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Active Learning in Higher Education in the Age of Artificial Intelligence A Literature-Based Review and the Proposed NASEER Framework for Faculty Development at KUST

Professor Dr. Muhammad Naseer Ud Din

Institute of Education and Research (IER)

Kohat University of Science and Technology (KUST), Kohat, Pakistan

Email: dr.naseeruddin@kust.edu.pk

Abstract

Artificial intelligence (AI) is changing how students study and how teachers assess, at the same time as universities are asked to teach in more active, outcome-based ways. This literature-based review asks how active learning can stay strong and become fairer, in the age of AI. It brings together research on innovative pedagogy; active, collaborative, experiential and inquiry-based learning; technology-enhanced learning; AI in education; AI literacy; responsible AI; student learning outcomes (SLOs); outcome-based education (OBE); constructive alignment; formative and summative assessment; feedback; and faculty professional development. The evidence shows that active learning works when tasks demand real thinking. Recent AI studies follow the same pattern: well-designed AI support can help learning, while unguided use can weaken it. The review links these findings to the KUST ORIC-funded project "Empowering Excellence", led by Principal Investigator Prof. Dr. Muhammad Naseer Ud Din, and to the three-day KUST ORIC-and collaboration with IER – KUST and CHRCO – KUST workshop on AI in education and pedagogical techniques. It offers four practical tools: an Innovative Pedagogy Cycle, an AI-SLO Lesson Model, a KUST ORIC Implementation Model, and a Faculty Transformation Model. It closes by proposing the NASEER Framework for Active Higher Education in the AI Age as a conceptual model for faculty development. The framework has not been tested and needs empirical validation.

Keywords: Active learning; higher education; artificial intelligence; AI literacy; responsible AI; SLO-based teaching; outcome-based education; constructive alignment; assessment and feedback; faculty professional development

Introduction

Universities are expected to prepare graduates who can reason, collaborate and act responsibly in a world where AI tools are always at hand. Since 2022, students have been able to ask a Chatbot to summarise a reading, solve a problem or draft an essay in seconds. This is both an opportunity and a risk for teaching. It could give every student patient feedback. It could also let students skip the effortful thinking through which learning happens.

Active learning offers a starting point. Decades of research show that students learn more when class time asks them to explain, solve, discuss and apply ideas, and not only to listen (Freeman et al., 2014;

Prince, 2004). Even so, lecturing remains common (Stains et al., 2018), and students often feel that they learn less from demanding, active lessons even when they learn more (Deslauriers et al., 2019). Generative AI adds a new layer. In one randomised trial, an AI tutor designed around good pedagogy helped physics students learn more in less time than an in-class active lesson (Kestin et al., 2025). In a large school-level field experiment, unrestricted access to a chatbot raised practice scores but lowered later exam scores, while a version with safeguards avoided most of that harm (Bastani et al., 2025). Both studies showed that the design of the learning task is more important than tool usage.

Universities that follow outcome-based education (OBE) face a further question. If teaching is organised around student learning outcomes (SLOs), then every task and every assessment must show that students can meet those outcomes, with or without AI (Biggs, 1996; Dawson et al., 2024; Harden, 2007). In Pakistan, accreditation and quality assurance have pushed universities towards OBE, yet practice is still developing (Haider et al., 2023; Mahmood, 2021). Faculty need the skills to do this work, and skills need structured development time.

This paper is written in that context. It is linked to a project funded by the Office of Research, Innovation and Commercialization (ORIC) at Kohat University of Science and Technology (KUST): “Empowering Excellence: A Comprehensive Framework for Holistic Faculty Professional Development in Pedagogical Skills, Artificial Intelligence (AI) in Education, Sustainable Practices, Student Learning Outcomes (SLOs)-Based Teaching, and Assessment Techniques at Kohat University of Science and Technology (KUST)”. The Principal Investigator is Prof. Dr. Muhammad Naseer Ud Din. A series of three-day workshops in collaboration among KUST ORIC, the Institute of Education and Research (IER –KUST), and the Center of Human Resource Career and Development (CHRC-D-KUST), “Faculty Professional Development Training in AI in Education and Pedagogical Techniques”, is connected to the project. Its focus is AI-integrated education, innovative pedagogy, and SLO-based teaching and assessment techniques.

The paper makes three contributions. It gives a critical, literature-based account of active learning in the age of AI. It builds four practical models for faculty development. And it proposes the NASEER Framework, a conceptual model that the KUST ORIC project could use and test. The paper is a literature review and reports no new empirical data from the project or the workshop.

Research Questions

Five questions guide the review.

- **RQ1.** What does the literature show about active, collaborative, experiential, inquiry-based and technology-enhanced learning in higher education?
- **RQ2.** How does AI change the conditions under which active learning works, and what does AI literacy and responsible AI require of universities?
- **RQ3.** How can SLO-based teaching, OBE, constructive alignment, assessment and feedback stay valid when students use AI?
- **RQ4.** What does the research on faculty professional development tell us about the change of teaching practice?
- **RQ5.** How can these strands be merged together into a framework that the KUST ORIC project could work in, and what would have to be tested?

Literature-Based Methodology

The study is a narrative integrative review with a conceptual model-building aim. This design suits the topic because the questions cross several research traditions: classroom experiments, meta-analyses, policy frameworks, assessment theory and professional development research. A narrower design would leave out evidence that is needed to explain how and why active learning changes when AI is present. Table 1 summarises the design.

Table 1

Design of the Literature-Based Review

Element	Description
Review type	Narrative integrative review with conceptual model building; not a systematic review or meta-analysis A narrative integrative review, not a systematic review or meta-analysis.
Sources	Peer-reviewed articles, meta-analyses and syntheses, with a few foundational conference papers; found through web-based scholarly searches, publisher and DOI records, and citation chaining
Time focus	Recent work (2020-2026) on active learning and assessment and professional development for AI-related evidence.
Inclusion	A focus on higher education or clear transfer; a clear teaching design, AI usage, assessment method and/or faculty development element; peer reviewed or widely used as foundation.
Exclusion	Opinion without evidence; commercial claims; papers that are only focused on the word AI; retracted work.
Appraisal	Clear design, fit of intervention with outcome measured, disclosure of limits; no formal risk-of-bias scoring
Synthesis	Thematic comparison of agreement, disagreement and gaps; themes were used to write conceptual propositions.
Project material	Only project title, Principal Investigator, thematic strands and the workshop title and focus were used, and no project or workshop outcome data are reported.

Note. The number of records screened is not reported as it was not systematic, thus it is not part of the review.

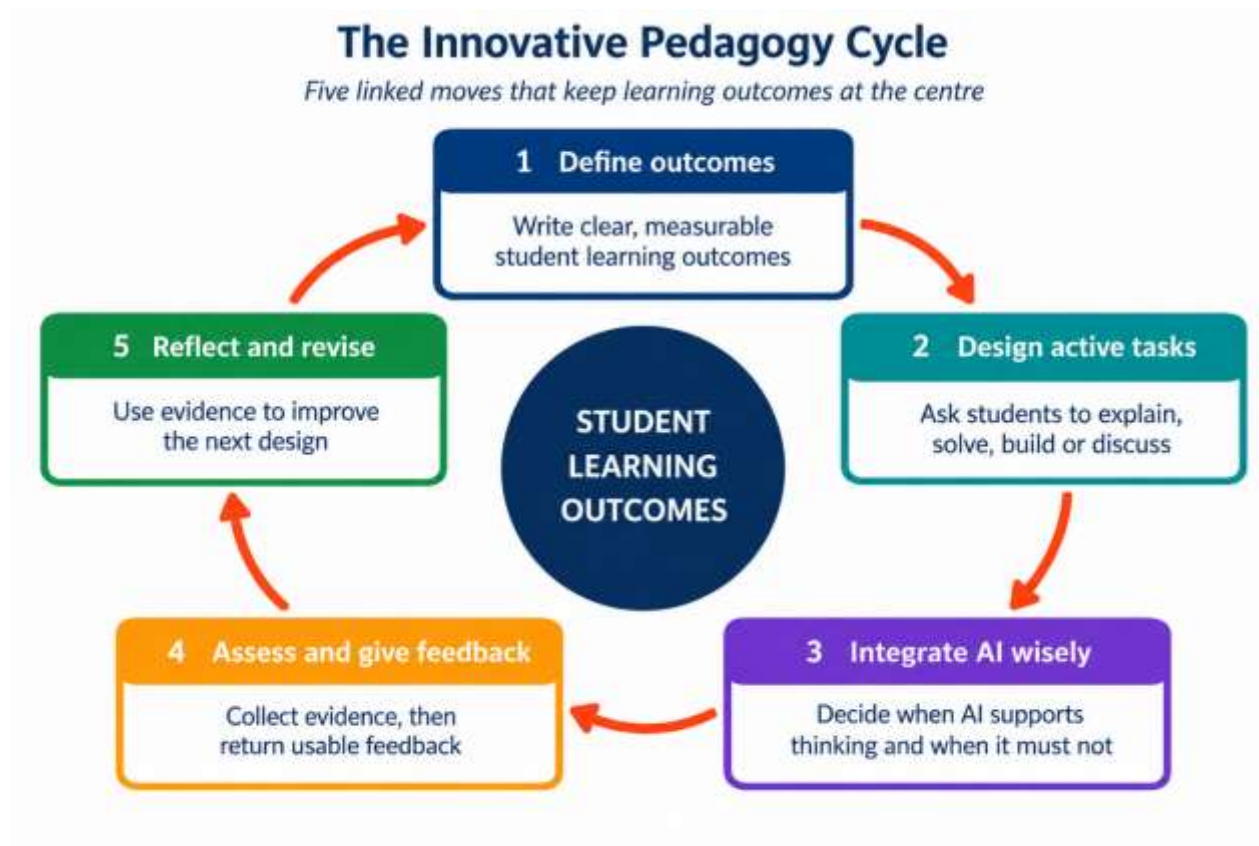
Three practical steps helped to achieve accuracy. To begin with, bibliographic information of the primary studies related to AI (authors, title, journal, and DOIs) were verified against publishers or indexing records and only studies that were verified were retained. Second, where a claim came from a single trial or a single site, the text says so. Third, findings from schools are labelled as such and are used only as cautionary evidence for universities. Effect sizes and percentages are reported as the original authors reported them. The synthesis was interpretive, so other reviewers could weigh the studies differently.

Literature Review

Innovative pedagogy and active learning

Active learning is best defined by what students think about, not by what they do with their bodies. The ICAP framework separates four modes of engagement: passive, active, constructive and interactive. Learning is predicted to improve as students move from receiving information to generating ideas and building them together (Chi & Wylie, 2014). Reviews of definitions show that the term is still used loosely (Doolittle et al., 2023), so a clear statement of the intended thinking is part of good design.

The evidence for active learning is strong. A meta-analysis of 225 undergraduate STEM studies found that exam scores rose by about 0.47 standard deviations and that failure rates fell from about 34% to 22% (Freeman et al., 2014). Structured active learning has also narrowed achievement gaps for students from disadvantaged backgrounds (Haak et al., 2011; Theobald et al., 2020). Outside STEM, a synthesis of 104 studies found a positive but smaller benefit in the humanities and social sciences (Kozanitis & Nenciovici, 2023). However, guidance is still needed: those who are new to a topic may be overwhelmed by unguided discovery (Kirschner et al., 2006; Sweller, 1988). These are put into one working sequence in the Innovative Pedagogy Cycle in Figure 1.

Figure 1*The Innovative Pedagogy Cycle*

Note. Original synthesis based on the literature reviewed (Author, 2026)

Collaborative, experiential, inquiry and problem-based learning

Collaborative learning is effective when the task is really interdependent; when each student is responsible for a portion of the outcome (Johnson et al., 1998; Springer et al., 1999). Experiential learning was based on the premise that learning occurs when people experience, reflect on, and then build and test their conceptions; good learning spaces reinforce this cycle (Kolb & Kolb, 2005). Problem-based learning requires students to do work on ill-structured problems with support from a facilitator (Hmelo-Silver, 2004). Meta-analyses indicate improvements in skills (Dochy et al., 2003), and that results are related to the level of knowledge being assessed (Gijbels et al., 2005). Project-based learning holds promise, but reviews cite that measures of outcomes are inadequate and that design is not sufficiently described (Guo et al., 2020; Kokotsaki et al., 2016). These approaches can leverage AI in a variety of ways, as demonstrated in Table 2, with the primary danger being located.

Table 2*Active-Learning Approaches, Possible AI-Supported Uses, Risks and Safeguards*

Approach	Possible AI-supported use	Main risk	Safeguard
Peer instruction and collaborative learning	AI drafts concept questions; students compare their reasoning with a peer, then with AI	The group defers to the AI answer	Individual vote first; students must justify or challenge the AI output
Experiential learning	AI scenario or simulation before a lab, field or clinical task; AI prompts reflection afterwards	A simulation replaces real practice	Keep the real task; use AI for preparation and reflection only
Inquiry and problem-based learning	AI offers counter-arguments, sample data or first hypotheses	Students accept AI claims without checking	Require source checks and a short record of how claims were verified
Flipped and technology-enhanced learning	AI tutor or summary tool for pre-class preparation	Passive reading of AI summaries	Short preparation quiz; use class time for constructive tasks
Project-based learning	AI supports planning, coding or drafting; process logs are kept	A polished product hides thin learning	Assess the process, an oral defence and a reflection

Note. The uses and safeguards are design suggestions drawn from the studies cited in this section and the next; they have not been tested as a set.

Technology-enhanced learning

Flipped learning is a useful case. The following is a helpful example in flipped learning. Moderate positive effects were reported in terms of student performance in the meta-analyses (Bredow et al., 2021; Strelan et al., 2020); and a smaller effect with conditioning on the use of class time in the other meta-analysis (Van Alten et al., 2019). The gains were found to be associated with the active learning in class, rather than with flipping itself (Jensen et al., 2015).

AI in education: promise and caution

Reviews describe a fast-growing but uneven body of AI research in higher education. One meta-systematic review called for stronger ethics, collaboration and rigour (Bond et al., 2024), and another mapped the state of the field (Crompton & Burke, 2023). Large language models can support learning, and they also require new competencies from both students and teachers (Kasneci et al., 2023). Table 3 lists the strongest studies discussed here.

Table 3*Selected Evidence on Active Learning and Generative AI*

Source	Design and setting	Main finding as reported	Meaning for practice
Freeman et al. (2014)	Meta-analysis, 225 undergraduate STEM studies	Higher exam scores (about 0.47 SD); lower failure rates (about 22% vs 34%)	Active designs beat lecture-only teaching in STEM
Deng et al. (2025)	Systematic review and meta-analysis, 69 experimental studies of ChatGPT	Better performance, motivation and higher-order thinking; lower reported mental effort; no clear change in self-efficacy	Benefits are possible; watch for reduced effort
Kestin et al. (2025)	Randomised trial, 194 students, one physics course	An AI tutor built on active-learning principles produced more learning in less time than an in-class active lesson	Good AI can match good pedagogy; single site, short term
Bastani et al. (2025)	Field experiment, nearly 1,000 high school mathematics students	Unrestricted GPT-4 raised practice scores but lowered later exam scores; a tutor with safeguards avoided most harm	Guardrails matter; school-level evidence
Fan et al. (2025)	Experimental study of generative AI support during learning	Reported a risk of “metacognitive laziness”, where learners hand thinking to the tool	Keep students in charge of planning and checking
Zhai et al. (2024)	Systematic review of over-reliance on AI dialogue systems	Over-reliance can affect students’ cognitive abilities	Design tasks that need student reasoning

Note. Findings are summarised as the authors reported them. Studies differ in age group, subject, tool and outcome, so the figures should not be compared directly.

The evidence points two ways. Positive results are real, and they come from designs in which AI is built around learning principles (Deng et al., 2025; Kestin et al., 2025). Negative results also appear when AI removes effort that learning needs (Bastani et al., 2025; Fan et al., 2025; Zhai et al., 2024). The correlation between using the AI tools often and lower scores on critical thinking was found by a correlational survey that the author related to the concept of cognitive offloading (Gerlich, 2025), which has been studied extensively in cognitive science (Risko & Gilbert, 2016). Jose et al. (2025) refer to this as a paradox of enhancement and erosion. Most of the studies are brief; some are conducted in schools, so statements about the persistent learning in universities should be modest.

Equity, access and inclusion

Equity is reflected in all of these themes. Though structured active learning has been shown to reduce performance gaps (Haak et al., 2011; Theobald et al., 2020), this is only possible if all students can engage. Access questions are added for devices, connectivity, paid tools and language for the use of AI. In e-learning, design quality mattered more than the delivery mode (Theelen & van Breukelen, 2022), so a policy that assumes equal access can widen the gap it hopes to close. Ethical frameworks add concerns about fairness and bias (Floridi & Cowls, 2019; Holmes et al., 2022). For faculty, a practical step is to offer a free route to every AI-supported task, and an AI-free route wherever the SLO calls for one.

AI literacy and responsible AI

AI literacy means having the competencies to evaluate AI critically, to work with it, and to use it as a tool (Long & Magerko, 2020). A review of the concept described several linked aspects, including knowing, using, evaluating and ethical awareness (Ng et al., 2021). Responsible AI adds principles. One widely used set names beneficence, non-maleficence, autonomy, justice and explicability (Floridi & Cowls, 2019), and a community-wide framework applies such ideas to education (Holmes et al., 2022). At university level, one policy framework groups the tasks into pedagogical, governance and operational dimensions (Chan, 2023). For faculty, this means that AI literacy is a teaching skill as well as a student outcome.

SLO-based teaching, OBE and constructive alignment

Constructive alignment asks teachers to state what students should be able to do, to choose activities that make that learning likely, and to assess it with tasks that match (Biggs, 1996). OBE builds on the same logic and links it to programme-level outcomes (Harden, 2007), and alignment can be measured (Deibl et al., 2018). In Pakistan, one account describes a move from teacher-centred syllabi to outcome-based practice in university courses (Mahmood, 2021). In engineering programmes, a critical evaluation found that employers rated some outcomes lower, including problem analysis, design of solutions, investigation, and environment and sustainability (Haider et al., 2023). These are the outcomes that active, inquiry-based learning is designed to build, and they are also the ones that AI could either strengthen or hollow out.

Assessment and feedback in the AI era

Formative assessment gathers evidence during learning so that teaching and study can change (Black & Wiliam, 1998; Black & Wiliam, 2009). Feedback helps when it closes the gap between where students are and the goal (Sadler, 1989), when it helps learners judge their own work (Nicol & Macfarlane-Dick, 2006), and when its type suits the task, since effects vary widely (Hattie & Timperley, 2007). AI can produce feedback quickly, but speed is not the same as quality.

AI also unsettles summative assessment. Authors have argued that assessment needs to change so that it supports learning and includes human–AI work (Swiecki et al., 2022), and that academic integrity is best treated as part of assessment validity, the assurance that graduates can do what their results say (Dawson et al., 2024). Guidance on integrity in the era of ChatGPT points the same way (Cotton et al., 2024). A practical tool is the AI Assessment Scale, which lets teachers set the level of AI use to suit the learning outcome (Perkins et al., 2024). Whatever the level, the assessment must still be sensitive to instruction, or good teaching will look like failure (Ruiz-Primo et al., 2002).

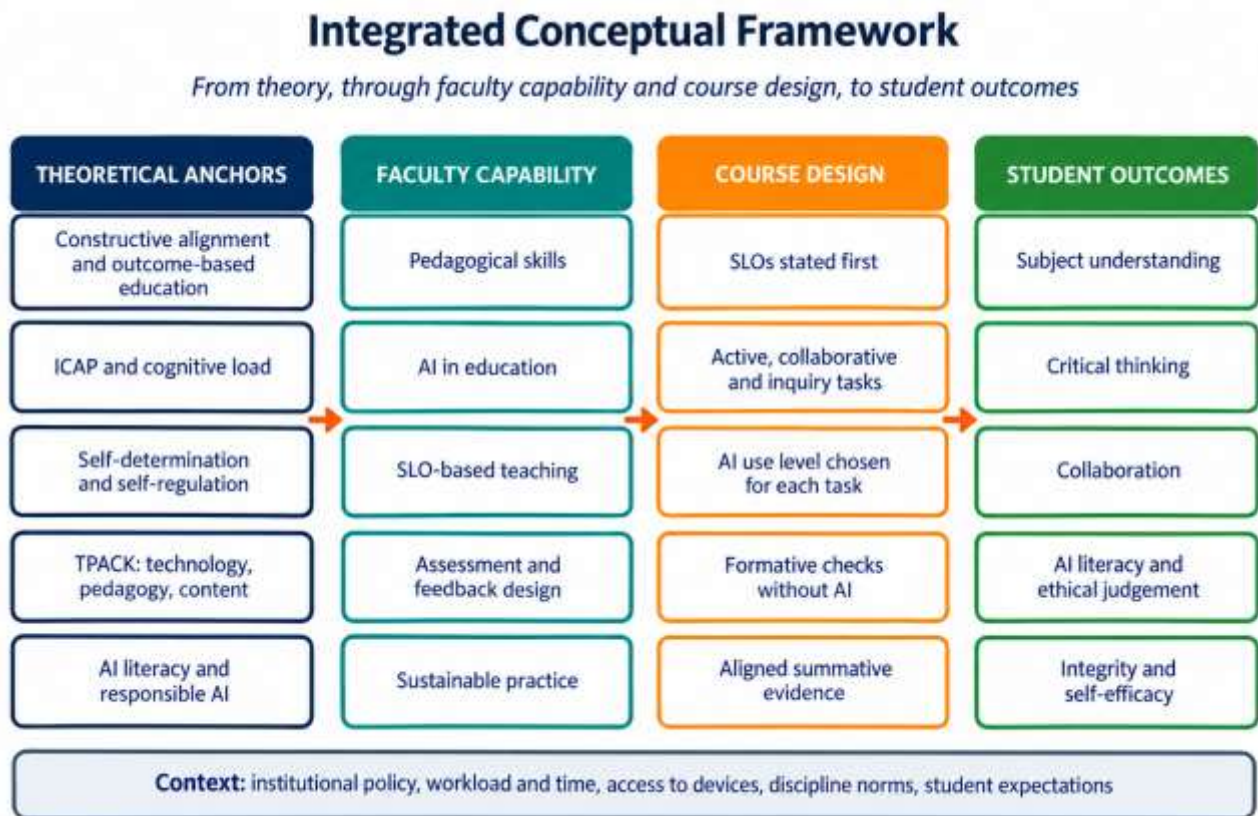
Faculty professional development

Changing teaching is hard. It is difficult to change teaching. It is not just attitude (Henderson & Dancy, 2007; Lund & Stains, 2015) that is a barrier, but also time, class size and departmental norms, and the spread of adoption is by social networks (Dancy et al., 2016). The research literature on professional development indicates that the focus of the content is a key factor, as is the practice of being actively involved in learning as a teacher, the coherence of the PD and whether the time is sufficiently long and the participation is collective (Desimone, 2009); and that how a programme attempts to change teaching is as important as what it teaches (Kennedy, 2016). From Guskey's research, it appears that beliefs can shift after teachers observe improved student outcomes, rather than prior to them. Guskey's research indicates that beliefs can shift following teachers' observation of improved student outcomes instead of before. (Guskey, 2002) There was evidence that a programme intervention at one university influenced faculty teaching (Slijepcevic & Huang, 2025), and that the easier instructors were able to explain the rationale behind activities, the smoother was the adoption (Nguyen et al., 2021). These studies make the case for development that provides teachers with practice, evidence, colleagues and not just one session of tips.

Theoretical and Conceptual Framework

The framework rests on five ideas. The framework is based on the following ideas. The design logic of constructive alignment and OBE is outcomes first, tasks second, assessment third (Biggs, 1996; Harden, 2007). The reason for some to help and some not is explained by the concept of cognitive load and ICAP: either constructive or interactive tasks require a sufficient degree of guidance to be productive (Chi & Wylie, 2014; Kirschner et al., 2006; Sweller, 1988). Students' motivation and feedback use can be explained by self-determination and self-regulation (Deci & Ryan, 2000; Nicol & Macfarlane-Dick, 2006). **TPACK** reminds us that technology choices depend on pedagogy and subject (Mishra & Koehler, 2006). **AI literacy and responsible AI** add the ethical and critical skills that AI-era teaching needs (Floridi & Cowls, 2019; Long & Magerko, 2020).

From these ideas, five conceptual propositions follow. They are offered for testing and are not established findings. **P1:** Active learning improves outcomes when the task demands constructive or interactive thinking. **P2:** AI supports that thinking when it is built into a task with guidance and limits, and it weakens it when it replaces effort that learning needs. **P3:** Outcomes, tasks and assessment must be aligned, and AI use must be stated for each, so that results remain valid. **P4:** Feedback improves learning when students act on it, whether it comes from a teacher, a peer or a tool. **P5:** Faculty change practice when development gives them practice, evidence and a community, and when the institution supports the change.

Figure 2*Integrated Conceptual Framework*

Note. Original synthesis based on the theories (Author, 2026)

Literature Synthesis

Five themes cut across the studies.

Activity is necessary but not sufficient. The mechanism is cognitive demand. Tasks that ask students to explain, argue and build work better than tasks that keep them busy (Chi & Wylie, 2014; Freeman et al., 2014). This is the base for everything else.

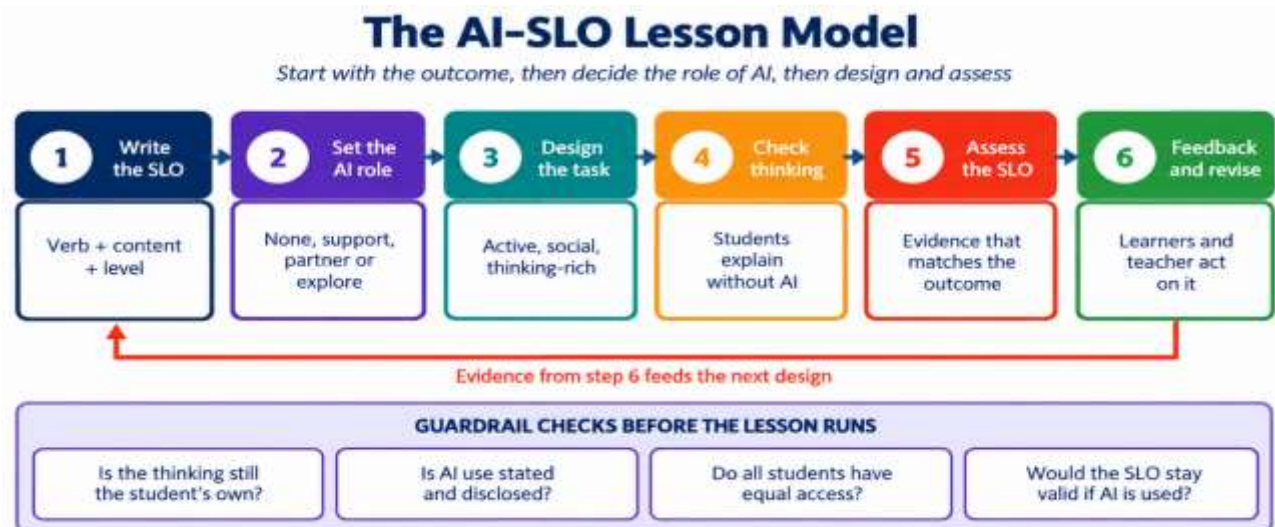
AI can raise or lower cognitive demand. Trials in which AI followed sound pedagogy were positive (Kestin et al., 2025), and trials with unrestricted access showed harm after the tool was removed (Bastani et al., 2025). The difference lies in design: what the tool does, what the student must still do, and whether the student can do it alone afterwards.

Alignment is the control point. If SLOs, tasks and assessments line up, then AI use can be decided task by task. If they do not, students will use AI to reach the mark and not the outcome (Biggs, 1996;

Dawson et al., 2024; Perkins et al., 2024). Figure 3 and Table 4 show a lesson model that starts from the SLO.

Figure 3

The AI-SLO Lesson Model



Note. Original synthesis. AI-use levels may follow a published scale such as the AI Assessment Scale based on Perkins et al., 2024, Modified Author, 2026

Table 4

AI-SLO Lesson Planning Template with an Illustrative Entry

Step	Question to ask	Illustrative entry
1. SLO	What must students be able to do, and at what level?	Compare two theories of motivation and justify which explains a classroom case better
2. AI role	Should AI be absent, a helper, a partner or a subject of study?	AI may suggest counter-arguments after students write their own first draft
3. Task	What will students do that needs their own thinking?	Pairs critique each other's drafts, then revise
4. Thinking check	How will I see the thinking without AI?	Two-minute written explanation in class
5. Assessment	Does the evidence match the SLO and stay valid with AI?	Case analysis with a short oral defence
6. Feedback	Who acts on feedback, and when?	Rubric-based peer and teacher comments before the final version

Note. The entry is a generic illustration for planning and does not describe any real course or data.

Feedback and assessment require redesign, not detection. A student cannot be seen as meeting an outcome when they are using a tool that detects AI use. A student cannot be deemed to have met an outcome if they are using a tool that detects AI use. Valid evidence, formative checks and clear AI-use statements do (Black & Wiliam, 2009; Dawson et al., 2024; Swiecki et al., 2022).

The resource constraint is faculty capability. The above tasks require pedagogic, AI and outcome design and assessment skills. The literature on the subject of professional development suggests that these grow naturally over time, as a result of evidence, and in the community, and therefore a single talk is insufficient (Desimone, 2009; Guskey, 2002; Kennedy, 2016).

It is recognised that active, aligned teaching is important. Size of the AI effects is debated and the longevity of gains is debated. The primary gaps are the lack of trials at the university level with long-term follow-up, research from South Asian universities, and evidence regarding faculty development in AI-integrated teaching.

Discussion

Based on the review, a conditional conclusion is reached. Active learning is associated with better outcomes and AI has the potential to be helpful or harmful in its application. The challenge for universities is to develop faculty capacity rather than to prohibit or promote tools simply. This is where the KUST ORIC project comes into the picture.

Reading the AI evidence critically

It appears there are two conflicting trials that are widely quoted. In one, an AI tutor performed better than an active lesson in class (Kestin et al., 2025). In the other, unrestricted chatbot access harmed later exam performance (Bastani et al., 2025). The disagreement fades when the designs are compared. The tutor in the first study was built on the same pedagogical principles as the lesson it was compared with, and the participants were university physics students in one course. The base tool in the second study made answers easy to get, and the participants were school students. Neither result shows that AI is good or bad for learning. Both show that the design of the tool shapes what students do with it.

A further caution comes from how learning feels. Students in an active lesson felt they had learned less than they had (Deslauriers et al., 2019). By the same logic, students may feel they have learned more from a fluent AI answer than they have. Faculty should therefore check learning with tasks completed without AI, and should not rely on self-report alone.

Context for Universities in Pakistan

Most of the studies reviewed come from North America, Europe, East Asia and Australia, and few come from Pakistani universities. Claims should therefore be checked locally. Three conditions deserve attention: access to devices and stable connectivity, class size and workload, and the language in which students study and in which AI tools respond. Accreditation and quality assurance already give universities a reason to state and assess SLOs (Haider et al., 2023; Mahmood, 2021). Faculty

development that starts from routines the university already follows is more likely to be adopted (Henderson & Dancy, 2007).

Linking the literature to the KUST ORIC project

The project “Empowering Excellence” addresses five strands: pedagogical skills, AI in education, sustainable practices, SLO-based teaching and assessment techniques. Each maps onto a finding in the literature. Pedagogical skills respond to the evidence on active learning. AI in education responds to the evidence on both benefits and risks. SLO-based teaching and assessment techniques respond to the alignment and validity concerns. The sustainable-practices strand can be read in two connected ways: lasting professional practice, and education for sustainability. This review found more evidence on the first than the second. The second is worth attention, because employers in one Pakistani engineering study rated the environment and sustainability outcome among the weaker ones (Haider et al., 2023).

Figure 4 shows a proposed implementation model. The three-day workshops in collaboration among KUST ORIC, the Institute of Education and Research (IER –KUST), and the Center of Human Resource Career and Development (CHRC-D-KUST), sits at the centre of the model as the point where the strands meet. Its focus on AI-integrated education, innovative pedagogy, SLO-based teaching and assessment techniques matches the literature themes above. Table 5 sets out the alignment.

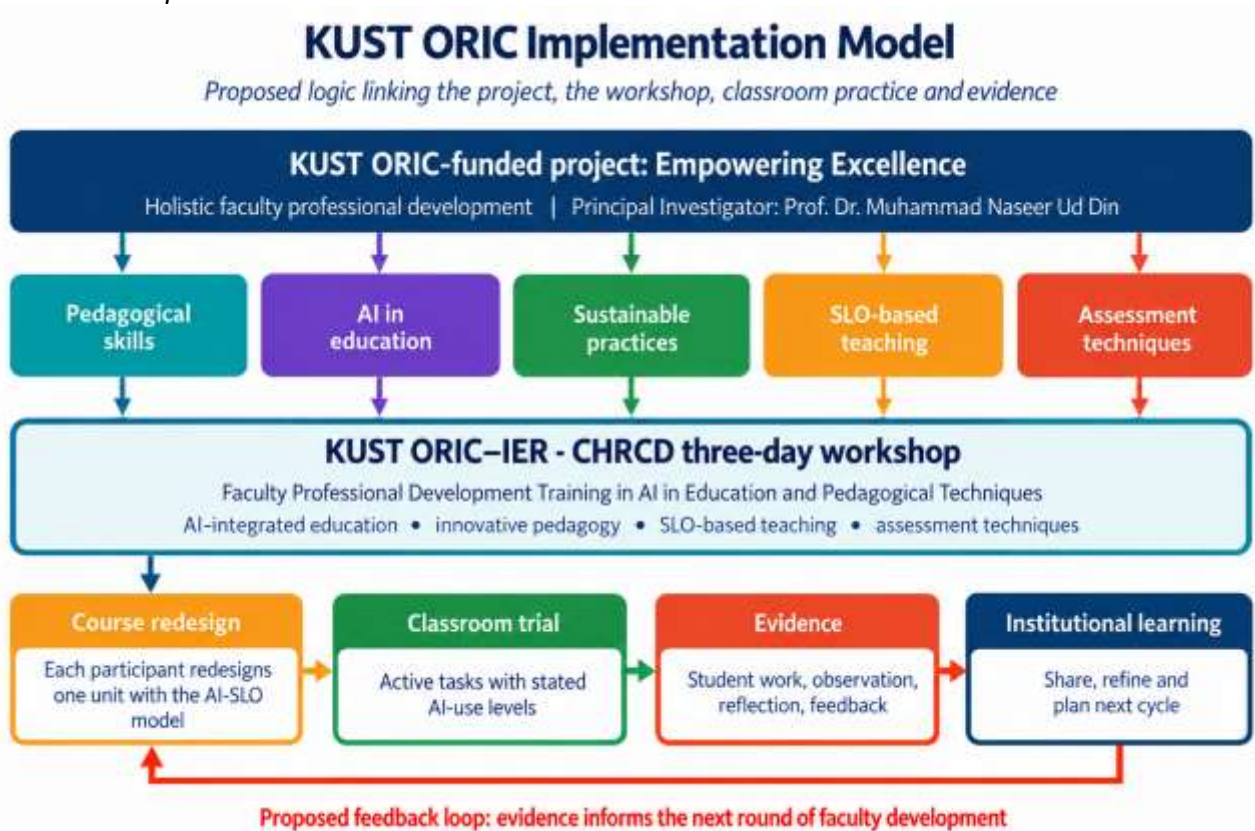
Table 5

Workshop Alignment Table

Workshop focus	Literature anchor	Project strand	NASEER component	Proposed evidence of learning
AI-integrated education	AI literacy and responsible AI; evidence on AI benefits and risks (Bastani et al., 2025; Holmes et al., 2022; Long & Magerko, 2020)	AI in education	Embed	AI-use statement in a redesigned unit; participant reflection on risks
Innovative pedagogy	ICAP; collaborative, experiential and inquiry learning (Chi & Wylie, 2014; Freeman et al., 2014; Kolb & Kolb, 2005)	Pedagogical skills	Nurture	Redesigned activity that needs constructive or interactive thinking
SLO-based teaching	Constructive alignment and OBE (Biggs, 1996; Harden, 2007)	SLO-based teaching	Align	Alignment map linking SLOs, tasks and assessment

Workshop focus	Literature anchor	Project strand	NASEER component	Proposed evidence of learning
Assessment techniques	Formative feedback; assessment validity; AI Assessment Scale (Black & Wiliam, 2009; Dawson et al., 2024; Perkins et al., 2024)	Assessment techniques	Evidence	Rubric and feedback plan; assessment with a stated AI level
Beyond the workshop	Professional development research (Desimone, 2009; Guskey, 2002)	Sustainable practices	Sustain, Refine	Peer observation, follow-up reflection, shared unit bank

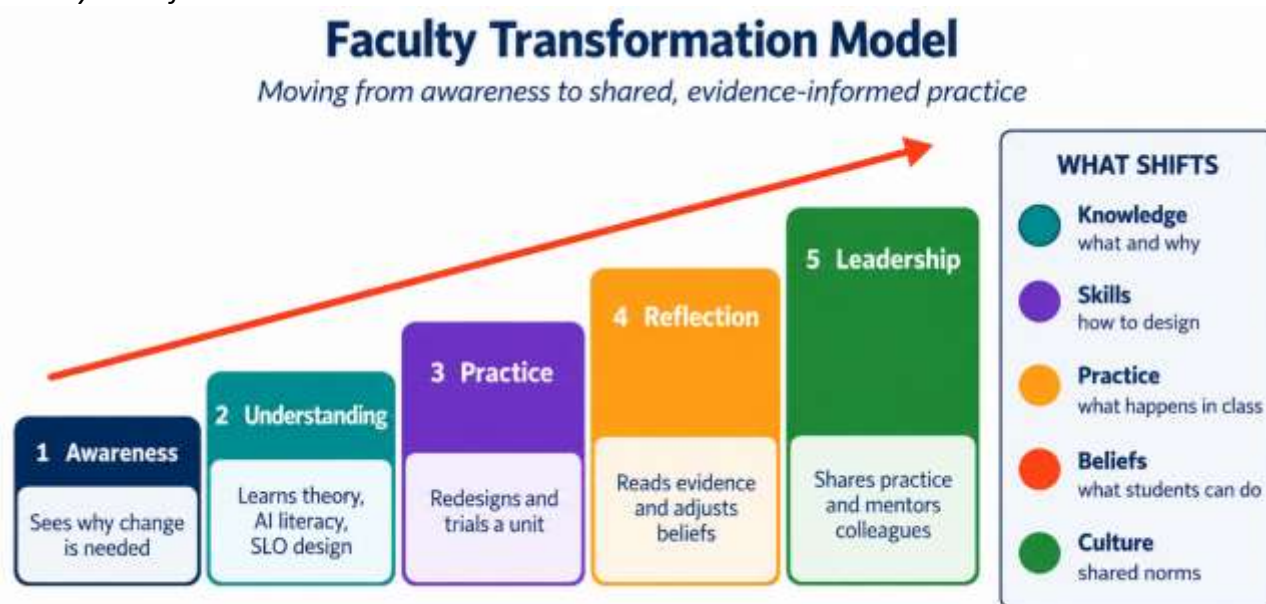
Note. This table shows how the workshop themes connect to the literature. It is a proposed alignment and does not report what happened in the workshop.

Figure 4*KUST ORIC Implementation Model*

Note. Proposed conceptual model. It shows intended logic and does not report project results.

Faculty transformation

Faculty development succeeds when participants change what they do and see results. The Faculty Transformation Model in Figure 5 follows the research on professional development: awareness first, then understanding, then practice, then reflection on evidence, and finally shared leadership (Desimone, 2009; Guskey, 2002). It puts practice before belief change, consistent with Guskey's argument. It also assumes that leadership is a result, since lasting change requires others to follow suit (Dancy et al., 2016).

Figure 5*Faculty Transformation Model*

Note. Original synthesis based on the professional development literature reviewed (Author, 2026)

Implications

For faculty. Start from the SLO, and decide the role of AI for each task. Provide at least one opportunity in every lesson where students share their ideas without AI. Explain to students the acceptable and acceptable usage of AI and the rationale behind it.

For programmes and departments. Confer over SLOs, tasks and assessments; and articulate levels of AI use in course outlines (Perkins et al., 2024). Implement units that have been redesigned with the intention of having good practice shared across the department (Dancy et al., 2016).

For University Leadership and KUST ORIC project. See faculty development as a process and not an event. Simple evidence can be gathered at each stage of the project: redesigned units, alignment maps, reflections and samples of student work. The length of time, the recognition of tools and access to tools determines whether change is permanent or not (Henderson & Dancy, 2007). The workshop can serve as the starting point of a community of practice.

For students. Students require AI literacy, and rules and feedback, demonstrating what they can do without AI assistance. They should also be informed that extra demands could be more challenging although beneficial to learning (Deslauriers et al., 2019).

For policy. Policies are most effective when they address teaching and governance and operation together (Chan, 2023) and when they focus on the issue of the validity of assessment (Dawson et al., 2024).

Limitations

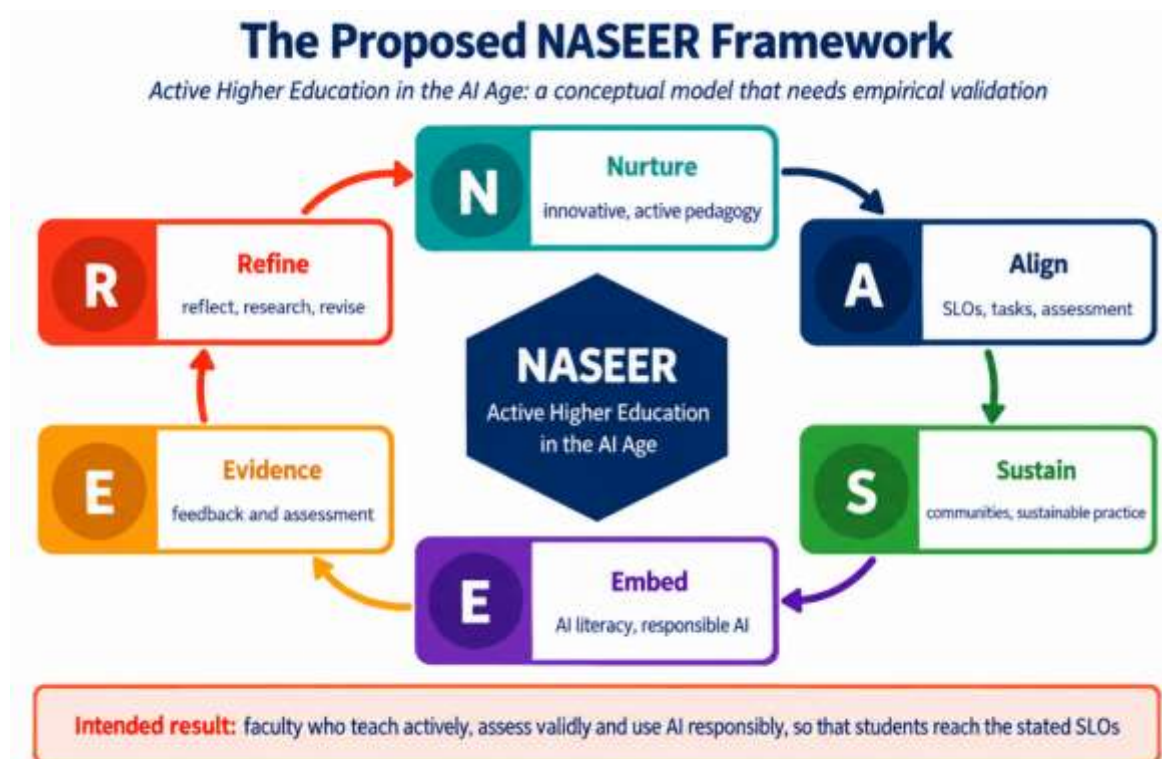
It was a narrative review, without any registered protocol, and it was possible that another team could choose and weigh studies differently. Much of the AI evidence is recent, short-term and from single sites. There is some from schools, and some is self-reported. There is more literature on the STEM field and more literature on the Western context than on the South Asian context of universities. All of the models here are conceptual, that is, they have not been tested and have been constructed from the literature. Only published title, thematic strands and focus of the KUST ORIC project are used in the paper. It fails to record project or workshop results and no claims are made regarding the impact of results.

Future Research

- **Test the models.** Test the designs of the AI–SLO Lesson Model and the Faculty Transformation Model in the field through design-based or mixed-methods studies.
- **Follow up the learning over time.** AI-supported improvements can be demonstrated to persist after delayed tests in University level trials
- **Study assessment validity.** Evaluate assessments for the alignment at different levels of AI use and to the specified SLOs (Dawson et al., 2024; Perkins et al., 2024).
- **Study faculty change.** Track how teachers' practice and beliefs change after AI-focused development, and what supports the change (Guskey, 2002; Kennedy, 2016).
- **Widen the evidence base.** Add studies from Pakistani and other South Asian universities, and studies on education for sustainability in AI-era teaching (Haider et al., 2023).

The Proposed NASEER Framework

The NASEER Framework for Active Higher Education in the AI Age is a proposed conceptual model. It gathers the propositions and tools above into six connected components (Figure 6). The name is an acronym, and each letter marks a component. The framework is a proposal and has not been tested, so it requires empirical validation before it is used as more than a planning guide.

Figure 6*The Proposed NASEER Framework*

Note. Proposed conceptual model. It requires empirical validation. (Author, 2026)

N: Nurture innovative pedagogy. Faculty design active, collaborative, experiential and inquiry-based tasks that need constructive or interactive thinking (Chi & Wylie, 2014; Freeman et al., 2014; Kolb & Kolb, 2005). **A: Align SLOs, tasks and assessment.** Outcomes come first, and each task and assessment is matched to them (Biggs, 1996; Harden, 2007). **S: Sustain practice.** Communities of practice, time and institutional support help change last, and sustainable practice is treated as both a teaching habit and a content area (Dancy et al., 2016; Henderson & Dancy, 2007). **E: Embed AI literacy and responsible AI.** AI use is chosen task by task, disclosed, and paired with guardrails and ethical judgement (Floridi & Cowls, 2019; Long & Magerko, 2020; Perkins et al., 2024). **E: Evidence through feedback and assessment.** Formative checks, usable feedback and valid summative evidence show whether students met the SLOs (Black & Wiliam, 2009; Dawson et al., 2024; Hattie & Timperley, 2007). **R: Refine through reflection and research.** Faculty use evidence to revise their designs and share what they learn (Desimone, 2009; Guskey, 2002). Table 6 links each component to the literature, to the KUST ORIC project and to indicators that a future study could use.

Table 6*NASEER Components, Literature Basis, KUST ORIC Link and Indicators for Validation*

Component	Literature basis	KUST ORIC link	Possible indicators
N Nurture innovative pedagogy	(Chi & Wylie, 2014; Freeman et al., 2014; Kolb & Kolb, 2005)	Pedagogical skills; workshop focus on innovative pedagogy	Observed student cognitive activity; task quality ratings
A Align SLOs, tasks, assessment	(Biggs, 1996; Deibl et al., 2018; Harden, 2007)	SLO-based teaching strand	Alignment map completeness; alignment scores
S Sustain practice	(Dancy et al., 2016; Henderson & Dancy, 2007; Slijepcevic & Huang, 2025)	Sustainable practices strand	Continued use after training; peer observation; shared unit bank
E Embed AI literacy and responsible AI	(Holmes et al., 2022; Long & Magerko, 2020; Perkins et al., 2024)	AI in education strand; AI-integrated education focus	AI-use statements; student AI-literacy tasks
E Evidence through feedback and assessment	(Black & Wiliam, 2009; Dawson et al., 2024; Hattie & Timperley, 2007)	Assessment techniques strand	Feedback quality; assessment validity review
R Refine through reflection and research	(Desimone, 2009; Guskey, 2002; Kennedy, 2016)	Project evidence cycle	Reflection logs; revised designs; student outcome data

Note. Indicators are suggestions for future validation studies. No data are reported here.

What NASEER adds to existing frameworks

NASEER does not replace existing frameworks. TPACK explains what teachers need to know (Mishra & Koehler, 2006). The AI Assessment Scale helps set AI use for assessment (Perkins et al., 2024). Policy frameworks organise institutional action (Chan, 2023). The literature on teacher learning reflects the ways in which teacher learning can be structured (Desimone, 2009).

NASEER's contribution is to place these pieces in one sequence for faculty development: begin with the pedagogy and outcomes, then add AI literacy and assessment, and finally add the conditions and the evidence cycle that enable change to persist. It is an empirical question whether this sequence is more effective than the existing methods.

How NASEER offers a possible solution for AI-era faculty development

The framework addresses the three issues identified in the literature. NASEER typically begins with outcomes and faculty development is taught as techniques that are not aligned. AI policy often focuses

on detection, so NASEER puts assessment validity and task design first. And change often fades after a workshop, so NASEER adds Sustain and Refine as standing components. In the KUST ORIC project, the five project strands map onto five components, and the evidence cycle supplies the sixth. The three-day workshop can act as the launch point for N, A, E and E, while S and R depend on what happens afterwards.

Validation would need a plan. A first step is expert review of the framework by education and AI specialists. A second is a pilot in which a small group of faculty redesign one unit, record AI-use levels and collect samples of student work. A third is a comparison of student outcomes and faculty practice before and after, ideally with a comparison group. Until such work is done, NASEER should be read as a well-grounded hypothesis and not as an established model.

Conclusion

Active learning remains one of the best-supported ideas in university teaching, and AI makes its design more important, not less. The research reviewed here suggests that learning depends on students doing the thinking, that AI can support or replace that thinking, and that alignment between outcomes, tasks and assessment keeps results valid.

The KUST ORIC-funded project “Empowering Excellence”, led by Principal Investigator Prof. Dr. Muhammad Naseer Ud Din, and the linked the three-day workshops in collaboration among KUST ORIC, the Institute of Education and Research (IER –KUST), and the Center of Human Resource Career and Development (CHRC-D-KUST), address the right problem: faculty capability in pedagogy, AI, SLO-based teaching and assessment. The four models in this paper, the Innovative Pedagogy Cycle, the AI–SLO Lesson Model, the KUST ORIC Implementation Model and the Faculty Transformation Model, offer practical ways to organise that work.

The NASEER Framework brings these strands together as a proposed conceptual model. It must be empirically validated and this paper has charted a roadmap for it. If the framework works, it may be a valuable tool for KUST and other universities to train staff to be active teachers, valid evaluators, and responsible users of AI tools that can help students achieve the goals their degrees promise.

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