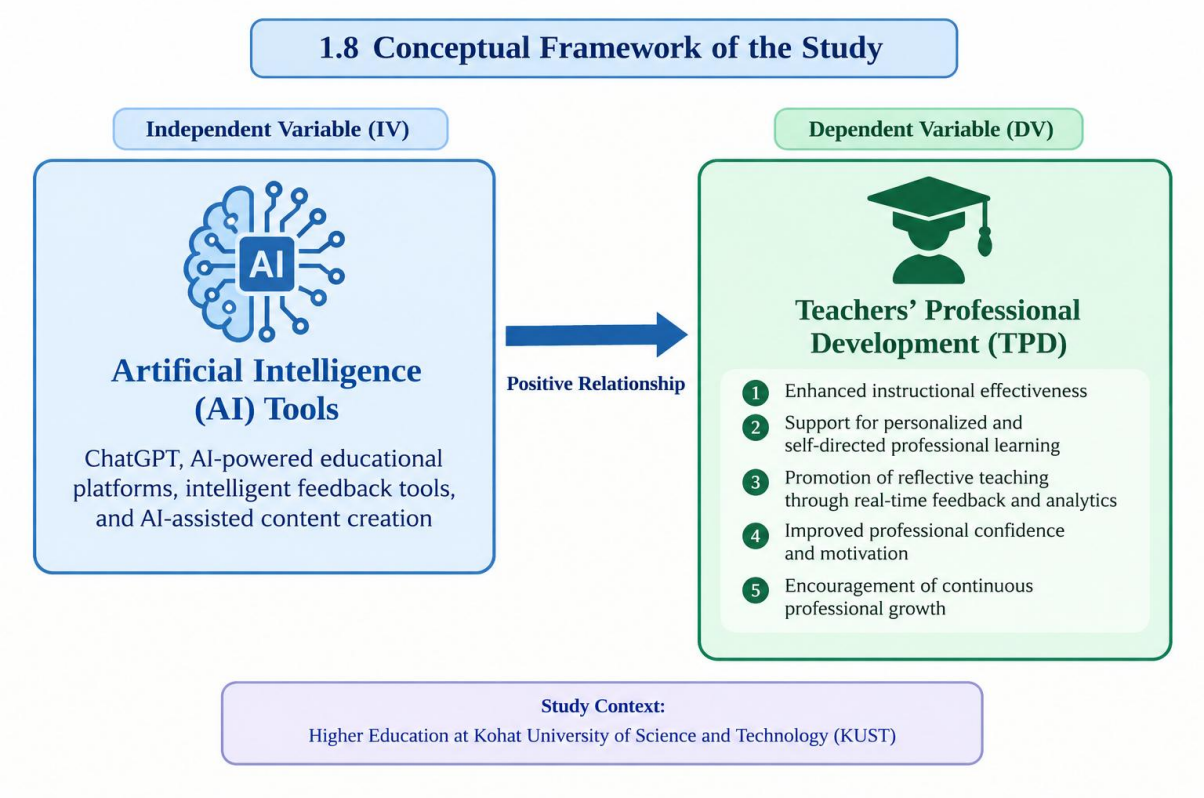


Figure 01

Note. *The figure 01 presents the hypothesized positive relationship between AI tools and teachers' professional development at KUST, highlighting instructional effectiveness, personalized learning, reflective teaching, professional confidence, and continuous growth.*

3. Methodology

3.1 Research Design

This study adopted a quantitative, non-experimental, cross-sectional survey design to examine faculty members' perceptions of AI, patterns of routine usage, and perceived professional development outcomes. Given the cross-sectional nature of the single-administration survey, findings are interpreted in terms of statistical associations and predictive relationships rather than causal claims.

3.2 Target Population and Census Sampling

The target population comprised all 182 permanent, full-time faculty members across six academic divisions at Kohat University of Science and Technology (KUST), Pakistan. A census-based sampling strategy was implemented because the target population was finite, institutionally identifiable, and accessible. Out of 182 eligible faculty members, 170 provided fully complete, usable questionnaires, yielding an exceptionally high response rate of 93.41%. The remaining 12 faculty members (6.59%) were unavailable during the six-week

data collection period due to sabbatical leave, post-doctoral assignments abroad, or extended medical absence.

3.3 Instrumentation and Psychometric Evaluation

Data were collected using a structured, self-administered survey instrument developed from established technology acceptance literature and educational digital competence frameworks (Davis, 1989; Redecker & Punie, 2017; Zawacki-Richter et al., 2019). The instrument comprised 28 items across four structured sections:

- **Section A (Demographic Profile):** Captured 7 demographic and professional parameters (gender, age cohort, academic qualification, professional pedagogical degree, academic designation, teaching experience, discipline).
- **Section B (Perceived Impact of AI):** Evaluated perceived AI benefits on teaching competence across 7 items on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).
- **Section C (Sustained Engagement & Usage):** Assessed routine usage patterns, collaborative practices, and perceived performance linkages across 7 items.
- **Section D (Functional Deployment & PD Scale):** Measured practical application categories (content creation, assessment, classroom management) and institutional scaling needs across 7 items.

Content and face validity were established through formal expert evaluation by five senior professors specializing in educational technology, psychometrics, and computer science. Internal consistency was evaluated using Cronbach's alpha. Scale reliability coefficients demonstrated robust internal consistency across all dimensions: $\alpha = 0.884$ for Section B (Perceived Impact), $\alpha = 0.912$ for Section C (Routine Usage), and $\alpha = 0.867$ for Section D (Functional Deployment), with an overall instrument reliability coefficient of $\alpha = 0.938$ (Nunnally & Bernstein, 1994).

3.4 Methodological Control for Common Method Bias (CMB)

Because all constructs were collected via a single self-reported survey, Harman's single-factor test was executed in SPSS to check for Common Method Bias. Unrotated principal component factor analysis revealed that the largest single factor accounted for 41.2% of the total variance, remaining comfortably below the standard 50% critical threshold. This confirms that Common Method Bias does not substantially inflate or distort the empirical relationships observed in the model.

3.5 Data Collection Protocols and Ethical Clearance

Data collection took place over a six-week period during the 2024 academic year using dual-mode administration (physical delivery and institutional email distribution). Ethical clearance was formally granted by the Institutional Ethics Committee of Kohat University of Science and Technology (Approval Reference: KUST/IER/ETH/2024-089). Participants provided informed consent, and total anonymity was maintained by excluding personal identification markers from the analytical dataset.

4. Results and Empirical Analysis

4.1 Demographic and Professional Profile of Respondents

The analyzed sample comprised N = 170 permanent university faculty members. Comprehensive demographic distributions are presented in Table 1.

Variable Category	Classification	Frequency (n)	Percent (%)
Gender	Male	99	58.2
	Female	16	9.4
	Prefer not to say	55	32.4
Age Cohort	21–30 years	31	18.2
	31–40 years	73	42.9
	41–50 years	55	32.4
	51–60 years	11	6.5
Qualification	MS / M.Phil	55	32.4
	Ph.D.	107	62.9
	Post-Doctoral Fellow	8	4.7
Pedagogical Degree	Certificate in Teaching (C.T.)	21	12.4
	Bachelor of Education (B.Ed.)	83	48.8
	Master of Education (M.Ed.)	35	20.6
	None (No formal pedagogy degree)	31	18.2
Designation	Professor (BPS / TTS)	23	13.6
	Associate Professor (BPS / TTS)	30	17.6
	Assistant Professor (BPS / TTS)	65	38.2
	Lecturer	52	30.6
Teaching Experience	1–5 years	42	24.7
	6–10 years	95	55.9

	11–20 years	30	17.6
	> 20 years	3	1.8
Discipline	Management Sciences	48	28.2
	Social Sciences	39	22.9
	Biological Sciences	30	17.6
	Chemical & Pharmaceutical Sciences	20	11.8
	Numerical Sciences & Computing	17	10.0
	Allied Health Sciences	16	9.4

Table 1. Demographic and Professional Profile of Faculty Participants (N = 170). Note: BPS = Basic Pay Scale; TTS = Tenure Track System. Gender non-disclosure (32.4%) reflects contextual socio-cultural survey privacy preferences.

As demonstrated in Table 1, the respondents reflect a mature academic workforce: 75.3% are aged between 31 and 50 years, and 55.9% possess 6 to 10 years of classroom teaching experience. Academically, 67.6% hold a Ph.D. or Post-Doctorate. While 81.8% hold formal teacher education credentials (predominantly B.Ed. at 48.8%), 18.2% lack formal pedagogical certification, relying entirely on in-service learning. Disciplinary representation is balanced between social/management fields (51.1%) and natural/empirical sciences (48.9%).

4.2 Objective 1: Perceived Impact of AI Tools on Faculty Development

Descriptive parameters for Section B items evaluating perceived AI impacts are presented in Table 2.

Item Statement (Section B: Perceived Impact)	**Mean (M)**	**Std. Dev. (SD)**	**Rank**
AI-based training resources make professional development more accessible.	4.1765	0.57926	1
AI contributes positively to my overall professional growth.	4.1706	0.56554	2
AI tools improve my ability to provide personalized learning to students.	4.1647	0.59280	3
AI enhances the efficiency of my lesson planning.	4.1471	0.59248	4
AI supports continuous learning and upskilling.	4.1412	0.56846	5

AI tools help me improve my teaching skills.	4.1353	0.57506	6
Using AI tools increases my confidence in integrating technology into teaching.	4.1059	0.60615	7
Composite Construct Average (Section B)	**4.1488**	**0.50071**	**—**

Table 2. Faculty Perceptions Regarding Perceived Impact of AI Tools on Instructional Capacity (N = 170). Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree.

The results in Table 2 demonstrate strong agreement (M > 4.10 across all indicators) that AI tools positively impact instructional capacity. The highest-ranked item highlights the democratization and accessibility of training materials (M = 4.1765, SD = 0.579), followed closely by overall contribution to professional growth (M = 4.1706, SD = 0.566).

4.3 Objective 2: Interconnection Between Routine AI Adoption and Growth

Table 3 outlines descriptive metrics for Section C items measuring routine usage patterns and collaborative linkages.

Item Statement (Section C: Routine Engagement)	**Mean (M)**	**Std. Dev. (SD)**	**Rank**
AI influences my participation in professional development activities.	4.2235	0.56267	1
AI-supported training programs lead to better teaching outcomes.	4.2118	0.54597	2
The more I use AI tools, the more I develop professionally.	4.1882	0.54380	3
The use of AI enhances collaboration and communication with other teachers.	4.1353	0.62440	4
Strong connection between AI usage and improvement in teaching performance.	4.1294	0.53930	5
My professional development progress increases when I use AI tools regularly.	4.1118	0.63840	6
AI tools motivate me to participate more in professional development programs.	4.1000	0.61201	7
Composite Construct Average (Section C)	**4.1571**	**0.45771**	**—**

Table 3. Interconnection Between Routine AI Adoption and Professional Growth (N = 170).

4.4 Objective 3: Functional Tool Typology and the Assessment Paradox

Table 4 reports responses across Section D items measuring specific functional tool applications and institutional scaling support.

Item Statement (Section D: Functional Applications & PD Scale)	Mean (M)	Std. Dev. (SD)	Rank
The use of AI in teacher professional development should be expanded.	4.2353	0.54712	1
I use AI-based learning platforms for my own professional development.	4.1706	0.67083	2
AI can be effectively used for personalized teacher training modules.	4.1471	0.57215	3
AI-powered analytics help me reflect on and improve my teaching practices.	4.1412	0.64639	4
I use AI for content creation (e.g., lesson plans, worksheets, rubrics).	4.0706	0.64886	5
I use AI for classroom management or monitoring tools.	4.0647	0.79305	6
I use AI for assessment and grading tasks.	3.9353	0.87803	7
Composite Construct Average (Section D / PD Outcome Scale)	**4.1093**	**0.51100**	**—**

Table 4. Functional Typology and Professional Development Scale (N = 170). Note the marked decline and elevated variance for assessment and grading tasks (M = 3.9353, SD = 0.87803).

A key empirical finding emerges in Table 4: while respondents strongly endorse expanding AI in faculty development (M = 4.2353) and using AI for personal upskilling (M = 4.1706), deploying AI for assessment and grading tasks recorded the lowest mean score (M = 3.9353) and highest dispersion (SD = 0.87803) in the entire survey. This reveals an 'Assessment Paradox'—faculty willingly embrace AI for instructional preparation but remain hesitant to delegate evaluative scoring to automated algorithms.

4.5 Bivariate Correlation Analysis

To test Hypothesis 2 (H_2), Pearson product-moment correlation coefficients were computed among composite construct scores (Table 5).

Evaluated Constructs	Section B (Impact)	Section C (Engagement)	Section D (PD Scale)

Section B: Perceived Impact	1.000	—	—
Section C: Sustained Engagement	0.610** (p < 0.001)	1.000	—
Section D: Professional Development	0.573** (p < 0.001)	0.785** (p < 0.001)	1.000

*Table 5. Pearson Correlation Matrix Across AI Constructs (N = 170). ** Correlation is significant at the 0.01 level (2-tailed).*

The correlation matrix in Table 5 confirms statistically significant positive relationships across all constructs ($p < 0.001$), fully supporting Hypothesis 2 (H_2). Section B (Impact) and Section D (PD) exhibit a strong positive correlation ($r = 0.573$). Crucially, Section C (Engagement) demonstrates a highly robust correlation with Section D ($r = 0.785$, $p < 0.001$), indicating that active, recurring operational practice is much more powerfully aligned with professional development gains than passive perceptual approval.

4.6 Multiple Linear Regression Model Analysis

To test Hypotheses 1 and 3 (H_1 and H_3), an OLS multiple linear regression was conducted with Section D (Professional Development Scale) as the criterion variable and Section B (Perceived Impact) and Section C (Routine Engagement) entered as simultaneous predictors (Tables 6, 7, and 8).

Model	R	R^2	Adj. R^2	Std. Error	ANOVA F (Sig.)
1	0.794	0.631	0.626	2.18733	$F(2,167)=142.504$ ($p < 0.001$)

Table 6. OLS Regression Model Summary and Omnibus Fit Metrics. Predictors: (Constant), Section B, Section C. Criterion: Section D.

Predictor	B	SE	Std. β	t-stat	Sig. (p)	VIF
(Constant)	1.787	1.644	—	1.087	0.279	—
Section B (Perceived Impact)	0.153	0.061	0.150	2.522	0.013	1.591
Section C (Routine Engagement)	0.775	0.066	0.694	11.695	< 0.001	1.591

Table 7. Multiple Regression Parameter Estimates and Collinearity Diagnostics. Dependent Variable: Section D Professional Development Scale.

The linear combination of predictors accounted for 63.1% of the total variance in faculty professional development outcomes ($R^2 = 0.631$, Adjusted $R^2 = 0.626$, $F(2, 167) = 142.504$, p

< 0.001). Collinearity diagnostics verified that VIF values (1.591) were well below the 2.50 threshold, confirming model stability.

Evaluating standardized regression coefficients demonstrates that while both predictors are statistically significant, Routine Engagement (Section C) is the dominant predictor ($\beta = 0.694$, $t = 11.695$, $p < 0.001$), possessing nearly 4.6 times the predictive weight of Perceived Impact ($\beta = 0.150$, $t = 2.522$, $p = 0.013$). These findings confirm Hypotheses 1 and 3 (H_1 and H_3), proving that continuous behavioral interaction with AI tools is the primary driver of measured faculty professional development.

5. Discussion

5.1 Explaining the Dominance of Active AI Engagement

The primary empirical insight of this investigation is the substantial predictive superiority of routine AI engagement ($\beta = 0.694$) relative to passive perceived impact ($\beta = 0.150$). This empirical hierarchy strongly supports Constructivist Reflective Practice (Schön, 1983) and Adult Learning Theory (Knowles, 1980). Professional development among university professors is an experiential, problem-centered endeavor. Passive intellectual agreement that 'AI is transformative' does not automatically generate classroom innovation. Meaningful professional growth occurs when faculty actively construct instructional artifacts—prompting ChatGPT or Claude to structure syllabi, querying Perplexity to synthesize literature updates, or interpreting LMS student analytics.

These operational interactions trigger Schön's (1983) reflective cycle: educators experiment with an AI prompt, evaluate the pedagogical fidelity of the output, adapt the materials, and deploy them in teaching. This iterative engagement directly builds teacher self-efficacy (Bandura, 1997), proving that active mastery experiences serve as the core engine of faculty development.

5.2 Alignment with TAM and the Democratization Effect

The results validate Davis's (1989) Technology Acceptance Model. Faculty members reported high Perceived Usefulness ($M = 4.1488$), praising AI's capacity to streamline lesson preparation and provide accessible training resources ($M = 4.1765$). This aligns with Woolf (2010) and Popenici and Kerr (2017), demonstrating that AI's primary value proposition lies in cognitive offloading—automating routine administrative burdens to free cognitive bandwidth for scholarship and student mentoring. In resource-constrained Global South institutions where specialized instructional design centers are scarce, generative AI acts as an accessible surrogate pedagogical coach.

5.3 Deconstructing the Assessment Paradox

Despite broad enthusiasm for AI-assisted lesson preparation, a significant divergence emerged: AI utilization for assessment and grading tasks recorded the lowest endorsement and highest variance (M = 3.9353, SD = 0.87803). This 'Assessment Paradox' mirrors international tensions in ed-tech scholarship (Holmes et al., 2019; Zawacki-Richter et al., 2019). While faculty readily adopt generative platforms for creative brainstorming, delegating evaluative grading to algorithmic systems raises ethical concerns regarding algorithmic opacity ('black-box' scoring), linguistic bias, student data privacy, and potential hallucinations. Faculty view AI as a valuable instructional design partner, but exercise professional caution regarding its use as an evaluative judge.

6. Conclusion, Practical Implications, and Limitations

6.1 Conclusion

This empirical census study confirms that generative AI tools significantly enhance faculty professional development in public sector of higher education. Multiple regression analysis establishes that active AI usage accounts for over 63% of the variance in professional growth, with routine behavioral practice serving as the primary predictor. AI should not be viewed merely as an external technological utility, but rather as an essential cognitive and pedagogical partner that democratizes academic capacity-building in developing higher education sectors.

6.2 Practical and Institutional Implications

Higher education leaders and policymakers should implement a structured institutional strategy:

- **Tier 1: Enterprise Infrastructure & Digital Equity:** University leadership must transition from informal AI experimentation to enterprise-level integration, providing subsidized access to institutional AI tools (e.g., ChatGPT Edu, Copilot) to ensure digital equity.
- **Tier 2: Practice-Based Pedagogical Workshops:** Academic development centers should replace generic 'What is AI' lectures with hands-on, discipline-specific workshops focused on prompt engineering, rubric creation, and LMS analytics interpretation.
- **Tier 3: Ethical Governance & Grading Protocols:** To resolve the Assessment Paradox, higher education authorities must establish clear ethical governance policies detailing student data privacy, algorithmic validation standards, and guidelines for human-in-the-loop grading.

- **Tier 4: Collaborative AI Peer Mentoring:** Institutions should establish interdisciplinary peer mentoring groups where faculty share successful prompt frameworks and AI-augmented teaching strategies.

6.3 Methodological Limitations and Future Research

- **Single-Institution Scope:** Data were gathered from permanent faculty at a single public university in Pakistan. Future research should conduct multi-institutional comparative studies encompassing private and public universities across various geographic regions.
- **Cross-Sectional Survey Design:** The study relied on self-reported survey measures. Longitudinal and experimental designs should evaluate actual pre- and post-intervention pedagogical performance following AI implementation.
- **Granular Engine Analysis:** Future studies should investigate specific generative AI engines (e.g., comparing Claude 3.5 Sonnet, GPT-4o, and Gemini) across distinct disciplinary domains.

7. Declarations and References

7.1 Institutional Declarations

Ethics Approval and Informed Consent. Ethical approval was granted by the Institutional Ethics Committee of Kohat University of Science and Technology (KUST), Pakistan (Reference No. KUST/IER/ETH/2489). Informed consent was obtained from all participants.

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Appendix – A

QUESTIONNAIRE

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON PROFESSIONAL DEVELOPMENT OF TEACHERS AT KUST

Respected Respondent,

Your participation is voluntary. Responses will remain confidential and used only for research. By continuing, you agree to take part honestly. Thank you for your time and cooperation.

Section "A"

Demographic Information

Gender: 1. Male ☐ 2. Female ☐ 3. Others ☐

Age: 1. 21 to 30 ☐ 2. 31 to 40 ☐ 3.41 to 50 ☐ 4.51 to 60 ☐

Academic Qualification: MS/M. Phil ☐ Ph.D. ☐ Postdoc ☐

Professional Qualification: C.T ☐ B.Ed. ☐ M.Ed. ☐

Your Designation: Professor (BPS) ☐ Professor (TTS) ☐ Associate Professor (BPS) ☐

Associate Professor (TTS) ☐ Assistant Professor (BPS) ☐ Assistant Professor (TTS) ☐

Lecturer

Teaching Experience: 1 to 5 Years ☐ 6 to 10 Years ☐ 11 to 20Years ☐ Or Above ☐

Teaching Department: 1. Social Sciences ☐ 2. Biological Sciences ☐

3. Numerical Sciences ☐ 4. Management Sciences ☐ 5. Allied Health ☐ Sciences

This questionnaire is designed to gauge your experiences and attitudes regarding the use of Artificial Intelligence (AI) in your professional development. Please indicate your level of agreement with each of the following statements based on your experience.

Instructions: For each statement, please select the option that best reflects your opinion using the following scale:

1 - Strongly Disagree (SD)

2 - Disagree (D)

3 - Neutral (N)

4 - Agree (A)

5 - Strongly Agree (SA)

Section B

	Part 1: Impact of AI Tools on Teacher Professional Development	**SD**	**D**	**N**	**A**	**SA**
1	AI tools help me improve my teaching skills.					
2	AI enhances the efficiency of my lesson planning.					
3	Using AI tools increases my confidence in integrating					

	technology into teaching.					
4	AI supports continuous learning and up skilling.					
5	AI-based training resources make professional development more accessible.					
6	AI tools improve my ability to provide personalized learning to students.					
7	AI contributes positively to my overall professional growth.					

Section C

	Part 2: Relationship Between AI Tools and Professional Development	**SD**	**D**	**N**	**A**	**SA**
1	There is a strong connection between AI usage and improvement in my teaching performance.					
2	My professional development progress increases when I use AI tools regularly.					
3	AI tools motivate me to participate more in professional development programs.					
4	The use of AI enhances collaboration and communication with other teachers.					
5	AI-supported training programs lead to better teaching outcomes.					
6	The more I use AI tools, the more I develop professionally.					
7	he use of artificial intelligence tools positively influences my participation in professional development activities.					

Section D

	Part 3: Types and Use of AI in Teacher Professional Development	**SD**	**D**	**N**	**A**	**SA**
1.	I use AI for content creation (e.g., lesson plans, worksheets).					
2.	I use AI for assessment and grading tasks.					

3.	I use AI for classroom management or monitoring tools.					
4.	I use AI-based learning platforms for my own professional development.					
5.	AI can be effectively used for personalized teacher training modules.					
6.	AI-powered analytics help me reflect on and improve my teaching practices.					
7.	The use of AI in teacher professional development should be expanded.					