ACADEMIA International Journal for Social Sciences
Volume 5, Issue 3(s8), 2026 ISSN-L (Online): 3006-6638

Role of Artificial Intelligence and Student Learning in Higher Education: A Qualitative Study in District Gwadar

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Received: 02-02-2026 **Revised:** 18-02-2026 **Accepted:** 07-03-2026 **Published:** 20-03-2026

ABSTRACT

Despite Artificial Intelligence tools becoming central to academic life in universities worldwide, the experiences of students and faculty in resource-constrained and geographically peripheral settings remain largely unexplored (Schmidt et al., 2025). This qualitative research explores the role of AI in students' learning in higher education institutions (HEIs) based in District Gwadar, Balochistan, Pakistan, which is strategically an important region of the China-Pakistan Economic Corridor (CPEC) but lacks digital infrastructure, and the institutions are not yet ready for it. The study will be based on a constructivist worldview and an interpretivist epistemology. It will employ a reflexive thematic analysis (Braun & Clarke, 2006, 2021) of 20 semi-structured interviews with 10 teachers and 10 students from the University of Gwadar and Gwadar Degree College.The analysis resulted in three main themes, namely, Accessibility of AI Tool and Its Relationship with Student Learning; AI-Engaged Academic Activities and Student Learning; and Faculty Preparedness towards AI and Student Learning. The results show that structural connectivity barriers limit access to AI for most students, that AI engagement is mostly informal, self-directed, and pedagogically unsupported, but that the faculty attitudinal disposition, in the absence of institutional policy, has become the principal determinant of whether students encounter AI as a guided educational resource. The contextual qualitative understanding from the study provides an alternative to literature dominated by quantitative studies. It has many implications for institutional policy, faculty development, and digital equity.

Keywords: *artificial intelligence; student learning; qualitative research; thematic analysis; faculty preparedness; digital equity; higher education; Gwadar; Pakistan.*

INTRODUCTION

Something worth looking into is happening in the classrooms of Gwadar's university and college. Students are trying out Artificial Intelligence tools – downloading apps on their mobile phones, sharing prompts through WhatsApp groups, and accidentally finding ChatGPT through YouTube tutorials – without faculty guidance, without institutional policy, and without reliable internet connectivity for those tools. The faculty are in the same boat; they know AI exists and students use it, yet they are unsure how to respond. There is yet no professional development, policy documentation, or institutional acknowledgement of AI in education. This research has arisen from the realization that the situation in which students use AI in a non-institutional manner, faculty respond without institutional support, and institutions remain largely silent is both educationally significant and under-researched (Mahnaz & Nayab, 2026).

Numerous scholars have keenly focused on AI and its effects on higher education institutions. Most of the focus has been optimistic about the impact of AI technology (Machaba & Age, 2025). As a whole, the current literature has not focused enough on the actual experiences of students and educators alike when using AI within an academic setting. This process takes place within an environment that is much less controlled than it should be according to pedagogically structured principles; yet the experience is still affected by AI interactions in everyday educational practice (Zawacki-Richter et al., 2019; Holmes et al., 2019).The gap is more than just geographical, as there is insufficient representation of the district and peripheral areas in Pakistan (Mahnaz & Akram, 2026). Such a gap can be considered under two main types, namely experience and interpretation. Firstly, it is worth noting that there is a lack of understanding of how students studying under resource-constrained conditions perceive AI technologies. Secondly, one should note that there is a necessity to understand what significance AI carries to the teachers who control its usage despite the lack of proper support from the institution.

The questions are very well illustrated in the context of District Gwadar. Being at the heart of the China-Pakistan Economic Corridor (CPEC), the deficiency of digital infrastructure makes it unfeasible for many students to use AI frequently (Mahnaz & Kiran, 2024a). Colleges and universities are operating without any AI governance framework; students are adopting tools on their own, whose educational impacts they are left to negotiate. Literature cannot fill this knowledge gap in AI in education, which touches on how it is experienced, what it enables, what it prevents, and how institutional conditions shape individual practice (Jan et al., 2026).

Objectives and Research Questions

The goal of this qualitative study is to examine how Artificial Intelligence affects the academic learning experiences of students and faculty at higher education institutions in District Gwadar. In particular, this study does not aim to evaluate the effects of AI or the statistical relationship, or lack thereof, between AI conditions and learning outcomes; it aims to understand how AI is experienced, what it means, and by what processes institutional, structural, and attitudinal factors shape its educational role in the context in question. The research questions given below shaped the inquiry.

RQ1: How do higher education students of District Gwadar perceive and experience the accessibility of AI tools in their academic learning?

RQ2: How do students characterize their use of AI for academic purposes, and how do they negotiate the educational benefits and tensions that result from this engagement?

RQ3: What is the impact of the level of preparedness of faculty members towards AI, including institutional support and attitudinal disposition of individual faculty members, on AI-related learning opportunities offered to students?

LITERATURE REVIEW

Theoretical Framework

This research was conducted within the constructivist ontology and interpretivist epistemology of Lincoln and Guba (1985) and Creswell and Poth (2016). According to this view, meaning comes from society. Moreover, humans have to interpret subjective experiences and understandings. AI tools in education are not neutral tools, the study explains. Their effects cannot be objectively classified as either educationally helpful or harmful. Rather, their educational significance is shaped by the specific social, institutional, and cultural conditions they encounter.

According to Vygotsky's (1978) view of social constructivism, we understand that cultural tools, relationships, and institutional contexts mediate learning. AItools are potentially mediators; their educational value is not inherent but produced through the conditions of use, which fall within the scope (Mahnaz & Kiran, 2024b). Vygotsky's Zone of Proximal Development suggests that an individual's peers, in this case, faculty members, help students leverage the tools available to them for productive purposes. If the instructor is unprepared or unsupportive of AI or has some attitude issue toward it, this mediation entails omission or distortion. This condition leads to real consequences for student learning. This framework is supported by an educational perspective (Selwyn, 2011) that highlights the structural inequalities – along the dimensions of connectivity, institutional investment, distribution, and access to resources – that will shape what AI can and cannot mean for students in Gwadar.

AI in Higher Education: Achievements and Limitations of Existing Research

So far, most AI education research has been conducted within a correlational quantitative paradigm, seeking to inform contexts in which broad enabling conditions for AI might exist. According to a systematic review of 146 publications by Zawacki-Richter et al. (2019), the primary focus of AI applications is institutional and administrative profiling and the improvement of administrative processes, rather than serving as an enabler of deep learning.According to Holmes et al. (2019), positive learning gains were more consistent when faculty members were trained and AI was incorporated into the course structure. However, in their absence, the results were unremarkable or inconsistent. The present study revolves around the contingent argument (Mahnaz & Kiran, 2024c).

Additionally, research on access and equity shows that AI adoption cannot be attributed solely to device availability. In their review, Luckin et al. highlight that the country's connectivity system and digital literacy have a far greater influence than AI technology. The implementation of TML in higher education in Balochistan has been significantly impacted by issues such as inadequate infrastructure and a lack of faculty skills, according to Iqbal and Riaz (2021). Crompton and Burke (2023) suggest that factors such as faculty preparedness and attitude disposition are the best predictors of the successful use of AI technology (Mahnaz et al., 2025). This paper examines how faculty disposition serves as a deciding factor in an environment lacking an institution-based framework. Related to this topic, Baidoo-Anu & Owusu Ansah (2023) note that, in the absence of a governing policy for AI use in institutions, it is not so much students' intentions as the policy void that motivates concerns about academic integrity (Mahnaz et al., 2021).

The Interpretive and Methodological Gap

The main gap this study seeks to address is not geographic, though qualitative research is absent in District Gwadar. It is interpretive: the existing literature has established correlations and identified predictors, but it cannot tell us how AI conditions are experienced; what they mean to participants; nor through what mechanisms structural factors translate into individual practice and institutional culture. These dimensions cannot be illuminated with quantitative methods (Mahnaz et al., 2023). This study provides a qualitative, interpretive understanding of how students and faculty at a poor, institutionally unsupported site negotiate, experience, and make sense of the arrival of AI in their educational lives.

METHOD

Research Design

This study follows an interpretivist epistemology and constructivist ontology. The phenomenon under investigation the manner in which students and faculty experience and make meaning of AI tools in the conditions of Gwadar's higher education institutions cannot be opted for statistical inference; it requires the sustained participant-centred interpretive inquiry that qualitative methodology can offer. The choice of the analytical method was reflective thematic analysis because of its epistemological flexibility, its fruitful fit with an exploratory research design, and its ability to generate thematically rich accounts of participants' experiences grounded in context. It was preferred over interpretive phenomenological analysis (IPA), as the analysis aimed to identify cross-participant patterns rather than to conduct an in-depth investigation of individual phenomenology. It was also preferred over grounded theory, as this project is not conducting research to derive a substantive theory of the adoption and implementation of AI technologies, but rather to achieve a thematic account of these processes that can inform practice. In qualitative inquiry, the researcher is acknowledged as the principal instrument of data generation (Lincoln and Guba, 1985). The quality of analysis is constituted in the researcher's interpretative engagement, theoretical sensibility, and reflexive management of prior assumptions.

Participants

Purposive sampling (Patton, 2015) was used to select 20 participants from two institutions: the University of Gwadar and Gwadar Degree College. Participants in the study needed at least some experience with AI tools in an academic context. The faculty sample (F1-F10) was drawn from six disciplines at both institutions. The student sample comprised S1-S10, who were first-year to fourth-year undergraduates in their programme. The faculty sample was intentionally varied by discipline, as the study was interested in how faculty attitudes mediate students' AI experience. This required exposure to the range of institutional cultures covered by this institution pair. The sample size was selected based on information power (Malterud et al., 2016). In other words, information power refers to how rich the data is and how specific the analysis is. Twenty participants produced a dataset that was rich in context and analytically sufficient—participant profiles, presented in **Table 1.**

Table 1: Participant Profiles

Note. F = Faculty; S = student. Exp. = years of teaching experience.

ID	Role / Programme	Institution	Exp.	Duration	Group
F1	Lecturer, Computer Science	University of Gwadar	7 yrs	52 min	Faculty
F2	Lecturer, Business Administration	University of Gwadar	4 yrs	48 min	Faculty
F3	Lecturer, Education	Gwadar Degree College	2 yrs	55 min	Faculty
F4	Lecturer, English Language & Literature	Gwadar Degree College	5 yrs	46 min	Faculty
F5	Lecturer, Computer Science	University of Gwadar	2 yrs	58 min	Faculty
F6	Lecturer, Economics	University of Gwadar	2 yrs	47 min	Faculty
F7	Lecturer, Zoology	Gwadar Degree College	11 yrs	54 min	Faculty
F8	Lecturer, Information Technology	University of Gwadar	8 yrs	45 min	Faculty

F9	Lecturer, Urdu Language & Literature	Gwadar Degree College	15 yrs	58 min	Faculty
F10	Asst. Professor, Education	University of Gwadar	3 yrs	51 min	Faculty
S1	BS Computer Science, Year 3	University of Gwadar	—	47 min	Student
S2	BS Business Administration, Year 2	University of Gwadar	—	44 min	Student
S3	B.Ed. Education, Year 4	University of Gwadar	—	50 min	Student
S4	BS Economics, Year 1	Gwadar Degree College	—	41 min	Student
S5	BS English Language & Literature, Year 3	Gwadar Degree College	—	49 min	Student
S6	BS Information Technology, Year 4	University of Gwadar	—	49 min	Student
S7	BS English, Year 2	University of Gwadar	—	46 min	Student
S8	BS Chemistry, Year 3	University of Gwadar	—	52 min	Student
S9	BS Urdu Language & Literature, Year 1	Gwadar Degree College	—	45 min	Student
S10	BS Baluchi, Year 4	Gwadar Degree College	—	57 min	Student

Data Collection

Semi-structured interviews were conducted in Academic Year 2026–2027. The interview guide was prepared with an iterative engagement with literature, consultation with peers, and two pilot interviews with teacher educators. The interview began in an unstructured way, but the questions were aligned with the three research questions (Rubin & Rubin, 2012; Seidman, 2019). They selected the interview setting. The interviews lasted between 45 and 60 minutes.

Field notes were kept after each session. Interviews were held predominantly in Balochi, with English translations. A bilingual research assistant vetted accuracy. Before data collection, ethical approval was obtained from the institutional ethics committee. The participants were given alphanumeric identifications (F1–F10, F1–F10; S1–S10 S1–S10) that ensured confidentiality during analysis and reporting.

Analysis of Data

The six-phase reflexive thematic analysis framework developed by Braun and Clarke will focus on the analysis. After extensive data familiarization- re-reading with active note-taking and reflective memo-writing- initial coding was done by systematically engaging line by line with the transcript data as per Saldaña (2021) – resulting in 72 initial codes in 9 provisional clusters and consolidated the 144 codes into 25 focused codes based on recurrence, analytical weight, and conceptual coherence through focused coding (Charmaz, 2014; Saldaña, 2021). These were later derived into six sub-themes and three overarching themes through the iterative nature and level of analysis (Ryan and Bernard, 2003; Boyatzis, 1998). The analytical process was iterative rather than linear; in two instances, candidate themes were reconceived after second visits to the transcripts showed that the first framing was inadequate. NVivo made data management easier; the researcher generated all the analytical decisions. The complete coding trail is present in the appendix.

Trustworthiness

Credibility was established through member checking with five participants. One participant requested clarification, prompting a revision and deeper analysis. Further analysis was done through several sustained peer debriefings and negative case analysis (Lincoln & Guba, 1986). This study's thick description of context, participants, and the analytical process makes it transferable. Dependability is proven via the analytic audit trail. The findings will not be more informed by researcher assumptions than by participants' accounts if they are continuously checked against participants' accounts through reflexive journaling during data collection and analysis (Braun & Clarke, 2019; Nowell et al., 2017).

RESULTS

Three prominent themes were developed, each with two sub-themes, and these themes showed convergence across the entire group. Data traceability is maintained through participant codes (F1–F10 for faculty and S1–S10 for students). Quotations of forty or more words are presented as an indented block quotation; quotations of a shorter length are embedded in the analytical text.

Theme One: Accessibility of AI Tools and Its Link with Learning

There is a certain kind of frustration that came through in almost every interview – knowing exactly what technology can do but being unable to use it. The students of Gwadar belong to the same global technological culture as one and all – they follow the same YouTube channels, participate in the same WhatsApp conversations, and so on. They are already acquainted with ChatGPT; they have seen what it can generate. While people know AI, they cannot consistently use it, according to the report. This gap in the educational use of AI was one of the study's key findings.

Awareness Without Access

None of the 20 respondents reported the presence of a formal institutional mechanism for introducing AI tools into the curricula. What students had instead was social-mediated awareness, found independently and without pedagogy. F3, a Senior Lecturer in Education, indicated, with unusual sharpness, the resulting disjuncture.

"Students are quite aware of ChatGPT; they stay up to date with online trends. Awareness is quite high. However, awareness and effective educational use are not synonymous (Mahnaz, 2023). Many students are using AI in a reactive, superficial mode- they will type in a question and accept the output. (F3)."

The participants constantly reaffirmed this explanation. As stated by S1, no one in any class had ever explained which AI tool was used. S4 explained that the following process occurred quite often: the participant discovered an app on social media, installed it, experimented independently without any help, only to find out later that there was no academic application for such personal experiments.

In other words, based on the information presented above, it can be assumed that this process of using AI tools has led to their employment to achieve the most effective outcomes – providing fast answers or creating texts - but not fulfilling other objectives that require some form of instruction.It is important to note that many participants reported feeling in the grey zone; it was unclear whether students' use of AI could be considered academically appropriate due to the lack of official guidance.

Structural Barrier: Connectivity

All 20 informants cited unreliable, slow internet connectivity as the greatest hindrance to using AI. The commonality of this finding suggests a structural rather than an incidental explanation. S1 explained what it is like to have unreliable connectivity.

“Itried using AI to help me understand a machine learning algorithm I could not wrap my head around. However,after trying it three times and finding the loading process very slow, I had to give up. It is difficult for AI resources, which are not always available, to contribute to a consistent routine. Sorry, I cannot help you with that.

It is interesting to see that students have been able to establish alternative means despite those difficulties. Students conduct their AI sessions during low-peak network hours, take screenshots of their interactions with the AI, and use AI resources where connectivity is better in the city (F2; S9). It highlights both the students’ motivations and the under-provisioning of infrastructure. The costly mobile data charges mentioned by the interviewees in F and S suggest a connection between access to AI technologies and economic inequality, creating a dual system based on circumstance rather than students’ skills. As one of the interviewees stated,“The problem of infrastructure is the basis of any problem here. Without access to the Internet, no integration will work."

Theme 2: AI-Assisted Academic Engagement and Student Learning

Our analysis of student transcripts, which focused on engagement rather than accessibility, revealed that the actual use of AI (the character of engagement) was more uniform than surprising in its particulars (the quantity and style of engagement).This means that a large number of students used ChatGPT primarily for concept clarification and draft assistance, without faculty guidance and without sustained reflection on whether the mode of use was educationally productive.

Informal and Self-Directed AI Use

F1’s account was perhaps the most accurate encapsulation of what the student data also revealed.Students are utilizing artificial intelligence tools- especially ChatGPT- but in an almost entirely informal manner. Students use mind maps daily for two reasons. First, they use them to review topics that were difficult to understand during lectures. Second, students find mind mapping a useful tool for drafting their assignments. I consider the first instance to be acceptable, even useful. The second use concerns me because I have seen submissions that are nearly entirely AI-generated, with the student’s own thinking hardly visible. (F1)

Students confirmed this characterization. S2 discussed using AI to create a structure for his assignment by preparing an outline and later writing the content himself. The main uses of S1 include concept simplification, research orientation, and code debugging. Specifics of the task according to the students’ sample include simplification of concepts (S1, S3, S4, S7, S8), summarizing research (S1, S2, S7, S10), drafting assignments (S2, S4, S5), and checking of codes (S1, S6, S8). Participants said little about repetitive, continuous, or guided learning experiences with the AI system. F3 noticed that students were “not using AI iteratively to either deepen their understanding, not using it to generate feedback on drafts, not using it in ways that demand active intellectual engagement.Students displayed a pattern of ‘surface-level adoption’, a term coined by Holmes et al. (2019), that contrasted starkly with the designed engagement encouraged in F5 and F10’s courses, which required students to document prompts, outputs, and critical evaluations. The gap in learning quality was quantifiable, as their students described.

Perceived Benefits and Emerging Academic Integrity Concerns

Participants did not shy away from discussing the two-faced nature of AI-enabled engagement, which was helpful in some cases but problematic in others. S1 identified a specific learning breakthrough that conveys what purposeful AI engagement can achieve.

“I required an answer to “Explain backpropagation using a simple numericalexample’”. Thanks to ChatGPT, I now have a step-by-step explanation that suddenly made things clear. After this, I refer to the textbook and understand it better. That experience demonstrates AI can serve as a link to deeper learning, but not as a cheat sheet. (S1)”

S4 articulated the democratizing dimension of AI access for students without typical home support structures. - I am coming from a background wherein there is no help from anyone – no tutors, no networks, no academic support in general, no explanation of complex concepts. If everything is going well, AI may act as an aid. Several students – S1, S3, S4, S6, S7, and S8 – noted the following tangible advantages: saving time, gaining more knowledge, and feeling more comfortable while learning. As shown by Popenici& Kerr (2017), such students tend to have greater motivation to work with AI when access to it is limited due to scarce resources.

In addition, several students (S1, F2, and S9) mentioned that one of the main disadvantages concerns academic integrity; the data indicate that this topic warrants detailed study and deserves thorough attention. S2 gave some explicit answers regarding this issue.

“I trusted AI to do the bulk of the work on my small task during exam time, although I was aware then that I was not thinking independently. However, I did not know back then whether what I did was actually cheating, because there was no formal university policy on AI use. Where there is no clarity, a grey zone emerges, and the student is at risk of overusing AI.”

It should be noted that the administrator has the same gap in their institution: “Sometimes I cannot recognize the results created using AI. There is still no formal academic integrity policy on AI use in my university. So I do not know how I should react if I detect cheating.”Based on this analysis, the lack of policy is the primary reason for academic dishonesty, not students’ desire to cheat. They also admitted they could be prepared to misuse AI as an autonomous danger.

Theme 3: Faculty Preparedness Toward AI and Student Learning

If we were to choose just one finding from this research to be the most impactful, the finding that most directly shapes the learning environments students ultimately experience was the following: faculty preparedness toward AI, both formal knowledge and attitudinal disposition, was the key mediator between AI availability and student learning quality. This discovery was not entirely unexpected, as it emerged from the collection of students’ accounts describing how differently they experienced AI across the courses they were enrolled in.

Limited Professional Development and Institutional Support

All participating faculty members (10 only) stated that they have received no institutional support to address the arrival of AI in their courses. The sentence is doing important work with the word “institutional”. Multiple participants did something, read articles, played with tools, talked with a colleague, but what they did did not relate to any institutional programme, policy or acknowledgement. F1’s account precisely captures this.

No one from the institution ever sat me down and said, "Here are the tools available; here is how you integrate them into your teaching." I have independently investigated ChatGPT, consulted several articles on AI in education, and trialled AI-generated explanations in preparing lecture notes. However, this is all self-directed learning - something the institution has not even supported or encouraged formally. (F1).

According to F6, "There has not been a single institutional communication, a workshop, seminar, email circular or departmental meeting which has taken up AI in education at this institution in any systematic way." Then F5 articulated the systemic effect: the lack of institutional structure has produced "huge variation in faculty AI readiness," driven entirely by personal motivation. For instance, faculty participants such as F2, F4, F6, and F9 claim to be uncomfortable with AI instructional decisions that exclude their opinions. F4 explained, "It means making a trade-off with a lack of information and institutional guidance. Thus, no good basis for educational decisions." The concerns raised by these participants align with the findings of Crompton and Burke (2023), who found that faculty preparedness was the only predictor of successful AI use cases.

Role of Faculty Attitudes as a Mediating Variable

The current research illustrates a diversity of approaches to AI integration in the sample – from a total AI ban in classes to active AI incorporation into learning processes. The next participant provides an illustrative quote that demonstrates how the structural phenomenon can be viewed from a purely human aspect.

"A lecturer I know actively employs AI in his classes. He demonstrates the technology in front of the class, asks students to write reflections on it and discuss AI flaws. I feel like I am preparing myself for an AI-related job during his classes. In contrast, I remember a lecturer who explicitly stated that she treats the use of AI in her classes as cheating. She would not let me use AI in any way,not because I shared her opinion, but because I did not want to risk anything. The simultaneous existence of completely different environments generated within the same university generates confusion and real inequalities in terms of preparation." (S3)

Participants S5 and S10 reported similar differences in their AI experiences in their own classes. F7 depicted the attitude path that results from prohibitive policies: AI is here to stay, and excluding institutionalized approaches does not eliminate students' use of AI; it just makes it harder to detect and possibly unethical. Finally, participant F1 explicitly highlighted the equity issue: students' AI skills might be determined by the lecturers they encounter during their academic period. Such an approach is clearly unjust and cannot be sustained for long. Faculty attitudes to AI that proved beneficial for learning included F5 and F10. As they report, AI helped participants create a learning process that featured an organized activity using AI output. According to the students, the difference in learning quality in these attitudinal environments was not a matter of personal choice but a structural injustice, with consequences that would follow them into professional life.

DISCUSSION

This study seeks to explore the role AI plays in helping students learn in previously unexplored contexts. In general terms, the literature has not provided much scope for the use of AI for learning in situations where typical factors such as internet availability, teacher training, supportive policies, and appropriate pedagogical integration have been lacking.

The main point that emerges from the above discussion is not about any specific technologies. Rather, it lies within the concept of control, which is exerted over the process itself. In the absence of proper policies, adaptations, and curriculum transformations, it is solely the instructor's disposition that determines whether learnershave the opportunity to learn about AI. What distinguishes it from the commonly stated importance of faculty support is the absence of the usual organizational environment that regulates a teacher's behaviour and disposition. As a result, the assertion made by Crompton & Burke (2023) that a faculty member's readiness best predicts the success of AI implementation gains additional credibility. Not necessarily because prepared teachers provide better outcomes, but rather because unprepared or reluctant teachers block this educational opportunity for all students assigned to them.

The findings regarding connectivity provide another dimension to the structural framework proposed by Iqbal and Riaz (2021), which is beyond its purview. The manner in which students will use the connectivity they have is entirely contingent on whether they have received any guidance. What becomes clear from qualitative research on the incorporation of AI into education is that when students collaborate with AI-receptive professors, the behaviours exhibited differ substantially from those otherwise: they become more self-reflective and well-grounded in pedagogy, and, in essence, they utilize AI critically. To put it simply, whether access to technology through AI is effective cannot be evaluated independently of the broader context in which it occurs.

It should be noted that the depiction of academic integrity deserves thorough analysis and discussion. Generally speaking, participants who indicated potentially unethical uses of AI in their narratives did not seem to be doing anything intentionally or opportunistically wrong. This can be seen, for example, in the refreshing honesty of S2's narrative and its inherent ethical disquiet; S5 mentioned making decisions to change their behaviour regarding AI use because of concerning outcomes they have noticed. Taking into consideration Baidoo-Anu & Owusu Ansah's (2023) conclusion regarding the critical role of policy non-existence in contributing to integrity risks, it became possible for scholars to make a more detailed description of how such a state manifests itself. The lack of clear institutional guidance left students facing genuine ethical ambiguity. The overall silence from institutions played a critical role in raising integrity issues, and it could be argued that the presence of appropriate governance structures could better resolve this problem than prohibitions and constant monitoring.

According to Lincoln and Guba, the results of this research should not be considered statistically generalizable. They can, however, be theoretically generalizable, as they may apply to other settings where similar processes occur. These dynamics are expected to be relevant to other audiences facing analogous conditions not only in Pakistan but also in the Global South. Two important points are highlighted in this case. Firstly, it is about the structural restrictions of accessibility which make engagement possible at all. Secondly, it relates to faculty members' current mindset, which shapes the depth of engagement when formal policies are absent.

CONCLUSION

Peripheral research in the process of technological innovation provides lessons that cannot be easily gleaned from central research, which usually takes a more traditional approach: it allows us to gain clarity regarding the gap between the possibilities promised by a particular technology and what would need to happen in order for these possibilities to be realized. Such a gap is clearly identified in this case, that of Gwadar. The researchers who participated in this experiment are not sceptical of AI; they believe there are real opportunities for learning through AI that students might not otherwise have access to. It became clear during this study that, on several occasions, the use of AI provided students with new understandings of various concepts or connections that even self-teaching and revising had failed to yield.

There were several instances in which learners reported having neither tutors nor connections within the academic network. Such instances were vividly reflected in the experiences shared by some learners participating in the research. They claimed they had no one to contact for assistance with their academic work. In such cases, AI also provided moral support to these learners.

The study also consistently reveals, across all 20 participants, the gap between those possibilities and what the majority of students experienced. The question of distance is not really a technical one, although unreliable connectivity is an important limitation. It is an institutional issue that there are currently no professional development frameworks, governance policies or anything else that gives faculty the tools and confidence to treat AI as a pedagogical issue rather than their own personal improvisation.

The absence of institutional mechanisms leads to the individual faculty member's attitude as the sole governing variable. This cannot be the basis for equitable education. Therefore, the most useful takeaway from this research is not so much about infrastructure (though that is important) as about institutional will – we can develop policy frameworks for AI use before we have better connectivity. Now, we can create faculty learning communities. This academic year may witness student orientation. The data suggests that a lack of knowledge is not the reason for many problems, such as climate change. What is missing, it suggests, is the urgent institutional recognition.

There should be longitudinal research done on what happens during the implementation of these interventions in Gwadar and similar contexts, as well as whether the mechanisms found to be at play in the research covered here are replicated elsewhere or whether they are specific to Gwadar and its particular combination of geographic isolation, institutional underdevelopment, and CPEC-adjacent digital aspiration.

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