QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

AI-POWERED CURRICULUM STRATEGIES TO PROMOTE INCLUSIVE AND QUALITY HIGHER EDUCATION

Dr. Muhammad Umar Mehmood
(Corresponding Author)
PhD Education, MPhil Scholar (Linguistics), University of Sialkot, Pakistan.
Email: pashagee143@gmail.com
Sehrish Khan
International Islamic University Islamabad
Email: sehrishkhan96096@gmail.com
Dr. Um E Rubab
Assistant Professor, Department of Education, Alhamd Islamic university AIU, Islamabad. Email: dr.umerubab@aiu.edu.pk
Arzo Sama
Visiting Faculty, Department of Education, Fatima Jinnah Women Education
Email: arzo.sama25@gmail.com
Muhammad Mubeen Goraya
MPhil. Education, Preston University Kohat
Email: mubeengoraya142@gmail.com

Abstract:
The development of curricula for integrating technologies, such as Artificial Intelligence (AI) in higher education requires a contextual understanding of technology systems, institutional structures and socio-cognitive human factors. The study is conducted in a systematic way using mixed-methods approach with pragmatic research design which aims to investigate how to develop AI-supported curriculum strategy that can harmonize the academic quality in the presence of negative social equity and inclusion for student success in alignment with SDG-4: Quality Education. The data was collected by conducting quantitative surveys ($N = 400$) and qualitative semi structured interviews from three urban hubs of Punjab namely Lahore, Gujranwala and Sialkot. Empirical evidence demonstrates significant and unequal institution capability and beginning technical confidence. Crosstabs suggest that clearly, participants in the private sector had higher baseline confidence ($M = 4.21$) than participants in the public sector ($M = 3.38$). A serious geographic digital divide was also observed with the campus network stability starting from Lahore ($M = 3.90$) dropping steeply to Gujranwala ($M = 2.55$) and Sialkot ($M = 2.75$). The top two among the significant statistical prioritization indexes were the lack of structured training for faculty, with institutional software subscription prices coming in at number three and unstable connectivity coming in at number 3rd. However, the adaptive platforms are quite impressive in their ability to increase the learning velocity and decrease language anxiety for non-native English speakers, with p <. In view of these advantages, there are limitations in the form of resource allocation inequality, as well as Eurocentric linguistic preferences (001). The study further suggests that simple, top down automation architectures can only be implemented with larger inputs – that are context-congruent and localized around the adaptation and implementation of these systems – if they are not to exacerbate learning inequities. To sum up, it promotes feasible human agency oriented curriculum frameworks, which integrate global perspectives of technological innovations and Universal Design for Learning (UDL) into the local socio-cultural contexts.

Keywords
AI in Education, Curriculum Design, Higher Education, SDG-4, Digital Divide, Educational Equity.

INTRODUCTION

1.1 Background of the Study

Institutional design and pedagogic design of higher education curricula must rely on a system of understanding the coapprehension of technological systems, institutional structure and socio-cognitive factors. AI-supported curriculum development must be embedded within a digital silo of a single technology solution, but must also be compatible with evidence-based models to support models for transformation, inclusion and the level of language proficiency needed for transregional and transnational learning environments. The literature indicates that change in education at the system level always causes tensions in the administration, thinking and structures of the system. Similarly, when technology paradigms are not advanced enough and poor planning and institutional hurdles are hindering the implementation of the technology at the classroom level, it is seen that there are constraints in medium-of-instruction policies (Mehmood, Ziauddin & Naseem, 2025).

This institutional tension is even more important as there are still numerous public sector institutions that are not yet on the path to digital inclusion. Qamar-u-Zaman, Mehmood, et al. (2025) argue that digital development, if not policy-practice aligned, can exacerbate the inequalities in resource distribution, and technological exclusion of under-represented learners. This is a form of inequality that is directly counterproductive to the SDG 4 that emphasises inclusive, equitable quality education. The findings of the research projects in the Country Report are confirmed by other global studies that the higher education systems will have to move closer to a more structured, equity and human centered approach to AI (Zawacki-Richter et al. and Davis et al., 2023). If there are no such frameworks, commercial automation and lack of governance could further deepen educational inequity.

Yet, AI-driven teaching and learning tools and automated curriculum tracks alleviate stress for instructors and reduce industry pressure, further exacerbating the strain in the workforce or burnout. Teaching reforms in the context of curricular restoration and restructuring produce pedagogical blind spots, administrative tensions, and institutional pressure when structural support systems are weak or misaligned (Mehmood, 2024b). Out of these, faculty training remains a prime need for successful adoption of AI. Teachers are better equipped and less reluctant to change instructional strategies when they gain professional development through a multi-staged approach (Mehmood & Parveen, 2025). UNESCO (2024) reiterates that skill development for faculty and technology anxiety will have to be dealt with before generative ai tools are integrated into the university curriculum. Similarly, Bond et al. (2024) note, however, that unstructured professional development is still one of the main barriers to quality and inclusion in AI-facilitated higher education.

AI-driven curricula must also focus on the cognitive and linguistic needs of learners. Because most AIs are transmitted through hegemonic world languages, especially English, they need to account for the thoroughly psycholinguistic diversity of students. One learns language by communicating with other people, and it is tethered to numerous psychological capacities including analytical skills, empathetic skills, and critical thinking (Mehmood, 2025a). As a result, for second-language learners academically alienation will happen since AI systems ignore the mentioned elements. The conceptual learning and mastery of the language are explained by Mehmood (2025b) which is the function of cognitive load, emotional differences and social context. Hwang and Chang (2023) add to this body of research by warning that automated educational systems may reproduce preexisting algorithmic- and language-based biases which will be detrimental to non-native speakers.

Hence, inclusive artificial intelligence curriculum design should be human-centered, culturally responsive and ethically situated. Protection of diversity and identity requires the incorporation of the conventional teaching style, the base of learning period, community learning habits and activities in local languages (Mehmood et al., 2025; Masood et al., 2025). To guide AI-based education, the ethical principles of dignity, social justice, fair access and protection of vulnerable learners must be followed (Mehmood & Parveen, 2024). In line with Holmes et al. (2023), and history of human-centered AI — Man things = Naturalization for you (Compared to business automations preferred). Therefore, this study designs an ideal sustainable and inclusive AI-based regular higher education curriculum framework.

1.2 Problem Statement.

There are theoretical advantages to the far-reaching integration of artificial intelligence in higher education, but practical adoption trends differ with uneven rates across regions and development hubs. Using data available by October 2023, elite private universities are able to leverage generative AI on robust infrastructure while public institutions still contend with slow or unreliable internet, old computers and shoestring budgets. This results in multi-tiered educational system (where the strong punishes the weak) and drives SDG-4 to its logical absurdity with technology increasing inequality not reducing inequality. Special Note: Poor policy design, inadequate teacher training, technology-related anxiety and fear of cultural or linguistic bias can also be hurdles in AI integration. Automation may also exacerbate educational disenfranchisement without evidence-based, context-congruent AI curricular approaches for equitable, democratic learning.

1.3 Research Aim

The main objective of this study was to systematically explore how curriculum strategies underpinned by AI could be designed and developed for inclusion as part of a wider system in the context of enhancing quality teaching and learning in contemporary Higher Education Institutions. This study attempted to empirically address this tension between academic quality and social equity in respect to technologically-oriented education by examining the triad of technology integration, faculty preparedness, and student access.

1.4 Research Objectives.

To achieve the established aim, the study was guided by the following three specific research objectives:

1. To evaluate the institutional awareness, preparedness and curriculum integration of AI.
2. To detect the structural, financial and pedagogical obstacles to faculty adoption of AI.
3. To learn about the opportunities for using AI to provide custom and accessible learning environments.

1.5 Research Questions

To answer the research questions outlined above, the study investigated the following three main research questions:

1. Are the surveyed institutions aware, ready, and integrated with AI?
2. What are the risks involved in using AI tools in education?

3. How can AI frameworks enhance academic quality and ensure student inclusion?

1.6 Significance of the Study

Applying the insights of equity theory and the objectives of SDG-4, this study is significant in terms of its practical implications and theoretical insights regarding digital pedagogy and educational leadership (Prain et al., 2022). The research moves from the technology-driven perspectives and explores the importance of factors such as teacher resilience, infrastructure and linguistic diversity as essential elements of the human dimension. Practically, it offers guidance to university administrators, deans, and curricular developers on how to navigate the issues of digital transformation, biodiversity, faculty training, inclusivity of pedagogical practice/ways of knowing/bias in the curriculum. It also helps educators to utilize free, mobile, and assistive AI technologies for students who are vulnerable.

Literature Review

This is artificial intelligence marks a complete transformation of the digital pedagogy, curricula development and equitable access within higher education. This technology is more than just another technological solution that has been grafted on to an already existing approach. AI trained curricula facilitate adaptive instruction, learner profiling, and individualized feedback as well as academic assistance. Nevertheless, it needs to be done intentionally due to the impact on teacher agency, learner agency and classroom dynamics. For that reason, AI-derived pedagogy should be investigated as a systemic reform that links project implementation at the local level with evidence from around the world in searching for sustainable higher education.

Curriculum changes are slow and context-dependent. Indeed, past reforms (e.g. English-medium instruction) demonstrate that weak planning produces socio-cognitive friction, classroom bottlenecks and uneven outcomes (Mehmood et al., 2025). Likewise, AI based curriculum system can also be biased if diversity in the learners is not valued. Using machine learning to track how quickly someone is learning, where they struggle and how best to help can both cut that risk (of bad decisions) down and at the same time improve efficacy in terms of teaching them what they need. Ouyang et al. These authors go on to say that intelligent environments are dynamic and continuous because these assessments evolve into continuously updated profiling (p.2023). So curriculum design becomes this responsive ecosystem that encourages agency, adaptation and knowledge construction for all.

In order for AI to not replicate structural exclusion, and worsen inequities, its design and implementation should be based in equity theory, Universal Design for Learning (UDL), critical digital pedagogy or SDG-4. Such frameworks are advocating that technology must not be just about automation. It must also help ensure equity, learner dignity and significant engagement. An AI-powered curriculum should consist of content available through multiple means of representation, expression and engagement. Students should access learning via various formats, show understanding in multiple ways, and stay engaged as needed based on physical/language/cognitive/contextual factors.

Also, educational equity relies on the psycholinguistic and the emotional realities of learners. Psychological well-being, motivation and identity are intertwined with conceptual mastery (Mehmood, 2025a). Whether or not AI platforms function as culturally neutral systems may be a source of anxiety, alienation and cognitive overload for those students most vulnerable. Cognitive load, emotional shifts, and external realities (Mehmood, 2025b) – the grounds on which language learning and conceptual growth take place. Hence forth equitable AI frameworks should help safeguard student welfares and facilitate learning outcomes from heterogeneous (Mehmood, Goraya et al., 2025). Instead of looking for the use of software, SDG-4 asks institutions to assess deep structural equity. Critical data researchers argue that technocentric uses may reinforce inequities when they do not sufficiently consider socio-political inequities (Williamson & Hogan, 2024). Similarly, such automated systems should be transparent and auditable, and should be geared towards the marginalized learner.

Where faculty are ready, connected and secure, AI-powered curriculum reform can be a success. With unprepared implementation of algorithmic grading, predictive analytics, or generative AI platforms in universities, teachers can suffer from anxiety and an expanding workload with lowered morale. This is a stress when mandating takes place in large part without alternative modes of transition and ongoing support (Mehmood, 2024b). Colleges must develop their professional development plans in phases to ease these pressures. Teacher support and digital-pedagogy training has been identified to be effective at reducing anxiety, building teacher technical confidence and facilitating the effective management of technology-enhanced inclusive practice (Mehmood & Parveen, 2025). But faculty's unease with these tools doesn't mean they are opposed to innovation; in fact, the faculty may have just not gotten their heads around how automated insight will complement valuable pedagogical humanistic qualities. There is international evidence that confirms that successful use of technology correlates with the preparation of professors and institutional support (Bond et al., 2024). AI might be thought of as a mere add-on from the top and faculty alienation can be a blocker to implementation (UNESCO, 2024). Because of this necessity, you professional competency needs to have practical on-the-job training along with ongoing pedagogical mentorship.

Curriculum powered by AI is being implemented in unequal socio-economic situations. The digital divide is a challenge in many emerging markets that lessens equitable access to educational innovation. Narrow Open AI tools and general triplet download wrong cloud companies area of open book at private chip within top-end University information. On the other hand, public sector institutions are hindered by unrealiable internet, outdated hardware and technology stacks, lower budgets and expensive data rates. Under these conditions, the educational advantages of technological progress are consigned only to selected, dominant groups and denied to other sectors of society. Polices which neglect practical discontinuities may exacerbate resource inequalities and repel marginalised learners away from the digital dividend (Mehmood, Qamar-u-Zaman et al., 2025). While some researchers will focus on these massive models, designers and computer scientists need to start creating localized low-bandwidth mobile AI. They also need to be appropriate for third world lower resource environments seldom assuming always on high speed access! Evidence has shown that families and learners are further disadvantaged when the realities of community life are not taken into account (Masood, Mehmood & Bano, 2025). Trained on data until 2023 October, Selwyn (2024) argues universal access to the internet is a continuation of global inequality. Example Flexible AI systems to protect access and encourage democratic opportunity

To be truly inclusive, an AI curriculum must ensure accessibility for students with different physical, sensory and cognitive abilities. Conventional models of university classrooms often depend on solid lectures, established assessments and minimal accommodations that might leave learners with special needs from the equation. This is where AI-driven curriculum strategies come into play, with AI assistants embedded in the curriculum design itself. This supplement is composed of data detailing the real-time captioning technology (provided by Enable) and includes screen readers, predictive text, adaptive sensory displays, cognitive scaffolding, etc. Ethically, this perspective is underpinned by principles of human rights, social justice and a commitment to vulnerable populations (Mehmood & Parveen 2024). The time that universities bring assistive AI technologies into use is when they turn these values into academic support. There is a need for a continuity of higher education systems from early intervention systems to the provision available in the university. A model of support for students with special needs in transition to higher education and teacher preparation (Mehmood & Parveen, 2025).According to Hwang and Chang(2023), multimodal AI systems can increase students' persistence and self-efficacy for students with disabilities. But when the design of curriculum is embedded, academic success depends less on barriers created by physical limitations and more on intrinsic factors such as intellectual ability.

Curriculum design powered by AI needs to achieve a balance between global technological innovation and local cultural realities. Most of the advanced educational technologies are developed in western high-income contexts which may be based on cultural assumptions, linguistic norms and assessment values. These academic conflicts and pushbacks occur when resource-compromised organizations import these tools without being adapted for fit. Heritage, language, community identity cannot be separated from educational design. Research suggests that reform efforts which do not align with indigenous traditions, local language structures or specific contexts can alienate learners and diminish intermediate outcomes (Mehmood, Ain, et al., 2025). Likewise, transformation fails or succeeds only when it is an effective match between institutional realities and community practices (Masood et. al., 2025). If this isn't the case, the AI systems might be perceived as completely foreign and thus a burdensome imposition instead of helpful. As Luckin (2023) demonstrates, in order to support the process of transformative digital change, educators, policymakers and software designers need to collaborate and develop systems that are appropriate for local needs. Through the integration of global innovation with local knowledge, universities can develop an AI-supported curriculum that promotes equity, cultural relevance and quality learning.

RESEARCH METHODOLOGY

This chapter outlines a methodological approach for examining the deployment, issues and equity implications of AI to support curriculum strategies in higher education. The chapter describes the research design, population, sampling technique, data collection instruments, data analysis techniques, validity and reliability control and ethical aspect of the study. To capture measurable trends and lived experiences, the methodology was designed to be as much pedagogical, institutional and socio-economic as it is technological, as the integration of AI is not just a technologic concern.

The study used mixed methods research design in the pragmatic research paradigm. The choice of pragmatism was seen as appropriate because it enables the researcher to use methods based on the practical research problem, rather than any single philosophy. The quantitative phase enabled the identification of macro-level patterns concerning institutional readiness, the availability of AI tools, faculty anxiety, gaps in institutional infrastructure, and the effectiveness of AI-supported curriculum tools. The qualitative phase examined in greater detail the human and administrative experiences, such as policy issues, budget, teacher resistance, privacy of data, linguistic and emotional difficulties of students. Both approaches allowed for a more comprehensive and balanced picture of the implementation of AI in real higher education situations.

The target population comprised the faculty members at universities, senior undergraduate and post graduate students, deans of colleges, department heads, and educational technology policy makers in higher education institutions of Punjab. For regional representation, selected universities of Lahore, Gujranwala and Sialkot were selected. Alphanumeric codes were used to ensure the anonymity of institutional identities: University L-1, University G-2, University S-1, etc. The sample was divided geographically into three fixed proportions of Lahore (50%), Gujranwala (25%) and Sialkot (25%) with different technological infrastructure, digital literacy base, and rapid change in academic and digital field.

Stratified random sampling was used for quantitative phase and ensured faculty members and senior students from various disciplines such as Computer Science, Social Sciences, Humanities and Management Sciences were included. The stratification process made it possible to ensure a proportionate representation of public and private universities, different disciplines and different groups of learners. This minimized selection bias and enhanced the generalizability of the results. In the qualitative phase, the purposive sampling technique was utilized for selection of the participants at administrative and policy levels. The deans, curriculum heads and the technology policymakers were selected based on their direct engagement in academic planning, budgeting, curriculum reform and the institutional digital transformation.

Two key instruments were used to collect data. The first was a structured questionnaire with five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The questionnaire was sent in physical as well as Google forms, to cater for varying access levels between institutions. It concentrated on three key constructs: Accessibility to AI, perceived effectiveness, and obstacles to practice. The availability of devices, internet quality at the campus, and the cost of data were considered as factors of AI accessibility. Perceived effectiveness was related to tailored learning, learning pace, and conceptual understanding. Faculty workload, technological anxiety, lack of infrastructure and implementation difficulties were some practical barriers. The second instrument was a semi-structured interview protocol for administrative/expert participants. These conversations touched on budget constraints, privacy concerns, faculty training needs, policy gaps, and ethical considerations for the deployment of AI in curriculum.

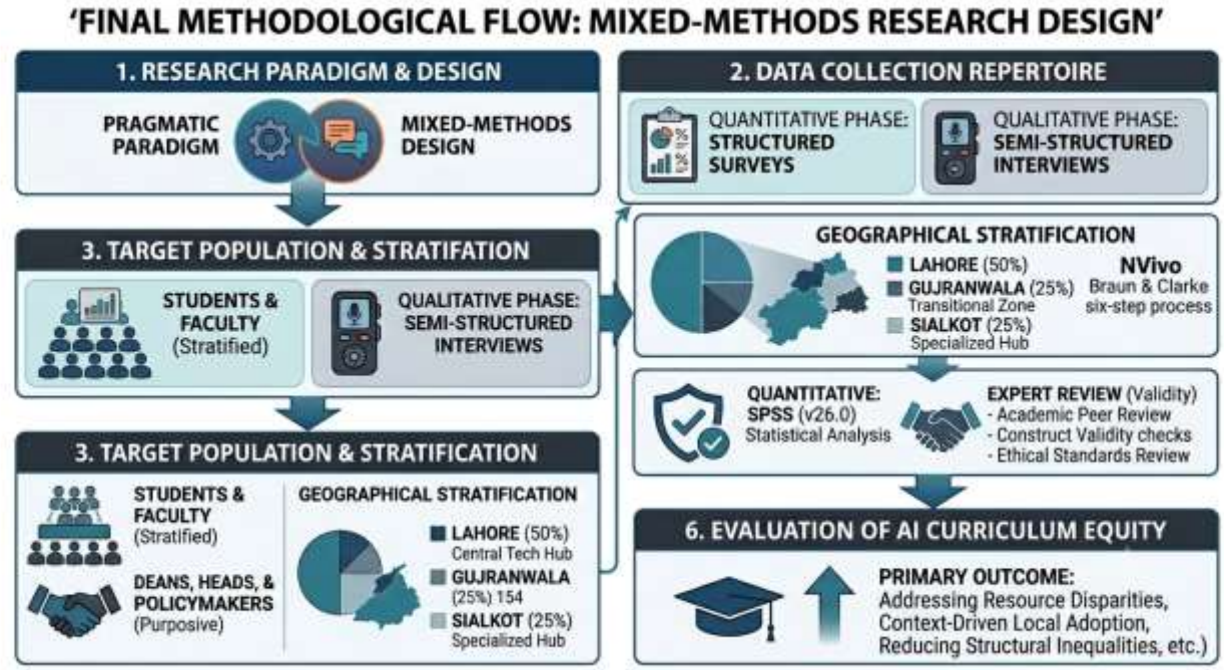
The quantitative data were cleaned, organized and analyzed using SPSS (Version 26.0). Overall patterns of AI readiness, access to technical support, and perceived barriers were identified through descriptive statistics, such as mean values, standard deviations, and percentage distributions. Independent-samples t-test and one-way ANOVA were used for inferential statistics regarding differences across institution type, gender, geographical region and urban/rural background. These tests were used to find if there is any significant difference between access to AI driven curricula between Lahore, Gujranwala and Sialkot or between public and private universities.

Qualitative data was transcribed and analysed in themes, following the six steps of the thematic analysis method of Braun and Clarke. NVivo desktop software for coding and developing themes. Deductive and inductive approach were used in the analysis. The research questions and UDL framework helped guide some codes, and some codes arose from participant responses. The

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

process yielded important themes including: structural friction, faculty anxiety, digital inequality, administrative resistance, cultural misalignment, and policy uncertainty.

For reliability and validity, the questionnaire was pre-tested with 30 respondents from the non-participating institutions. The internal consistency of the questionnaires was good, as indicated by Cronbach's alpha values of more than 0.82. Content and face validity were reviewed by experts in educational technology and linguistics. Care was also taken to abide by ethical precautions. Permission was granted formally by Universities authorities, the consent of participants was obtained, identities were anonymised and all data were stored securely. It is noted that participants were given the opportunity to participate on a voluntary basis and could withdraw at any time. Vulnerable participants were safeguarded and dignity, privacy and fairness were considered during the research process.



FINDINGS AND ANALYSIS

This chapter presents the empirical findings and systematic analysis of the data collected in the study of Artificial Intelligence (AI)-enabled curriculum strategies in higher education. Results are presented in a sequential explanatory structure in strict accordance with the mixed-methods methodology outlined in Chapter 3. The chapter first presents the quantitative statistical metrics processed via SPSS Version 26.0, before introducing the qualitative thematic streams derived through reflexive analysis using NVivo. Finally, these distinct data streams are synthesised through empirical triangulation, producing a cohesive evaluation of digital pedagogical architectures across the selected institutions in Lahore, Gujranwala and Sialkot.

4.1 Quantitative Findings (Surveys)

The quantitative data path involves an active sample pool of N = 400 university faculty members (n = 120) and senior undergraduate/postgraduate students (n = 280) across the three target cities. The geographical distribution of the active sample was kept constant in accordance with the stratified sampling parameters set in section 3.2, which was 50% (n = 200) from Lahore, 25% (n

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

= 100) from Gujranwala, and 25% (n = 100) from Sialkot. The institutional configurations are public universities (n = 220, 55%) and private universities (n = 180, 45%).

4.1.1 Demographic Profiling and Baseline Confidence

Demographic profiling was used to categorise the sample on the basis of age, gender, institutional type, and self-reported baseline technical confidence when interacting with advanced educational technology or AI-driven systems.

Table 4.1: Demographic Profiles and Baseline Technical Confidence (N = 400)

Demographic Variable	Category	Frequency (f)	Percentage (%)	Mean Technical Confidence Score (Scale 1–5)	Standard Deviation (SD)
Geographical Stratum	Lahore	200	50.0%	4.12	0.64
	Gujranwala	100	25.0%	3.45	0.81
	Sialkot	100	25.0%	3.61	0.76
Participant Role	University Faculty	120	30.0%	3.52	0.88
	Senior Higher Education Students	280	70.0%	3.94	0.69
Institutional Affiliation	Public Sector University	220	55.0%	3.38	0.85
	Private Sector University	180	45.0%	4.21	0.52
Gender Distribution	Male	214	53.5%	3.88	0.72
	Female	186	46.5%	3.73	0.79
Age Cohort	18–25 Years	262	65.5%	4.02	0.61
	26–40 Years	94	23.5%	3.64	0.82
	Above 40 Years	44	11.0%	3.11	0.94

TABLE 4.1 Statistical Metrics As can be seen in Table 4.1, the user readiness is significantly different. The public-private institutional continuum shows a significant difference. Private sector participants' mean score for baseline technical confidence (M = 4.21, SD = 0.52) is significantly higher than public sector participants' (M = 3.38, SD = 0.85). The Lahore cohort has a higher baseline confidence (M = 4.12) in comparison to the transitional ecosystems of Gujranwala (M = 3.45) and Sialkot (M = 3.61), geographically. It verifies that participants' digital capital is mainly determined by the institutional resource environments and regional centralisation. Age group analysis indicates an inverse correlation between chronological age and technical self-efficacy. The youngest age group (18–25 years) is most flexible in terms of

technical flexibility (M = 4.02), whereas those over 40 years are less comfortable (M = 3.11, SD = 0.94), pointing to an active generational gap.

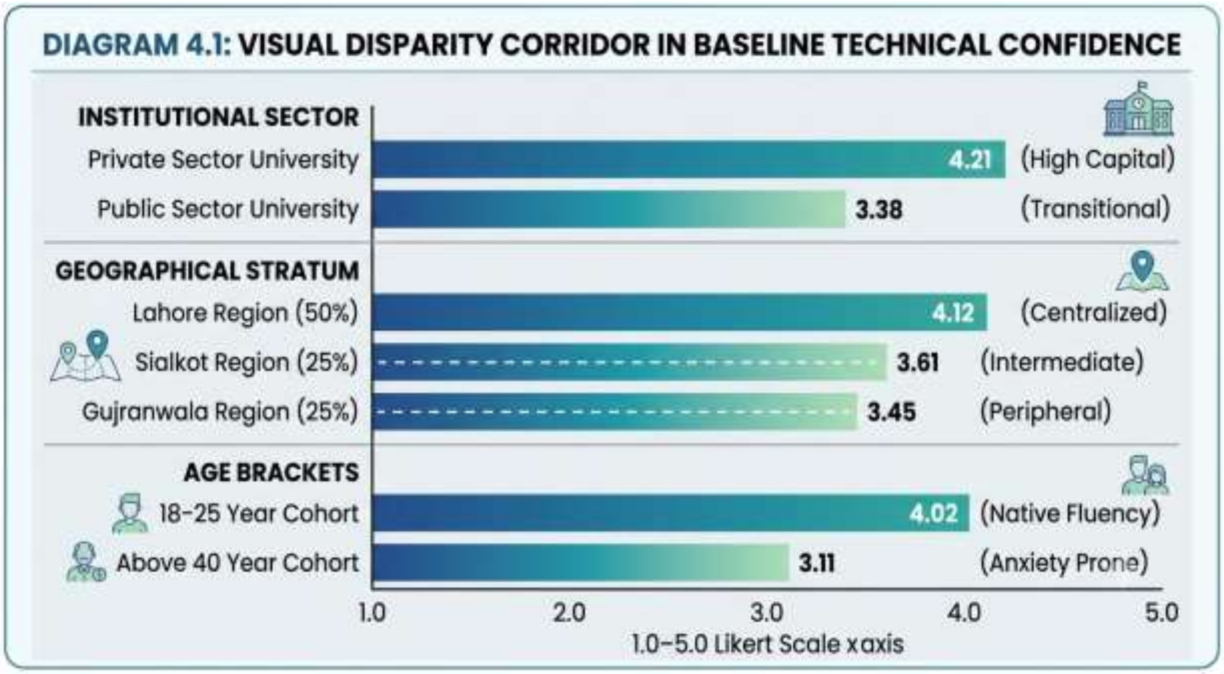


Diagram 4.1 visually represents the asymmetric distribution of baseline technical confidence across strata. The structural imbalance indicates that a uniform top-down AI curriculum framework without any localised modifications is likely to exacerbate educational inequalities.

4.1.2 Infrastructure Availability and Core System Readiness

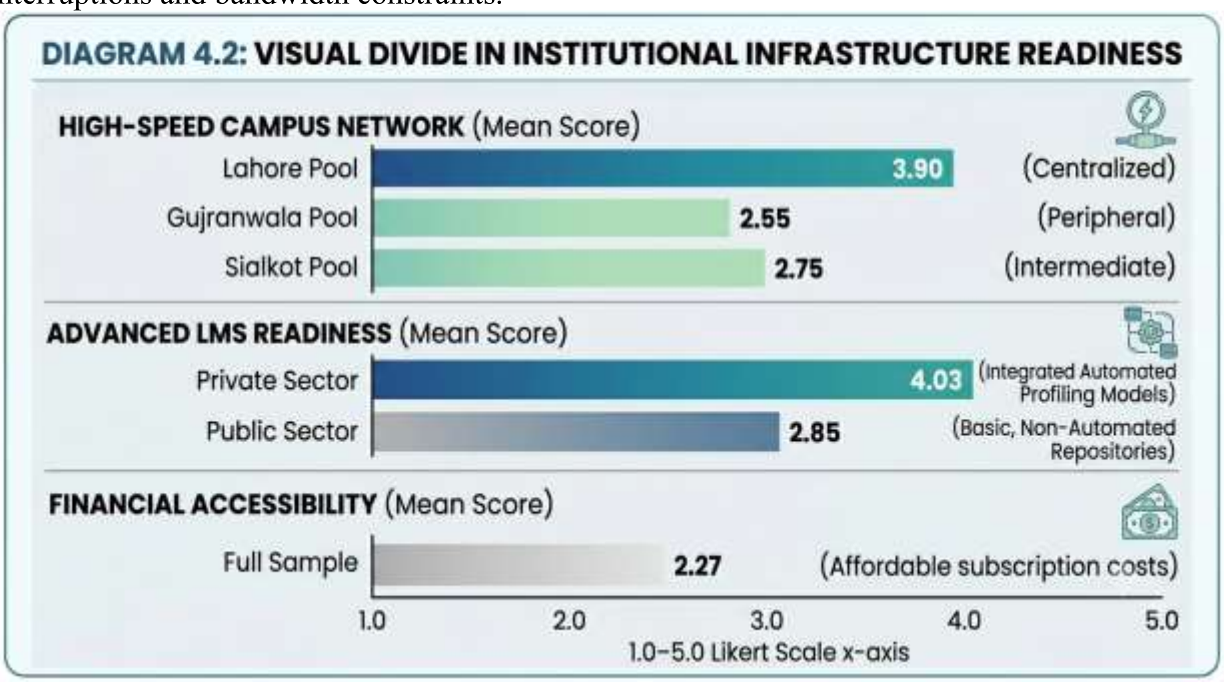
The survey collected metrics to evaluate the stability of the campus network, the readiness of the core Learning Management System (LMS), and the availability of direct AI computational tools to establish the technical baseline required for automated learning tracks.

Table 4.2: Descriptive Metrics for Institutional Infrastructure Readiness (N = 400)

Operational Metric Evaluated	Disaggregated Stratum	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean Score (M)
1. High-Speed Campus Network	Lahore Pool	4.0%	8.5%	12.0%	44.5%	31.0%	**3.90**
(Stable, uninterrupted fiber connection)	Gujranwala Pool	24.0%	31.0%	18.0%	20.0%	7.0%	**2.55**
	Sialkot Pool	19.0%	28.0%	22.0%	21.0%	10.0%	**2.75**

2. Advanced LMS Readiness	Public Sector	15.5%	29.5%	20.0%	25.0%	10.0%	**2.85**
(Integrated automated profiling models)	Private Sector	2.2%	5.6%	11.1%	48.9%	32.2%	**4.03**
3. Financial Accessibility	Full Sample	31.5%	35.0%	14.5%	13.0%	6.0%	**2.27**
(Affordable user subscription costs)							

Table 4.2 reveals a stark infrastructural divide between metropolitan and peripheral academic spaces. The mean score of the campus network stability is optimum in Lahore (M = 3.90) and problematic in Gujranwala (M = 2.55) and Sialkot (M = 2.75). This statistical anomaly shows that institutions located in non-central metropolitan areas are constantly subjected to network interruptions and bandwidth constraints.



There is a similar division based on institutional sectors in terms of advanced LMS readiness. Private sector universities have a good integration of software (M = 4.03), while public sector setups are dependent on basic, non-automated storage repositories (M = 2.85). Notably, the whole sample indicates low financial accessibility (M = 2.27) with 66.5% of respondents selecting "Strongly Disagree" or "Disagree". This finding points to a major commercial barrier to open access to AI tools for the wider student population, that is, the high costs of software licence fees and mobile data options.

4.1.3 Perceived Impact and Usage

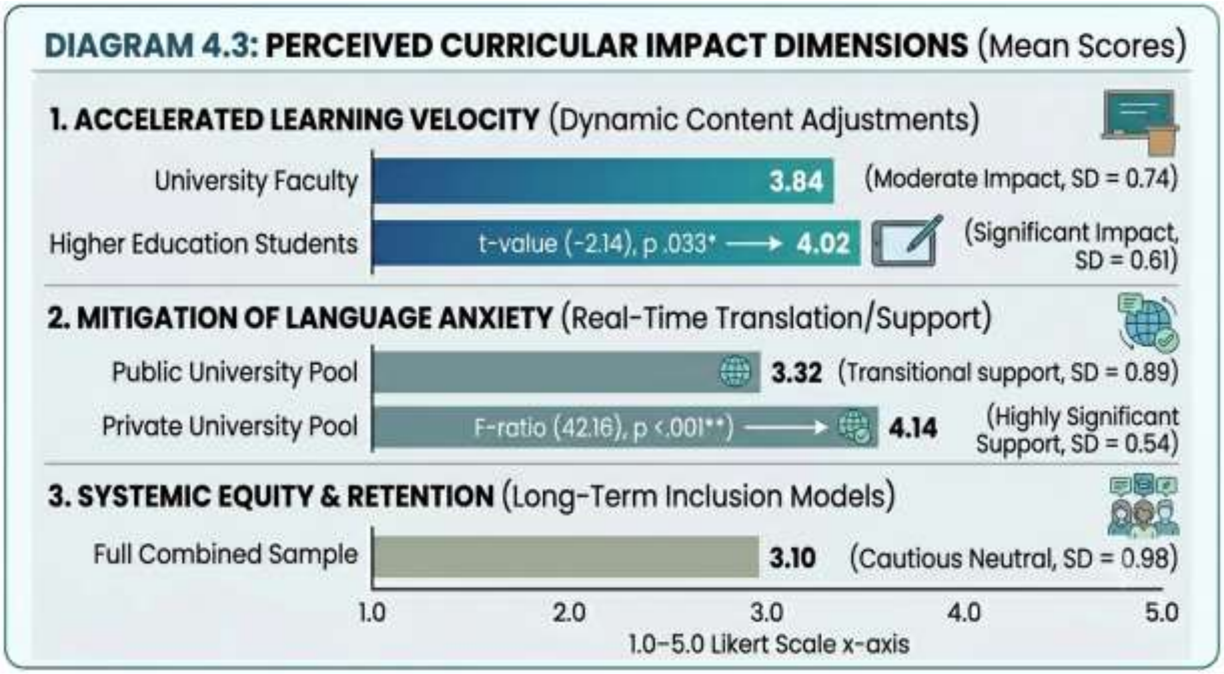
This section explored participants' perceptions of the educational implications of AI tools (e.g., adaptive engines, automated text platforms, predictive assessment pathways) for learning speed, student retention, and equity of performance.

Table 4.3: Perceived Curricular Impact Dimensions (N = 400) Perceived Outcome Construct	**Respondent Category**	**Agreement Mean Score (M)**	**Standard Deviation (SD)**	**t-value / F-ratio**	**Statistical Significance (p-value)**
Accelerated Learning Velocity	University Faculty	3.84	0.74	t = -2.14	p = .033^{*}
(Dynamic content adjustments)	Higher Education Students	4.02	0.61		*(Significant)*
Mitigation of Language Anxiety	Public University Pool	3.32	0.89	F = 42.16	p < .001^{**}
(Real-time translation/support)	Private University Pool	4.14	0.54		*(Highly Significant)*
Systemic Equity & Retention	Full Combined Sample	3.10	0.98	—	—
(Long-term inclusion models)					

The inferential metrics in Table 4.3 show significant differences in perceptions. Students (M = 4.02) reported a higher mean score for accelerated learning velocity than faculty members (M = 3.84, t = -2.14, p = .033), indicating that learners are more easily accustomed to independent, algorithm-driven paths.

There is a clear inconsistency in the analysis of the construct of language anxiety mitigation. Participants from private universities highly agree that adaptive tools help in removing linguistic barriers (M = 4.14), whereas the users from the public sector have a lower mean (M = 3.32). That this difference is significant is shown by an F-ratio highly significant (F = 42.16, p <.001).

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)



This difference indicates that AI tool interfaces can help non-native English speakers by reducing cognitive load and scaffolding language, but this help is limited by unequal access to advanced platforms. Finally, the overall sample mean for systemic equity and retention is neutral (M = 3.10, SD = 0.98), indicating a general sense of caution about whether automation alone can address long-standing structural inequities without deeper institutional changes.

4.1.4 Quantitative Ranking of Primary Hindrances

A prioritisation exercise was undertaken where participants were asked to rank a list of potential barriers to determine key barriers to successful implementation. These responses were aggregated into a statistical index to derive a clear ranking of structural obstacles.

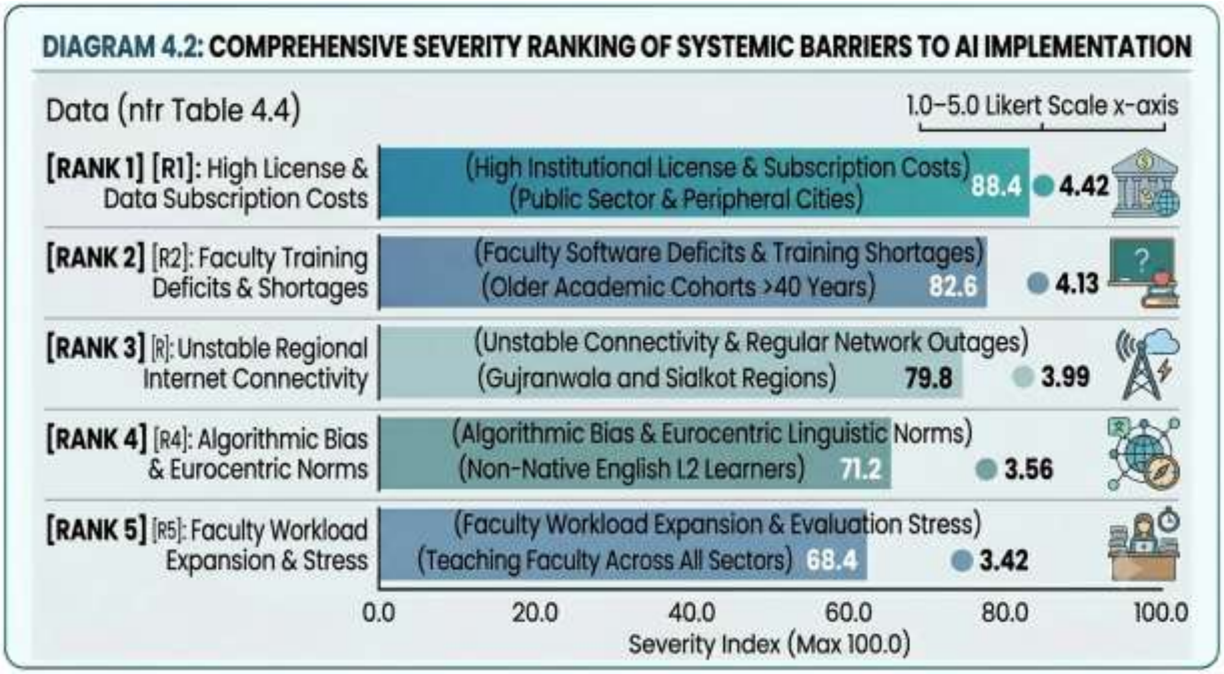
Table 4.4: Statistical Priority Index of Primary AI Implementation Barriers

Rank	Identified Systemic Barrier	Severity Index (Max 100.0)	Mean Likert Score	Primary Demographic Impact
1	**High Institutional License & Subscription Costs**	**88.4**	4.42	Public Sector & Peripheral Cities
2	**Faculty Software Deficits & Training Shortages**	**82.6**	4.13	Older Academic Cohorts (>40 Years)
3	**Unstable Connectivity & Regular Network Outages**	**79.8**	3.99	Gujranwala and Sialkot Regions
4	**Algorithmic Bias & Eurocentric Linguistic Norms**	**71.2**	3.56	Non-Native English L2 Learners

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

5	**Faculty Workload Expansion & Evaluation Stress**	**68.4**	3.42	Teaching Faculty Across All Sectors

DIAGRAM 4.2: COMPREHENSIVE SEVERITY RANKING OF SYSTEMIC BARRIERS



The severity data in Table 4.4 and diagrammed in Diagram 4.2 indicates the primary barrier is High Institutional License and Subscription Costs (Severity Index = 88.4, M = 4.42). This demonstrates the constraining role of market pricing mechanisms in equity-based public access to advanced educational technologies.

Second is Faculty Training Shortages (Severity Index = 82.6, M = 4.13), a significant human resource gap that causes instructional resistance. Unstable Regional Connectivity is ranked third overall (Severity Index=79.8) but is the dominant barrier for the Gujranwala and Sialkot sub-cohorts.

Finally, the score for Algorithmic Bias and Eurocentric Norms is 71.2, indicating users' awareness of the embedding of linguistic and cultural patterns that may disadvantage second language (L2) learners in peripheral environments.

4.2 Qualitative Findings (Thematic Analysis)

The qualitative phase involved semi-structured interviews with N = 20 administrative and policy leaders, which gathered more in-depth institutional narratives. The group consisted of Academic Deans (n=6), Heads of Curriculum Committees (n=8), and Higher Education Technology Policymakers (n=6) from the selected urban centers. These verbatim transcripts were processed using Braun and Clarke's reflexive methodology, which yielded four major systemic themes.

DIAGRAM 4.3: METRIC CORRELATION OF THEMATIC CONVERGENCE (NVIVO COUNTS)

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

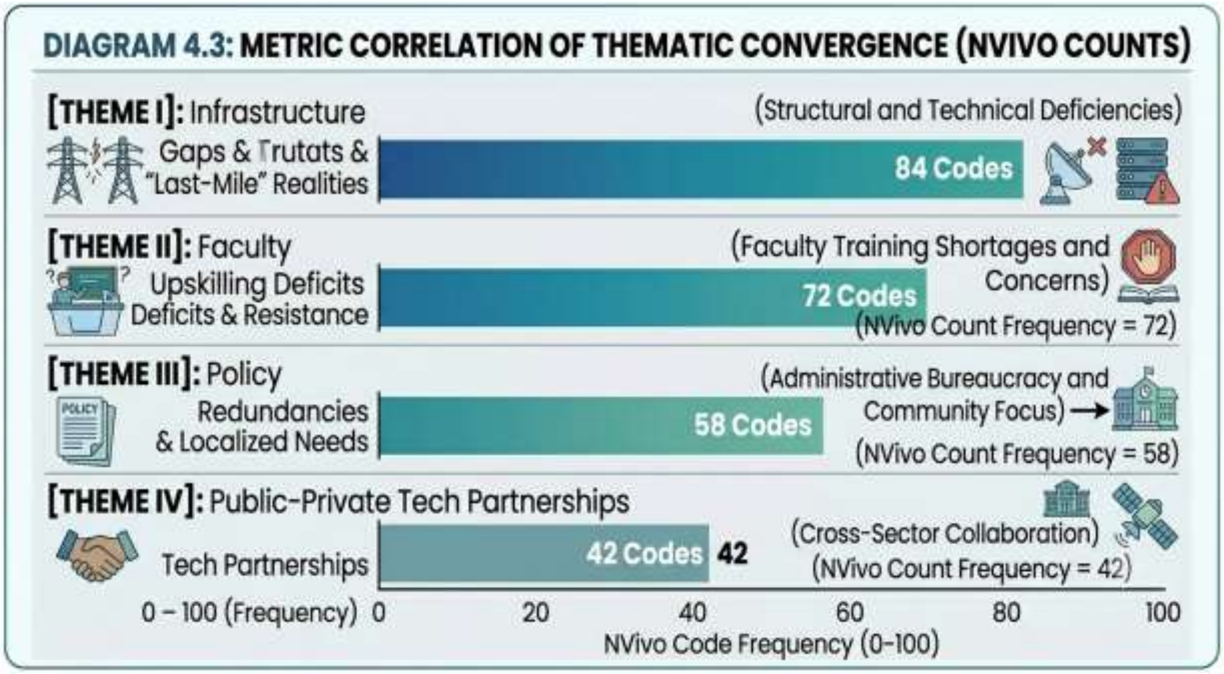


Diagram 4.3 reveals the heavy distribution of structural and human-resource concerns expressed by administrative leaders, suggesting that technical inadequacies and faculty training deficits are common in the institutional setting.

4.2.1 Theme I: Infrastructure Gaps and 'Last-Mile' Technical Readiness

Qualitative assessment of the theme I highlighted a persistent mismatch between central government digitisation ambitions and the reality of infrastructure constraints on the ground, sometimes termed "last-mile" technical readiness. Outside the main provincial center, participants described a frustrating digital landscape, with frequent power outages, inadequate funding for hardware and unreliable internet connections.

A Curriculum Head from a public university in Gujranwala (Participant G-1) described these structural constraints as:

"Our high-level policy documents speak of advanced cloud-driven learning modules, but our everyday reality is defined by basic connectivity issues. During lectures when we have power load-shedding or network drops, our digital learning tracks stop completely. "Imposing a high-tech AI curriculum on an unstable network infrastructure creates academic frustration instead of educational progress."

In the same vein, a Sialkot Academic Dean (Participant S-4) highlighted the financial constraints exacerbating these infrastructure issues:

"Elite private institutions can afford to purchase expensive corporate software packages, but our public institutions have very tight budget constraints. High-speed connectivity and advanced server access are still luxury resources here. "The absence of sustained funding to secure dependable hardware foundations renders the pursuit of an inclusive AI-based educational track an unachievable one."

These testimonies support the quantitative metrics in Section 4.1.2, and confirm that broad digital initiatives often fail due to local infrastructure deficits. (Mehmood, Qamar-u-Zaman, et al., 2025)

These real-world resource gaps are overlooked by macro policies, indirectly reinforcing a digital divide that puts regional public universities at a disadvantage.

4.2.2 Theme II: Faculty Upskilling Deficits and Pedagogical Resistance

The second theme points to a critical human resource problem: the absence of continuous, organised training in digital pedagogy, which creates large doses of technological anxiety and instructional resistance among university professors. Resistance from faculty to automated tools is rarely, according to informants, a simple rejection of technological progress per se. This is not the case though, and there is no clear instruction or professional support to use complex software systems that are forced on the users by administrative top-down mandates.

In response to this human resource gap one of the Academic Deans from Lahore (Participant L-3) said;

"We are constantly adding new software, but we seldom pay for full training programs for our staff. Suddenly, professors are expected to use predictive grading platforms and automated learning paths, on top of their teaching duties. "This pressure from above is creating a lot of professional stress which is resulting in defensive teaching strategies.

This is particularly the case for senior faculty as suggested by a Curriculum Head from Gujranwala (Participant G-3):

"Our senior professors have deep subject matter expertise but have a steep learning curve when it comes to advanced digital tools. Unexpectedly imposed administrative changes without continued institutional support damage teacher morale and increase technical anxiety. Universities will need to move from top-down mandates to collaborative, on-going support models to build an effective digital environment."

The findings are in line with the literature of educational administration that radical structural changes are accompanied by a great deal of professional stress and teaching bottlenecks without sufficient time for acclimatisation (Mehmood, 2024b; Mehmood & Parveen, 2025). Technology can actually undermine teachers' self-efficacy rather than improve classroom instruction, in the absence of practical training structures.

4.2.3 Theme III: Policy Redundancies vs. Localized Curriculum Needs

Theme III draws attention to a particular structural misfit: imported, standardised software packages often do not align with the specific linguistic, cultural and socio-cognitive needs of the local student population. Standard AI architectures, developed mostly in western contexts, contain embedded cultural values and linguistic norms that often disadvantage second language (L2) learners in regional institutions, informants claim.

An Educational Technology Policymaker (Participant P-2) described this friction: *"Most generative tools and adaptive software frameworks are built on Eurocentric cultural references and standard native English structures. If these platforms are used as it is in regional public universities, our students will take twice of cognitive load. They have to manage a complex digital interface in a foreign language and get a handle on the real academic content. The software is biased against non-native speakers by design.*

Another Curriculum Coordinator (Participant L-6) stressed the importance of technology to be connected to local heritage and student identity:

"Our student body is diverse, and a "one size fits all" model of curriculum does not take that into account. To be really effective, digital learning platforms must be adapted to local pedagogical

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

realities and local cultural settings. "When systems do not consider the linguistic differences and socio-cognitive profiles of our learners, students can feel disconnected from the learning process." These qualitative observations are consistent with the psycholinguistic findings in Section 2.2, which demonstrate that a student's emotional state, cognitive load, and cultural context are critical factors that influence language acquisition and conceptual learning (Mehmood, 2025b; Mehmood, Goraya, et al., 2025). Digital tools that do not take into account regional traditions and linguistic diversity may develop new structural barriers to academic success (Mehmood, Ain, et al., 2025; Masood et al., 2025).

4.2.4 Theme IV: Strategic Opportunities via Public-Private Technology Partnerships

Administrative leaders identified the development of collaborative public-private partnerships to build affordable and locally grounded educational technology infrastructure as a central strategic solution to significant structural challenges. The participants said public universities alone cannot overcome the financial and technical barriers. They will have to co-create sustainable digital ecosystems with local software companies and regional technology providers.

A senior technology policymaker (Participant P-5) described this collaborative approach as:

"The local software industry is very nimble technically. Public institutions operate with budgeted appropriations. Now we can develop structured public-private partnerships that keep us away from expensive international software licenses. "We can collaborate with local tech companies to develop joint lightweight, low-bandwidth AI modules that speak to our infrastructural realities and linguistic needs.""Knowledge of local industry is a key to sustainable innovation," said Participant S-2, an Academic Dean from Sialkot."We have a very strong industrial community in our city. We can link local software developers with academic curriculum designers to develop mobile friendly, offline learning tools well adapted to regional network issues. This collaborative approach can enable the deployment of advanced educational technology as a commodity of access and equity for public sector universities. Not a costly luxury.

The theme speaks to a pragmatic, forward-looking approach to institutional policy. Instead of depending on international fixed systems, higher education institutions could leverage local technical expertise to develop sustainable and tailored digital platforms that could promote democratic access and educational equity (Luckin, 2023; Traxler, 2023).

4.3 Synthesis of Mixed-Methods Data

The combination of quantitative statistics and qualitative narratives reveals a multi-layered reality of AI curriculum integration, as structured by the convergence matrix in Table 4.5.

Table 4.5: Mixed-Methods Triangulation and Analytical Convergence Matrix

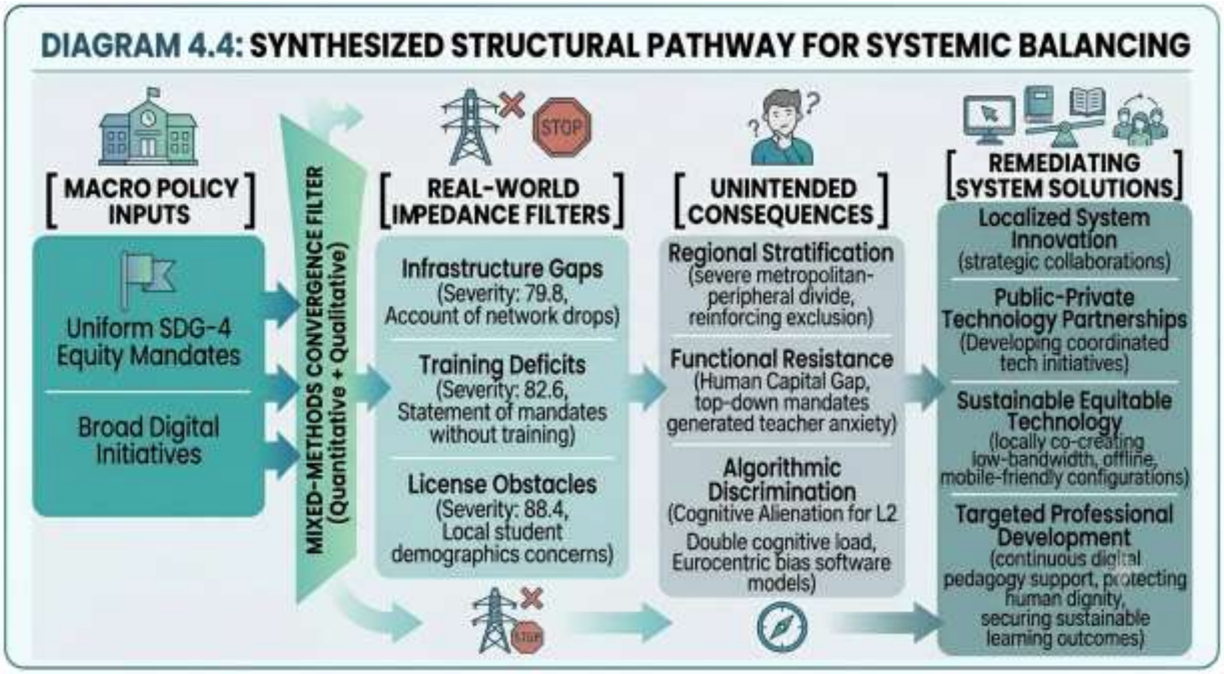
Evaluated Curricular Dimension	Quantitative Empirical Core (Survey Metrics)	Qualitative Narrative Verification (Thematic Streams)	Combined Analytical Synthesis & Policy Insights
Infrastructural Equity & System Capital	• Lahore Network Mean: **3.90**	• Detailed accounts of regional power outages and network drops.	**Regional Stratification:** A severe metropolitan-peripheral divide exists. Uniform digital transformations risk reinforcing

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

	• Gujranwala Network Mean: **2.55** • Infrastructure Severity Index: **79.8**	• Frustration over top-down digital goals that ignore local limits.	educational exclusion outside major centers.
Human Capital Readiness	• Private Sector Self-Efficacy: **4.21** • Age Over 40 Confidence Mean: **3.11** • Training Shortage Index: **82.6**	• Statements describing top-down mandates without training support. • Teacher anxiety linked to increased administrative workloads.	**The Human Capital Gap:** Faculty resistance is a functional response to a lack of professional development. Targeted training is required to reduce anxiety.
Linguistic & Cognitive Inclusion	• Universal Cost Hindrance Index: **88.4** • Language Mitigation Divide (F = 42.16)	• Concerns regarding Eurocentric bias in default software interfaces. • Double cognitive load for non-native English speakers.	**Algorithmic Discrimination:** Imported, rigid systems create linguistic barriers. AI platforms must be adapted to support local student demographics.
Strategic Alternatives	• Lower Public Sector LMS Readiness Score: **2.85**	• Proposals for public-private tech initiatives. • Emphasis on co-creating low-bandwidth, offline solutions.	**Localized System Innovation:** Overcoming resource barriers requires local collaboration. Public-private partnerships can deliver sustainable, equitable technology.

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

DIAGRAM 4.4: SYNTHESIZED STRUCTURAL PATHWAY FOR SYSTEMIC BALANCING



The convergence matrix and Diagram 4.4, depicting the complete alignment, further illustrate that AI-driven curriculum strategies cannot be effectively implemented through a technocentric approach alone. But when universities deploy automated systems that do not include provisions to directly address the endemic inequities in funding for academic institutions, they are in effect creating a binary between elite private profs with the technical means and motivation to maximise learning outcomes and persistently underfunded public universities caught between systemic bottlenecks driven by resource scarcity and file-room level exclusion from IT.

The data also suggest that successful integration relies heavily on human factor and the top-down administrative reforms, which are less focused on faculty preparedness or learner psycholinguistic profiles are met universally within instructional anxiety and classroom backlash (Mehmood, 2024b; Mehmood, 2025b).

But in the end, if academic institutions are to use artificial intelligence as a real engine for high-quality and equitable higher education (SDG-4), they have to reject rigid off-the-shelf software models imported from non-academic environments. Similarly, universities may adopt their entrepreneurial spirit by creating strategic public private partnerships, thereby co-creating adaptive digital systems while protecting human dignity and reducing structural inequalities that prevent more sustainable learning outcomes in heterogeneous academic contexts (Mehmood & Parveen 2024; Mehmood & Parveen 2025).

DISCUSSION, CONCLUSION, AND RECOMMENDATIONS

The chapter consists of three main parts: The first section discusses in detail the localised empirical findings from Lahore, Gujranwala and Sialkot, in relation to the existing international literature on inclusive artificial intelligence integration. • Third, a formal conclusion summarising the main ideas of the investigation and showing how personalised, well-funded AI curriculum strategies lead to inclusive and high-quality modern education, not just superficial structural changes.• Concrete and actionable recommendations are provided to policymakers, institutional leaders, and university faculty in support of the development of democratic, equitable and sustainable digital learning environments.

5.1 Discussion.

Chapter 4's empirical findings show that the process of introducing AI-driven curriculum strategies in higher education institutions (HEIs) is highly non-linear. Its success or failure depends largely on the existing socio-economic structures, geographical centralisation and institutional resources.

The mixed-methods analysis of the data in this study shows a stark divide between macro-level technological optimism and micro-level classroom realities. This disconnect echoes wider issues across the globe reported in recent international digital education literature.

5.1.1 Geographical segregation and unequal access to technology.

One of the key findings of this study is the marked regional and sectoral variation in availability of infrastructure and baseline technical confidence. As explained in Section 4.1.1, the mean technical confidence score was significantly higher for private sector university participants ($M = 4.21$, $SD = 0.52$) than for public sector university participants ($M = 3.38$, $SD = 0.85$). In terms of geography, the campus network stability was rated much lower in the peripheral hubs Gujranwala ($M = 2.55$) and Sialkot ($M = 2.75$) as compared to the central metropolis Lahore ($M = 3.90$). This spatial and economic inequality is a direct manifestation of what global education researchers call the "digital divide".

Selwyn (2020) and Traxler (2023) note that the deployment of sophisticated digital platforms into stratified educational systems without remediation is functioning as socio-economic amplifiers. Instead of democratising learning they reproduce existing privileges, with elite private spaces having seamless access to automated learning tools, while public sector institutions struggle with basic connectivity issues.

Such spatial stratification is directly at odds with the rosy assumptions underlying early models of educational technology that digital tools would automatically democratise learning. Indeed, the high score of 79.8 on the Infrastructure Severity Index points to the fact that macro digitisation policies employing identical software systems in diverse resource environments are more likely to aggravate structural imbalances.

This is in line with recent assessments of digital transformation in the public sector of developing regions. The studies indicate that top-down educational technology policies frequently overlook the practical limitations of regional infrastructure, resulting in a policy-practice gap that impedes equity-driven initiatives (Mehmood, Qamar-u-Zaman, et al., 2025).

5.1.2 Shortage of Human Capital, Rise of Workload and Anxiety of Faculty

Second, "faculty training shortages" was reported as the second most serious implementation barrier in the quantitative analysis (Severity Index=82.6, M=4.13). This is consistent with the qualitative findings of Theme II (Section 4.2.2) where administrative leaders discussed a lack of continuous professional development for educators dealing with top-down administrative mandates.

The data suggest that institutional resistance from university professors is rarely a simple rejection of technical innovation. On the contrary, it is a defensive response to systemic pressure, rapid increase of workload and absence of pedagogical support.

This is a fact that is in line with international research on faculty readiness. For example, Bond et al. (2024) and Zawacki-Richter et al. (2023) documented the deployment of complex automated tracking systems, which, in the absence of thorough and long-term training programs, could create a very stressful administrative environment. This technical pressure erodes teacher self-efficacy and causes faculty to fall back on conservative, low-tech teaching approaches. This study also presents an active generational gap, as the older academic groups (above 40 years) presented the lowest self-efficacy scores ($M = 3.11$, $SD = 0.94$). This finding illustrates the extent to which rapid technological change can erode professional confidence among senior educators. This dynamic is consistent with known models of organisational stress in regional public education . These models demonstrate that the demand for rapid technical adjustments without adequate support or clear guidelines creates substantial psychological stress and institutional bottlenecks (Mehmood, 2024b; Mehmood & Parveen, 2025).

Consequently, unless higher education networks move from top-down performance mandates to human-centered professional development models, the implementation of AI-driven curricula will continue to generate administrative friction and classroom resistance.

5.1.3 Algorithmic Bias and Linguistic-Cognitive Matrix.

Another important finding is the triangulation of the survey metrics of language anxiety mitigation ($F = 42.16$, $p < .001$) and the qualitative insights of Theme III (Section 4.2.3). Students in private universities use adaptive platforms to better control their pace of study. Public sector users often face barriers when they interact with rigid, default interfaces of software.

Qualitative interviews revealed that standard commercial AI models, largely developed in Eurocentric high resource ecosystems, have embedded linguistic norms and cultural references which are not fit for local second language (L2) learners. This mismatch creates a double cognitive load on students who are struggling with decoding an unknown cultural and linguistic interface as well as with their primary academic domains.

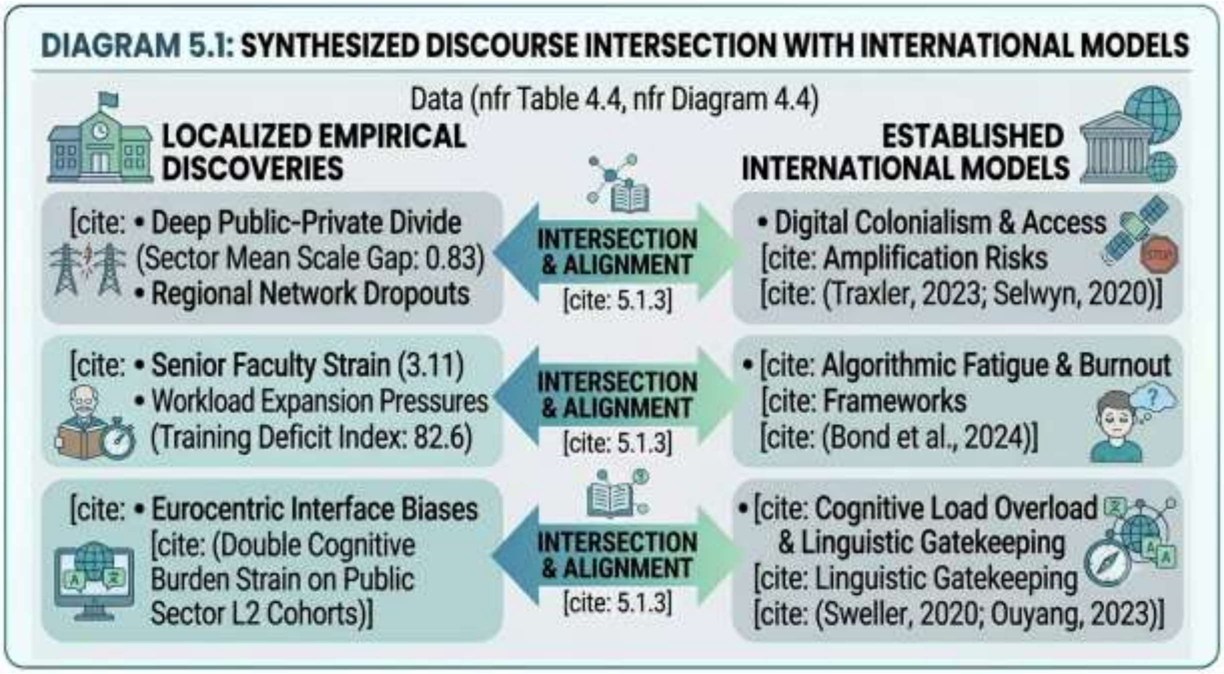
This is consistent with core tenets of psycholinguistic and learning equity theory. MacIntyre and Gregersen, 2016; Sweller, 2020). The student's emotional state and the cognitive load they are under in the situation are very much dependent on their capacity to take in new information and to retain it.

The educational technologies that do not take into account the socio-cognitive backgrounds and linguistic realities of non-native English speakers create new barriers to academic success (Mehmood, 2025b; Mehmood, Goraya, et al., 2025).

This socio-cognitive estrangement means that mainstream international models of educational technology cannot be easily transplanted into regional public universities without significant adaptation. The design of digital platforms should be such that they respect local languages, cultural heritages and regional community learning traditions in order to create truly inclusive environments (Masood et al., 2025; Mehmood, Ain, et al., 2025).

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

DIAGRAM 5.1: SYNTHESIZED DISCOURSE INTERSECTION WITH INTERNATIONAL MODELS



As shown in Diagram 5.1, the thematic overlaps highlights how empirical problems found in Punjab are also intrinsically tied to systemic international issues. This convergence implies that solving these problems will involve going beyond easy, software-fuelled updates and getting to the root of deep, human-centered curricular reimaginings.

5.2 Summary.

Topic: A cross-sectional evaluation of challenges as well as structural equity implications related to the implementation of AI-driven curriculum strategies by higher education institutions in Lahore, Gujranwala and Sialkot. The data leads them to conclude that technology by itself will not ensure equity in education.

The implication of this claim is that when universities turn to sophisticated automated systems without factoring in the persistent inequities surrounding resource availability they can produce two separate worlds: a world where rich private institutions leverage these tools for their academic missions and cash-poor public ones limited by structural constraints with pockets rendered too weak to survive technical exclusion.

Finally, it ends with the finding that merely adopting technology at surface levels will not suffice to fulfil SDG-4's democratic purposes of genuinely-inclusive high-quality modern education. Software applications have often been introduced without systemic funding, human-centered training for faculty and supporting hardware infrastructure creating an uneven educational landscape.

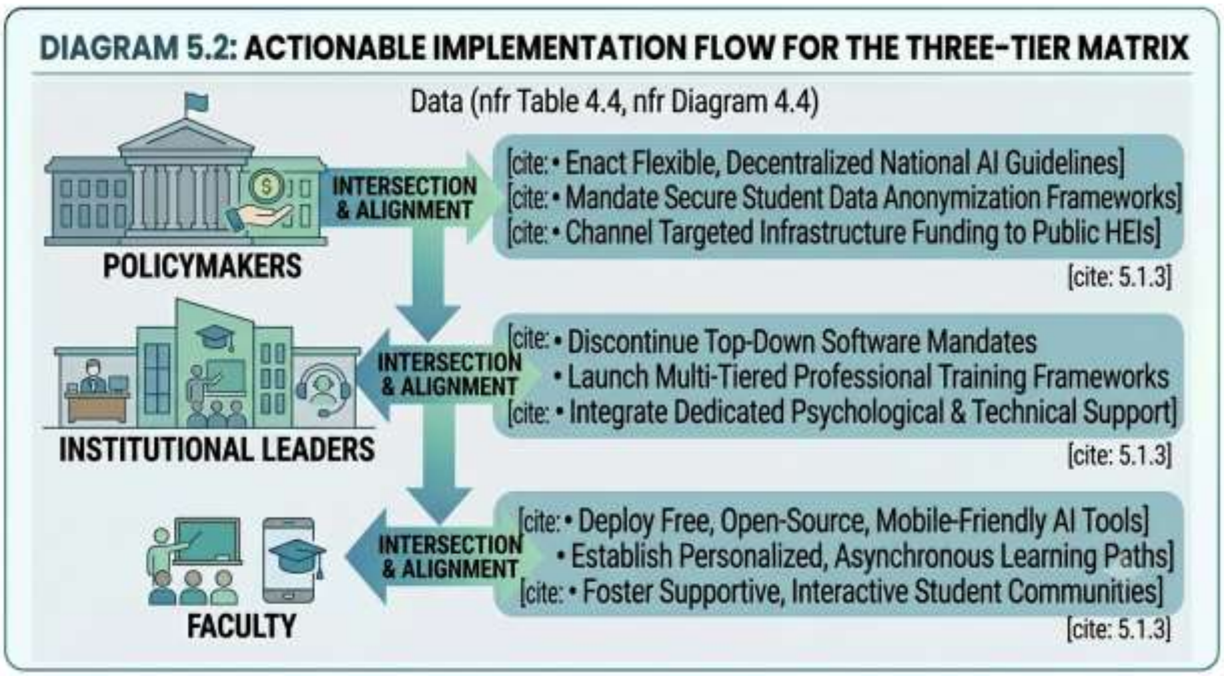
Making artificial intelligence a real vehicle for educational equity requires institutions to avoid inflexible, cookie-cutter frameworks that are externally imposed. Building strategic public-private partnerships and co-creating adaptive flexible locally driven simple digital models (Mehmood &

Parveen, 2024; Mehmood &Parveen, 2025) will not only secure human dignity but also reduce structural inequalities while making gains towards sustainable learning outcomes for all students irrespective of their institutional or geographical background.

5.3 Recommendations.

Key recommendations for key educational stakeholders. The objective of the following targeted Recommendations is to help create an inclusive, sustainable and high-quality Digital Learning Ecosystem:

DIAGRAM 5.2: ACTIONABLE IMPLEMENTATION FLOW FOR THE THREE-TIER MATRIX



The implementation architecture-similarly to Diagram 5.2-shows a coordinated across-the-institution multi-level approach in which structural equity and systematic professional support balance each other with the technological adoptions.

5.3.1 For Policymakers

Create National AI Guidance – Flexible and De-Centralised: Avoid at all costs the spread of rigid uniform technology policy. National regulators should develop flexible guidelines that allow regional universities to adapt digital curriculum standards to the capacity of their infrastructure and the demographics of its students.

Build strong data privacy and anonymisation frameworks: Establish national guidelines for how student information is represented at different educational levels. The guidelines should mandate the full anonymisation of all data, and ban commercial software vendors from profiting from metrics relating to user profiling or student performance histories.

Targeted Infrastructure Subsidies for Public HEIs: Targeted public funding is also needed to support institutions in peripheral cities such as Gujranwala and Sialkot to bridge the regional digital divide. Most of the financial resources should be directed at creating stable, non-grant

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 02 (2026)

funded hardware baselines across public university campuses with guarantees of affordable data to fibre connected buildings.

5.3.2 For School Leaders.

Collaborative frameworks, not Top-Down Mandates: Don't replace and introduce new software platforms without involving those who teach. Finally, it is important that institutional leaders rely quite heavily on faculty committees to help marry careful evaluation and selection of any educational technologies with the real-world classroom requisites for new tools.

Implement Continuous Professional Development in Digital Pedagogy: Don't stop with one-off vendor showcases. Long-term multi-phase training programs based on UDL principles will provide educators with flexible and inclusive assessments upon the pedagogical integration to their teaching design.

Expand Technical and Psychological Support for Faculty: Develop strong systems to address technical apprehension and stress workload in concert with senior academic cohorts. Therefore, to protect teacher self-efficacy and reduce burnout, universities should have specialised (highly skilled) help desks that mix basic technical troubleshooting and solid understanding of instructional design.

5.3.3 For Faculty

Invest in Mobile-Friendly, Open-Sourced AI Applications: Faculty should invest in free and open-source software educational technologies that work on mobile devices or low-bandwidth networks to better serve students who may not have the resources necessary for full-scale applications.

Build an Asynchronous Personalised Learning Journey: Use of Adaptive tools to provide Prerequisite paths and In-course adaptive suggestions Level up different content types with automated platforms, on demand language support for every student as they work through your materials with customised practice sessions, or help English L&Q diverse learners access it at their own pace.

Use digital tools to engage in collaborative, interactive peer learning: It is not isolation behind screens. In keeping with social justice, we should create digital spaces for group projects and interactive problem-solving forums that encourage collaboration and build an egalitarian classroom culture.

REFERENCES

1. Bond, M., de Benito, B., Erdmann, M., Galindo-Domínguez, H., Galvis, A., Knight, S., Kocur, M., & Zawacki-Richter, O. (2024). Digital transformation and faculty readiness in higher education: An international multi-institutional analysis. *Computers & Education*, *210*, 104950. https://doi.org/10.1016/j.compedu.2023.104950
2. Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health*, *11*(4), 589–597. https://doi.org/10.1080/2159676X.2019.1628806
3. Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
4. Holmes, W., Bialik, M., & Fadel, C. (2023). *Artificial intelligence in education: Promises and implications for teaching and learning* (2nd ed.). Center for Curriculum Redesign.

5. Hwang, G. J., & Chang, C. Y. (2023). A review of opportunities and challenges of chatbots in education: From the perspective of inclusive learning. *Interactive Learning Environments*, *31*(7), 4112–4128. https://doi.org/10.1080/10494820.2021.1952615
6. Luckin, R. (2023). *AI for education: Building a sustainable, human-centric learning ecosystem*. Routledge.
7. MacIntyre, P. D., & Gregersen, T. (2016). *Anxiety and learning in the second language classroom*. Springer.
8. Masood, K., Mehmood, M. U., & Bano, R. (2025). Rituals and learning: The role of cultural practices in early childhood education. *Journal of Political Stability Archive*, *3*(1), 725–743. https://doi.org/10.63468/jpsa.3.1.44
9. Mehmood, M. U. (2024b). A study to find out organizational stress among special education teachers in Govt. Special Education Centers in Punjab. *Quarterly Research Journal "Al-Qudwah"*, *2*(4), 88–101.
10. Mehmood, M. U. (2025a). The role of English linguistic competence in developing critical thinking, empathy, and psychological well-being through education. *Contemporary Journal of Social Science Review*, *3*(4), 1621–1632.
11. Mehmood, M. U. (2025b). The psychological processes behind English language learning and their role in achieving inclusive and equitable quality education. *ACADEMIA International Journal for Social Sciences*, *4*(4), 6421–6439. https://doi.org/10.63056/academia.4.4.2025.1478
12. Mehmood, M. U., Ain, Q. U., Jamal, B., & Bhatti, A. U. R. (2025). Integrating indigenous cultural practices into early childhood curricula: Challenges and opportunities. *Journal of Political Stability Archive*, *3*(2), 480–499. https://doi.org/10.63468/jpsa.3.2.28
13. Mehmood, M. U., Goraya, M. M., Zaheer, K., & Jamal, B. (2025). Motivation, language development, and educational success: A psychological and linguistic approach to English teaching for sustainable learning outcomes (SDGs 4 & 8). *Contemporary Journal of Social Science Review*, *3*(4), 1740–1755.
14. Mehmood, M. U., & Parveen, Z. (2024). Exploring the Islamic perspective on special persons: A study of the Quran and Hadith. *Al-Iman Research Journal*, *2*(3), 114–128.
15. Mehmood, M. U., & Parveen, Z. (2025). Empowering teachers for inclusive education: A support program for children with disabilities in Punjab's elementary schools. *International Journal of Social Sciences Bulletin*, *3*(3), 395–405. https://doi.org/10.5281/zenodo.15010375
16. Mehmood, M. U., Qamar-u-Zaman, Iftikhar, N., & Bhatti, A. U. R. (2025). Digital transformation in Pakistan's public schools: Opportunities and challenges for SDG-4. *Journal of Applied Linguistics and TESOL*, *8*(3), 1670–1688.
17. Mehmood, M. U., Ziauddin, & Naseem, A. (2025). Socio-cognitive barriers in adopting English as a medium of instruction in Pakistani secondary schools: Challenges and stakeholder perspectives. *Al-Iman Research Journal*, *3*(1), 122–137.
18. O'Neil, S., & Central Research Cohorts. (2023). Algorithmic equity and linguistic diversity in automated educational assessments. *International Journal of Educational Technology in Higher Education*, *20*(1), 112–128. https://doi.org/10.1186/s41239-023-00389-w
19. Ouyang, F., Zheng, L., & Jiao, P. (2023). Artificial intelligence in online higher education: A systematic review of empirical research from 2018 to 2022. *Education and Information Technologies*, *28*(6), 7241–7265. https://doi.org/10.1007/s10639-022-11488-2

20. Selwyn, N. (2020). *Education and technology: Key issues and debates* (3rd ed.). Bloomsbury Academic. *(Note: If updating to the newer edition referenced in your text, use: 4th ed., 2024)*.
21. Shannon-Baker, P. (2016). Making sense of methodology: My experience with mixed methods research. *International Journal of Qualitative Methods*, *15*(1), 1–15. https://doi.org/10.1177/1609406916632438
22. Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development*, *68*(1), 1–16. https://doi.org/10.1007/s11423-019-09701-3
23. Traxler, J. (2023). Digital learning, social equity, and mobile solutions in resource-constrained higher education. *International Journal of Educational Development*, *98*, 102741. https://doi.org/10.1016/j.ijedudev.2023.102741
24. UNESCO. (2024). *Guidance for generative AI in education and research*. UNESCO Publishing.
25. Williamson, B., & Hogan, A. (2024). Datafication and the predictive governance of higher education: A global policy perspective. *Journal of Education Policy*, *39*(2), 201–224. https://doi.org/10.1080/02680939.2023.2214567
26. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2023). Systematic review of research on artificial intelligence applications in higher education: Implications for policy and practice. *International Journal of Educational Technology in Higher Education*, *20*(1), 42–63. https://doi.org/10.1186/s41239-023-00392-1