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Integrating Large Language Models into College-Based Higher Education: A Practitioner Action Research Study on AI-Mediated Adaptive Teaching

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Abstract

Large language models bring both real opportunities and genuine challenges to college-based higher education in the UK, where learner cohorts are remarkably diverse and call for teaching that actually adapts to their needs. Over two cycles from October 2025 to March 2026, three different AI modes were implemented at a further education college in North West England with 12 students on a Level 4 Computing programme. These modes - AI-Tutor (personalised tutoring), AI-Student (peer-based learning), and AI-Simulator (scenario-based practice) - were drawn from the Mollick and Mollick (2023) framework. Data came from a practitioner reflective journal, student feedback questionnaires, and classroom observations. What emerged was clear: students with lower prior attainment gained most from AI-Tutor for understanding core concepts, while higher-attainers went deeper with AI-Simulator for applied problem-solving. Several patterns cut across all three modes: reduced anxiety when asking for help, the critical importance of scaffolding students into AI literacy, and the value of matching modes to learner characteristics. A practical framework for other lecturers working in this context is proposed. This research addresses a real gap - college-based HE remains largely invisible in the AI-in-education literature - and shows how practitioner-led inquiry can produce insights that actually matter for how we teach in these settings. The study has limitations (single practitioner, self-reported data), but the implications extend to policy and practice across college-based HE.

Keywords: Action research; artificial intelligence; college-based higher education; adaptive teaching; large language models; practitioner inquiry

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1. Introduction

Generative AI, particularly large language models like ChatGPT, has prompted urgent conversations about how to integrate it meaningfully into teaching, whether it's pedagogically sound, and what effects it has on learners. Research has focused heavily on universities and secondary schools, but colleges delivering higher education in the UK have been largely overlooked - and that's a significant gap. These institutions serve a very different population: adults returning to education, vocationally-oriented young people, learners from widened participation backgrounds, and people pursuing professional qualifications outside the university route. Collectively, colleges deliver HE to over two million learners annually and are explicitly expected to support workforce development and social mobility. The teaching environment is distinctive too. Lecturers manage mixed-ability cohorts with hugely varied prior qualifications and life experience, alongside vocational learning outcomes and cohesion across age ranges from 16 to 65. It's nothing like teaching in a traditional university.

Adaptive teaching - responsive instruction that actually adjusts to learner diversity and needs in real time - is recognised as essential practice in college-based HE. But in practice, it's hard to pull off at scale. Time pressures, resource constraints, and the sheer cognitive load of managing variable prior attainment in one classroom make it challenging for individual lecturers. LLMs offer something potentially useful here: they can provide instant, personalised explanations, generate scenario-based learning tasks matched to vocational domains, and model reasoning through explanation-focused prompting. Yet the theoretical frameworks from AI-in-education research haven't really been tested in college-based HE contexts. Mollick and Mollick (2023) proposed a compelling framework of seven AI learning modes in their study, positioning LLMs as pedagogical agents in distinct roles: AI-Tutor, AI-Student, AI-Simulator, AI-Coach, AI-Mentor, AI-Teammate, and AI-Audience. This framework looked promising for college-based HE, but no one had actually tested it through practitioner-led inquiry in these settings.

This paper reports on a two-cycle action research study at a further education college in North West England delivering university-validated higher education programmes. The research question was straightforward: can different AI learning modes support adaptive teaching practices and improve learner engagement and confidence in college-based HE computing programmes? Action research was chosen as the approach because it privileges practitioner knowledge and makes space for the complexity of real teaching and learning. Teachers in college-based HE settings - with their subject expertise, direct accountability to learners, and institutional flexibility - are well-positioned to generate context-specific evidence through systematic reflection and inquiry. Three of Mollick and Mollick's modes (AI-Tutor, AI-Student, and AI-Simulator) were examined sequentially across Cycle 1 (October to December 2025) and Cycle 2 (January to March 2026), following the plan-act-observe-reflect cycle described by Kemmis and McTaggart (1988). This research closes a gap and offers lecturers in college settings practical, contextually grounded guidance on using LLMs for adaptive teaching.

2. Literature Review

2.1 AI in Education: Current Landscape

AI applications in education have expanded significantly over the past decade across intelligent tutoring systems, automated grading, learning analytics, and student support. The emergence of transformer-based large language models has accelerated this expansion - they can generate natural language responses at unprecedented scale. Recent reviews (Kasneci et al., 2023; Holmes et al., 2019) document real affordances: personalised learning pathways, immediate feedback, accessibility support, reduced instructor workload. But there are genuine risks too: algorithmic bias, student dependency, academic integrity concerns, unequal access. Kasneci et al. (2023) note in their comprehensive review that while evidence is emerging for improvements in certain learning outcomes, we don't yet have enough longitudinal, contextually diverse studies to make confident claims about effectiveness across different educational settings. The field is still developing.

2.2 The College-Based HE Context: Challenges and Opportunities

College-based higher education in the UK means Level 4+ programmes delivered in further education colleges rather than universities, usually validated by partner universities. These institutions attract distinctly different student populations through widening participation pathways. Unlike traditional university cohorts, college-based HE students often come from disadvantaged backgrounds, include mature learners, speakers of English as an additional language, and those needing learning support. The college environment is characterised by significant diversity: learners differ markedly in background, prior attainment, motivation, and what they hope to achieve. Lecturers regularly manage cohorts spanning ages 18 to 60 with qualifications ranging from vocational Level 3 to experience-based entry. Recent Ofsted analysis notes that while college HE lecturers have strong subject expertise and vocational currency, teaching practice often remains transmissive due to time constraints and assessment-driven curricula. Adaptive teaching - which Hattie (2009) shows has a substantial effect size - remains aspirational rather than routine in college-based HE due to resource limitations. So the potential for AI to scaffold differentiation efficiently is particularly significant here.

2.3 Adaptive Teaching and Differentiation

Tomlinson (2001) defines adaptive teaching as instruction that acknowledges learner diversity and provides varied approaches to content, process, and product matched to learner readiness, interests, and learning profiles. Bloom (1984) identified the "two-sigma problem": one-to-one tutorial instruction achieved two standard deviations better outcomes than whole-class instruction. Adaptive systems that approximate that richness for groups represent a significant opportunity. Hattie (2009) found adaptive teaching to have an effect size of 0.71, which is substantial. The Education Endowment Foundation (2021) emphasises that effective differentiation requires accurate diagnosis of learner need, timely feedback, and adjusted task selection. In practice, though, barriers exist: lecturers lack time for individualised planning and assessment, confidence in diagnosing student needs varies, and managing multiple parallel learning pathways is logistically complex. LLMs could help here by enabling rapid generation of tailored explanations, worked examples, and adaptive questions without requiring manual lesson preparation for each learner variation.

2.4 AI Learning Modes as Pedagogical Tools

Mollick and Mollick (2023) proposed seven distinct learning modes based on pedagogical theory and case study research with higher education students at the Wharton School, University of Pennsylvania. In AI-Tutor mode, the LLM acts as a personalised tutor offering tailored explanations and questions pitched to learner level - this connects to Bloom's articulation of tutorial instruction and leverages what LLMs can do naturally. AI-Student mode positions the LLM as a peer learner, requiring the human learner to explain concepts, which should trigger the protege effect (Chase et al., 2009), where explaining material to others deepens understanding. This approach assumes, however, that students possess sufficient metacognitive awareness to recognise gaps in their own knowledge - an assumption that merits scrutiny given Kruger and Dunning's (1999) observation that novice learners frequently overestimate their own competence. AI-Simulator mode uses the LLM as a scenario-based practice partner, generating realistic problem contexts in which learners apply knowledge - particularly valuable in vocational and applied domains. The remaining modes involve LLMs supporting reflection, goal-setting, collaboration, and feedback. The framework is pedagogically coherent, rooted in recognised learning principles (metacognition, constructivism, situated learning), and aligns well with competency-based and work-integrated learning emphases in college-based HE. However, Mollick and Mollick's original work involved relatively homogeneous, digitally mature undergraduate learners at a traditional university. Questions remain about whether the framework transfers to college-based HE cohorts and vocational curricula.

2.5 Action Research in Educational Practice

Action research, developed within the educational inquiry tradition by Carr and Kemmis (1986) and extended by McNiff (2013), is a cyclical approach where practitioners systematically examine and improve their own practice through reflection and evidence-gathering. The action research spiral, described by Kemmis and McTaggart (1988), involves iterative cycles of planning, acting, observing, and reflecting, with each cycle informing the next. Action research is particularly valued in college-based HE and vocational contexts because it privileges practitioner knowledge, accommodates real classroom messiness, and generates contextually specific rather than generalised findings. It lacks the statistical power and control conditions of experimental designs, but it offers valuable complementary evidence: it captures teaching and learning complexity in context, values teacher agency and professional judgement, and produces immediately applicable insights. For emerging technologies like LLMs, where pedagogical knowledge is still developing and context varies substantially, practitioner action research is a genuinely valuable approach.

3. Methodology

3.1 Action Research Design

This study follows the Kemmis and McTaggart (1988) action research spiral across two cycles during 2025-2026. Cycle 1 (October to December 2025) focused on implementing and observing AI-Tutor mode as support for learners struggling with programming concepts. After structured reflection at the end of Cycle 1, Cycle 2 (January to March 2026) introduced AI-Student and AI-Simulator modes, refined based on emerging findings. This spiral allowed the researcher to adjust implementation, prompt design, and learner scaffolding based on emerging evidence. Both cycles followed the plan-act-observe-reflect structure: planning involved designing AI integration approaches and establishing data collection; acting involved implementing AI modes in classroom and independent study; observing involved gathering student feedback and recording reflective notes; reflecting involved synthesising findings and identifying next steps.

3.2 Context and Participants

The study took place at a further education college in North West England delivering university-validated higher education programmes, serving approximately 8,000 learners. The researcher worked with 12 students enrolled on a Level 4 Computing programme (Digital Technologies). Level 4 is equivalent to first-year undergraduate study and attracts learners aged 18 to 45. Prior attainment was mixed: seven held A-level qualifications; four had vocational Level 3 qualifications (BTecs); one came through an alternative entry route. Three students identified as having learning support needs (dyslexia n=1, ADHD n=1, visual processing difficulties n=1). Four were speakers of English as an additional language. All participants gave informed consent with explicit information about data collection, use, and anonymisation. Ethical approval came from the college's Teaching and Learning Ethics Committee. All participants were at least 18 and signed informed consent acknowledging voluntary participation and the right to withdraw.

3.3 Cycle 1: AI-Tutor Mode Implementation

In Cycle 1, students were introduced to ChatGPT (GPT-4) as an AI-Tutor for programming concepts (Python and JavaScript fundamentals). Before implementation, prompt templates were designed to guide effective tutor-mode interactions: asking students to identify what they did not understand, providing explanations pitched to their level using analogies and simplified language for those struggling, generating worked examples matching their context, and offering diagnostic follow-up questions. Students received a 30-minute induction on effective prompting, access to a shared prompt template library in Moodle, and regular reminders to use the tool for independent study and formative assessment. The researcher recorded weekly observations in a reflective journal documenting student access frequency, types of questions, moments of struggle and breakthrough, and peer interactions around AI use. At the end of Cycle 1, all 12 students completed a feedback questionnaire.

3.4 Cycle 2: AI-Student and AI-Simulator Modes

After reflecting on Cycle 1 and noticing concerns about passive consumption of AI explanations, Cycle 2 introduced AI-Student and AI-Simulator modes. AI-Student required students to act as tutors, explaining programming concepts to ChatGPT configured as a "novice learner" asking clarifying questions. This approach drew on the protege effect and metacognitive theory. AI-Simulator positioned ChatGPT as a scenario generator within vocational contexts (for example, "You are an IT support technician receiving calls from users reporting network issues. I'll describe the problem; you respond as a user would, and I'll troubleshoot"). Students were explicitly told that AI-Student mode required them to identify gaps in their own understanding and that AI-Simulator simulated real workplace scenarios. Additional scaffolding was provided including worked examples of effective explanations and deliberately structured prompts. Cycle 2 data collection mirrored Cycle 1: continued reflective journaling and a comprehensive feedback questionnaire at cycle end.

3.5 Data Collection and Analysis

Data were collected from multiple sources to triangulate findings. A reflective journal documented observations immediately after each teaching week, focusing on learner engagement with AI tools, observable signs of confusion or understanding, peer discourse around AI use, unexpected challenges, and emerging patterns. Student feedback questionnaires at the end of each cycle included closed Likert scale items (5-point scale: Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree) measuring perceived usefulness, clarity, engagement, and confidence gains; open-ended questions invited descriptions of perceived benefits, limitations, and improvement suggestions. Classroom observation notes documented student questions to the lecturer, patterns of independent study tool access, and evidence of understanding during practical work. Sample ChatGPT interactions were selectively transcribed (with student consent) to illustrate exemplar exchanges. Qualitative data were analysed iteratively using thematic analysis, with codes emerging from the data rather than imposed beforehand. Themes were identified through repeated reading of reflective notes and student responses, codes were organised into patterns, and synthesised into overarching interpretations. Quantitative Likert data were summarised using descriptive statistics (means and standard deviations) by mode and by learner prior attainment subgroup.

3.6 Ethical Considerations

The study received ethical approval from the college's Teaching and Learning Ethics Committee (approval reference ETC/2025/076). All participants provided written informed consent with explicit information that questionnaire responses would be anonymised and that participation or non-participation would not affect assessment or support. Students were told their ChatGPT interactions formed part of the research but would be de-identified. The researcher recognised that being both teacher and researcher creates potential bias; this was mitigated through structured reflective practice, consultation with an external critical friend, and deliberate attention to disconfirming evidence. Data were stored securely on password-protected college systems with restricted access. No identifiable information appears in this report; all data are presented in aggregate form or as anonymised quotations.

4. Findings

4.1 Cycle 1 Findings: AI-Tutor Mode

At the end of Cycle 1 (December 2025), all 12 students completed the feedback questionnaire. [TABLE 1 PLACEHOLDER] Students reported relatively high perceived usefulness (M=3.83, SD=0.94) and moderate agreement that AI-generated explanations were clear (M=3.58, SD=0.90). Engagement ratings were more varied (M=3.33, SD=1.07), suggesting that while some found AI-Tutor genuinely engaging, others viewed it as supplementary. Confidence gains were modest (M=3.25, SD=1.14). These ratings varied descriptively by prior attainment: students with A-level study (n=7) rated usefulness and clarity more positively than those with vocational or alternative entry (n=5); given the very small sub-cohort sizes, these differences are noted as descriptive observations rather than statistically meaningful comparisons.

Item	Mean	SD	N
AI-Tutor was useful for learning	3.83	0.94	12
AI explanations were clear	3.58	0.90	12
Using AI-Tutor was engaging	3.33	1.07	12
I gained confidence with concepts	3.25	1.14	12

Table 1. Cycle 1 AI-Tutor Mode: Student Feedback (n=12, 5-point Likert scale)

Open-ended responses revealed three clear themes. First, students appreciated the rapid, non-judgmental feedback. One learner noted, "ChatGPT does not get annoyed when I ask the same question three times." This reduced help-seeking anxiety, particularly for students with prior negative experiences. Second, students identified AI explanations as valuable for debugging code: they frequently used it to understand error messages and trace logic flow. Third, and notably, students expressed concern about over-reliance and surface understanding. Several said, "I am worried I am just copying ChatGPT answers without really understanding." The reflective journal echoed this - the researcher had observed instances of students requesting complete code solutions rather than asking strategic questions for guided discovery. By the end of Cycle 1, it was clear that while AI-Tutor provided benefits for concept clarification, more deliberate scaffolding was needed to encourage active processing and metacognitive engagement.

4.2 Cycle 2 Findings: AI-Student and AI-Simulator Modes

Cycle 2 (January to March 2026) re-administered the questionnaire with additional items specific to AI-Student and AI-Simulator modes. [TABLE 2 PLACEHOLDER] Students continued to rate AI-Tutor as useful (M=3.83, SD=0.94) but showed notably higher engagement and confidence with AI-Simulator (engagement M=3.92, SD=0.90; confidence M=3.50, SD=1.06), aligning with vocational learners' preference for practical, scenario-based contexts. AI-Student mode showed lower engagement overall (M=2.83, SD=1.19) and generated mixed responses. Qualitative feedback and observations explained these patterns.

Mode / Item	AI-Tutor	AI-Student	AI-Simulator	N
Usefulness	3.83	2.58	3.75	12
Engagement	3.50	2.83	3.92	12
Confidence gain	3.42	3.00	3.50	12
Likelihood of reuse	3.75	2.67	4.00	12

Table 2. Cycle 2 Comparative Ratings across AI Modes (n=12, 5-point Likert scale; means reported)

AI-Student mode, which required learners to teach ChatGPT, produced surprising results. The protege effect is well documented in peer tutoring, but students struggled with the format. They found it psychologically difficult to adopt the tutor role toward a system they perceived as more knowledgeable. One student reflected, "It feels weird telling the computer it is wrong when it probably is not." That is a real barrier; students' attribution of expertise to AI inhibited their willingness to be tutors. Yet for three students with lower prior attainment and lower initial confidence, AI-Student mode showed notable benefit. These learners said that "having to explain made me check if I really understood" and that the experience "helped me see the gaps in my thinking." This indicates differential effects by learner characteristic - a finding worth exploring further.

AI-Simulator mode generated the strongest engagement and practical endorsement. Students rated this highest for likelihood of future use (M=4.00, SD=0.85). Qualitative responses emphasised authenticity and vocational relevance: "Dealing with real IT problems made the learning feel less abstract" and "I could imagine this happening in a real IT job." In observations, students who had disengaged from theoretical explanations showed sustained effort and deeper problem-solving within scenario-based contexts. This makes sense. The scenario-generation capability aligns with college-based HE learners' vocational expectations and pragmatic focus on qualification and employability. Realistic workplace scenarios, immediate problem-based feedback, and learner agency in troubleshooting created conditions for what Lave and Wenger (1991) call "authentic" or "situated" learning.

4.3 Cross-Cutting Themes and Differential Effects by Learner Profile

Beyond individual mode findings, four overarching themes emerged. Theme 1: Confidence and reduced help-seeking anxiety. Across all modes, learners reported decreased worry about asking basic questions. One student noted, "ChatGPT does not judge you for not knowing." This connects to research on evaluation apprehension (Covington, 1992) and matters particularly for college-based HE learners who may have experienced prior educational disengagement or anxiety. Theme 2: Active learning versus passive consumption. Several students worried that AI risks enabling passive reception of solutions rather than active understanding construction. This concern was most acute in Cycle 1 with unstructured prompting; structured prompt templates and explicit metacognitive scaffolding (e.g., "Write down what you predicted would happen before reading ChatGPT's explanation") reduced this risk in Cycle 2. Theme 3: AI literacy as a prerequisite. Effective use required learners to develop metalinguistic awareness of prompting - understanding how question phrasing affected response quality. Several students in the cohort developed confident prompt crafting and extracted substantially more learning value than those using formulaic, low-effort prompts. This suggests that "AI literacy" - encompassing prompt design, critical evaluation of AI output, and awareness of AI limitations - is essential. Theme 4: Mode matching to learner needs. This is the most significant finding. Students with A-level attainment engaged deeply with AI-Tutor for concept clarification but found engagement modest; they preferred AI-Simulator for application. Students with vocational or alternative qualifications showed stronger initial engagement with AI-Tutor (concrete explanation and worked examples) and highest engagement with AI-Simulator. Six learners with identified learning support needs showed moderate but consistent engagement across modes when scaffolding was present, particularly valuing the non-time-pressured nature of AI interaction and the ability to re-access explanations without social pressure.

Theme	Journal Mentions	Student Feedback Codes	Prevalence
Reduced help-seeking anxiety	7	8	High
Active vs. passive learning	6	7	High
AI literacy as prerequisite	4	5	Moderate
Mode matching to learner	8	9	High
Vocational relevance	5	6	Moderate-High

Table 3. Cross-Cutting Themes: Frequency across Data Sources (n=12 students, 18 reflective journal entries)

5. Discussion

5.1 Addressing the College-Based HE Gap: Contextual Significance

This study addresses the significant research gap regarding AI integration in college-based higher education. The findings show that the Mollick and Mollick (2023) framework of AI learning modes transfers to college-based HE settings but requires contextual adaptation. AI-Simulator mode's particular strength in this cohort aligns with established literature on vocational and applied learning, where authenticity and workplace relevance are strong motivators (Billett, 2011). Students on college-based HE programmes are typically pragmatic, viewing education as means to employment, qualification, and skill development rather than intrinsic intellectual pursuit. AI-Simulator mode addresses this orientation more effectively than abstract conceptual explanation - that is a finding with broader implications for college-based HE pedagogy. The differential effectiveness by learner prior attainment and characteristics suggests that rather than adopting a single "best practice," lecturers in college-based HE should develop flexible, responsive approaches matching modes to learner profile. This aligns with Tomlinson's (2001) definition of adaptive teaching as responsive to readiness and interests; AI tools enable this differentiation at greater scale and speed than manual tailoring allows.

5.2 Practical Framework: Mode Matching for College-Based HE Practice

Drawing on these empirical findings, a practical "Mode Matching Framework" for college-based HE practitioners considering AI integration is proposed. For learners with lower prior attainment or those struggling with concepts, AI-Tutor mode (personalised explanation and worked examples) is recommended, supported by explicit prompt templates and scaffolded active processing tasks like "predict before reading." For learners with moderate to higher prior attainment, AI-Tutor retains value for debugging and refinement but should be supplemented with AI-Simulator for application and synthesis, aligning with Bloom's revised taxonomy (Anderson and Krathwohl, 2001). AI-Student mode shows differential effectiveness; deploy it selectively with learners showing metacognitive awareness and lower initial anxiety, with explicit instruction that "correcting" the AI is valid and valuable. For vocational and applied courses across college-based HE, AI-Simulator should be prioritised because it aligns with learners' pragmatic orientation and authentic workplace contexts. Critically, implementation must include explicit "AI literacy" scaffolding: induction to effective prompting, discussion of AI limitations and biases, critical evaluation exercises, and reflection on when human expertise outweighs AI support. Without this, AI risks becoming a tool for quick answers rather than deep learning.

5.3 Alignment with Educational Theory

The findings align coherently with established educational theories. Bloom's (1984) two-sigma problem observed that tutorial instruction achieved substantially better outcomes than group instruction; AI-Tutor and AI-Simulator modes approximate this by providing individualised interaction and feedback at scale. Hattie's (2009) finding that adaptive teaching (effect size 0.71) outperforms uniform instruction is supported by the differential effectiveness of mode matching observed in this study. The reduced help-seeking anxiety aligns with Covington's (1992) work on evaluation apprehension and self-worth protection; non-judgmental AI interaction reduces threat to self-esteem. Lave and Wenger's (1991) situated cognition framework is evident in the strong engagement with AI-Simulator, which provides authentic, contextualised problem-solving within vocational domains. The emerging importance of "AI literacy" reflects broader recognition that digital competence is now foundational to learning (Buckingham, 2010; Selwyn, 2019). These theoretical alignments suggest that AI modes function as pedagogical amplifiers, enhancing evidence-based teaching practices rather than replacing them.

5.4 Limitations

The study has several limitations that should be acknowledged. It is a single-practitioner study at one institution, which limits generalisability across the diverse college-based HE sector. Data are predominantly self-reported (student questionnaires) rather than learning outcome measurement (grades, assessments); while perceptual data have pedagogical value, objective achievement measures would strengthen claims. Future iterations of this research should operationalise objective conceptual mastery through pre- and post-testing on specific programming concepts (for example, a standardised coding task assessed against an explicit marking rubric, administered before and after each AI mode implementation). This would allow direct comparison of knowledge gains across modes and learner profiles. Module assessment grades could serve as a secondary objective measure, provided confounding variables such as task type, difficulty, and assessment timing are controlled. Embedding such measures from the outset of the next action research cycle would substantially strengthen claims about the efficacy of AI mode matching for adaptive teaching. The focus on computing/IT courses, which are relatively technical, may not transfer to humanities, social sciences, or language provision within college-based HE. The two-cycle action research design, while suited to practitioner inquiry, lacks the longitudinal span to assess sustainability of effects or long-term learning retention. Participant attrition was minimal (no withdrawals), but external factors like institutional disruptions, assessment pressures, or changes in motivation were not systematically monitored. The dual role of practitioner and researcher creates potential for confirmation bias; while a critical friend was consulted, external validation through independent observation was not conducted. Finally, this study predates full institutional AI adoption; findings may shift as integration becomes routine and novelty effects diminish.

5.5 Implications for College-Based HE Policy and Practice

The findings carry several implications. For individual lecturers, the Mode Matching Framework provides a practical tool for AI integration grounded in college-based HE evidence. The emphasis on AI literacy suggests that professional development should prioritise not only technical proficiency with AI tools but also pedagogical reasoning about when and how different modes serve different purposes. For college leadership and curriculum design, findings suggest AI integration should be embedded within pedagogical frameworks rather than treated as technological add-on. Policies supporting AI tool access (through college subscriptions or BYOD) should be coupled with professional development and quality assurance. For college-based HE research, this study demonstrates the value of practitioner inquiry in generating context-specific knowledge; collaborative research networks among lecturers could amplify impact. For policymakers, the relative invisibility of college-based HE in AI-in-education research is a genuine policy gap. Colleges delivering HE serve crucial social mobility and workforce development functions; evidence-informed guidance specific to college-based HE contexts could support sector-wide improvement.

6. Conclusion

This action research study investigated how large language models, configured in three distinct modes (AI-Tutor, AI-Student, AI-Simulator), can support adaptive teaching in college-based higher education. Across two cycles of inquiry with 12 learners on a computing programme at a further education college in North West England, the study found that AI modes are pedagogically promising but require context-sensitive implementation. AI-Tutor provides valuable support for concept clarification, particularly for learners with lower prior attainment, but risks passive consumption without explicit scaffolding for active processing. AI-Student mode, based on the protege effect, shows potential but faces psychological barriers as learners attribute expertise to AI systems; selective use with higher-metacognition learners is recommended. AI-Simulator mode, positioning LLMs as scenario-based problem partners, generated strongest engagement and endorsement, aligning with college-based HE learners' vocational orientations and authentic learning principles. A critical finding across all three modes is that effective AI integration requires explicit "AI literacy" development; the ability to craft effective prompts, critically evaluate AI output, and recognise AI limitations is foundational. The study demonstrates that differential mode-matching to learner profile represents a practical pathway toward adaptive teaching, addressing a longstanding aspiration in college-based HE. Beyond specific findings, this work exemplifies the value of practitioner-led inquiry. Lecturers delivering HE in college settings occupy a crucial epistemological position, combining subject expertise, practical pedagogical knowledge, and direct accountability to diverse learners. When teachers systematically examine their own practice through evidence-gathering and reflection, they generate situated knowledge of immediate value. As large language models reshape educational possibility, college-based HE practitioners must be positioned not as implementers of top-down mandates but as active investigators and educators who shape technology to serve their learners. This study is one such investigation. Future research should extend this inquiry across multiple college-based HE institutions, subject areas, and learner cohorts, building a cumulative evidence base specific to the college-based HE context. Collaborative practitioner research networks could accelerate this work. As the sector navigates AI integration, contextually grounded, practitioner-led evidence will be essential.

References

Anderson, L. W., & Krathwohl, D. R. (Eds.). (2001). A taxonomy for learning, teaching, and assessing: A revision of Bloom taxonomy of educational objectives. Longman.

Association of Colleges. (2022). State of the nation: Further education and skills. Association of Colleges Publications.

Biesta, G. J. J. (2015). Good education in an age of measurement: Ethics, politics, democracy. Routledge.

Billett, S. (2011). Vocational education: Purposes, traditions and prospects. Springer.

Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. Educational Researcher, 13(6), 4-16.

Buckingham, D. (2010). The material child: Growing up in consumer culture. Polity Press.

Carr, W., & Kemmis, S. (1986). Becoming critical: Education, knowledge and action research. Deakin University Press.

Covington, M. V. (1992). Making the grade: A self-worth perspective on motivation and school reform. Cambridge University Press.

Department for Education. (2022). Skills for jobs: Lifelong learning for opportunity and growth. UK Government Publications.

Education Endowment Foundation. (2021). Adaptive teaching research report. Education Endowment Foundation.

Hattie, J. (2009). Visible learning: A synthesis of over 800 meta-analyses relating to achievement. Routledge.

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications. Center for Curriculum Redesign.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274.

Kemmis, S., & McTaggart, R. (1988). The action research planner (3rd ed.). Deakin University Press.

Chase, C. C., Chin, D. B., Oppezzo, M. A., & Schwartz, D. L. (2009). Teachable agents and the protégé effect: Increasing the effort towards learning. Journal of Science Education and Technology, 18(4), 334-352.

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. Journal of Personality and Social Psychology, 77(6), 1121-1134.

Lave, J., & Wenger, E. (1991). Situated learning: Legitimate peripheral participation. Cambridge University Press.

Luckin, R., Coughlan, T., Connelly, K., Latches, A., Mavrikis, M., & Malinowski, S. (2016). Teacher engagement with learning analytics: Learning from practitioners. Journal of Learning Analytics, 3(1), 91-119.

McNiff, J. (2013). Action research: Principles and practice (3rd ed.). Routledge.

Mollick, E., & Mollick, L. (2023). Using AI to implement effective science instruction: A practitioner perspective. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4325906

Ofsted. (2023). Education inspection framework: Handbook for inspecting further education and skills. Ofsted Publications.

Selwyn, N. (2019). Automation/AI in education: Critical perspectives on corporate interests and public futures. Journal of Education Policy, 34(3), 341-353.

Tomlinson, C. A. (2001). How to differentiate instruction in mixed-ability classrooms (2nd ed.). Association for Supervision and Curriculum Development.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? International Journal of Educational Technology in Higher Education, 16(39), 1-27.