# Evaluating Learner Competency in GenAI-Enhanced Learning: A Framework for Process-Oriented Assessment of Human-AI Collaboration

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### Abstract

Generative AI has created a fundamental crisis in higher education assessment, where traditional output-based evaluation cannot distinguish genuine learner competency from AI-assisted performance. This paper proposes a framework for process-oriented competency evaluation comprising three interconnected components: (1) Competency Model defining what to assess in AI-augmented learning; (2) Analytics Integration capturing processes where learning happens; (3) Actionable Guidelines providing practical tools for educators. Ethical principles are embedded within the framework to ensure responsible practice. Grounded in Self-Regulated Learning, Bloom's Taxonomy, and Learning Design theory, this framework addresses, how authentic learner competency can be evaluated in GenAI-enhanced learning environments, bridging the adoption-to-actionability gap through theoretically grounded, and practically actionable foundations for responsible Generative AI integration that enhances rather than replaces human learning.

### Keywords

Generative AI, Competency Assessment, Human-AI Collaboration, Process-Oriented Assessment, Learning Analytics

## 1. Introduction

The integration of Generative AI (GenAI) in higher education has disrupted traditional assessment paradigms. When AI can produce essays that meet rubric standards, solve complex problems, and generate functional code, a critical question emerges: how do educators authentically evaluate learner competencies? Traditional output-based assessments—essays, reports, code submissions, problem solutions—can no longer reliably distinguish genuine student competency from AI-assisted or AI-generated performance [1], creating competency misalignment - a disconnect between what assessments measure and what learners actually know. This crisis manifests across the dimensions where assessments increasingly measure AI capability rather than learner achievement, detection tools prove inadequate whilst creating adversarial dynamics, educators cannot observe how learners engage with AI (prompts, iterations, critical evaluation), and insufficient frameworks exist for responsible integration. Many learning analytics studies fail to provide practical guidance for teaching practice [2]. This paper proposes a framework addressing:

**RQ:** How can authentic learner competency be evaluated in GenAI-enhanced learning environments?

- RO-1: what competencies should be assessed when learning involves AI collaboration.
- RO-2: how learning processes can be systematically captured and analysed.
- RO-3: what practical frameworks enable educators to implement process-oriented assessment.

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The framework employs learning analytics to capture process-oriented evidence - the iterative refinement, critical evaluation, and strategic decision-making that characterise genuine learning, enabling assessment of authentic competencies even when outputs may be AI-influenced.

## 2. Related Work

### 2.1. GenAI in Education and Assessment

GenAI fundamentally challenges assessment validity [3], as learners can submit work that AI-generated work, making genuine understanding difficult to evaluate. Detection tools have proven unreliable, with high false-positive rates that damage trust [4]. The field has responded with opposing approaches—complete restriction or uncritical embrace—neither addressing how to assess competency when AI can simulate outputs. Recent work emphasises assessment redesign acknowledging AI's role whilst maintaining educational integrity [5]. However, concrete frameworks for implementing such assessment remain limited.

### 2.2. Learning Analytics for Assessment

Learning analytics traditionally focuses on outcomes and at-risk identification [6], with recent work on formative assessment [7], addressing assessment of learning rather than AI-augmented contexts. Process-oriented analytics capturing how they produce work offers promise for GenAI contexts [8]. However, existing approaches focus on individual learning processes rather than human-AI collaboration processes. The challenge of translating analytic insights into practical assessment strategies remains acute, particularly in GenAI contexts where educators need concrete guidance for implementation.

### 2.3. Competency Frameworks and Assessment

Competency-based approaches emphasise authentic demonstration of knowledge, skills, and dispositions [9]. The Knowledge-Skills-Dispositions (KSD) framework provides comprehensive models across cognitive, performance, and affective domains [10], assuming human-only performance. Recent revisions to Bloom's Taxonomy map AI capabilities to cognitive levels, showing AI excels at lower-order thinking but struggles with higher-order thinking requiring judgment and creativity [11]. Similarly, OULDI's learning design activity types [12] can be mapped to AI appropriateness, identifying where AI support is legitimate versus where independent human performance is essential.

### 2.4. Research Gap

Despite growing recognition of GenAI's impact, three critical gaps remain. First, existing frameworks focus on detecting AI use rather than evaluating competency in AI-augmented contexts. Second, whilst learning analytics can capture student-AI interaction data, systematic approaches to analysing and interpreting these data for competency evaluation are lacking. Third, the adoption-to-actionability gap means educators have limited practical guidance for implementing process-oriented assessment at scale. This paper addresses these gaps through an integrated framework defining competencies for AI-assisted learning, providing methodologies for capturing and analysing process data, and offering practical implementation tools.

## 3. Theoretical Foundations

The framework integrates four established theoretical perspectives: the Knowledge-Skills-Dispositions (KSD) framework for defining competencies, Bloom's Taxonomy revised for the AI era, OULDI Learning Design activity types, and Self-Regulated Learning theory.

### 3.1. Knowledge-Skills-Dispositions (KSD) Framework

The KSD framework [9], [10] conceptualises competency as integration across three domains: Knowledge (declarative, procedural, conditional), Skills (technical, cognitive, metacognitive), and Dispositions (attitudes, habits of mind, self-regulatory behaviours). In GenAI contexts, this framework distinguishes surface performance, where AI generates outputs without learner understanding, from genuine competency, where learners strategically collaborate with AI whilst maintaining deep understanding and critical judgment.

### 3.2. Bloom's Taxonomy Revised for AI Capability

Bloom's Taxonomy [13] provides a hierarchical framework for cognitive complexity. Recent work [11] has mapped AI capability to Bloom's cognitive levels: high capability at Remember/Understand levels, moderate at Apply, decreasing at Analyse/Evaluate, and lowest at Create requiring original synthesis. This suggests assessment must target higher-order levels where humans retain advantage. However, students can submit AI-generated analysis without understanding, the solution lies in assessing the process through which students engage at each level.

### 3.3. OULDI Learning Design Activity Types

OULDI's framework [12] categorises learning activities into seven types: Assimilative, Finding and Handling Information, Communication, Productive, Experiential, Interactive, and Assessment, each mappable to AI appropriateness (operationalised in Table 5).

### 3.4. Self-Regulated Learning Theory

Self-Regulated Learning (SRL) theory [14] conceptualises learning as a cyclical process of forethought (goal setting, planning), performance (monitoring, control), and self-reflection (evaluation, adjustment). In GenAI contexts, SRL becomes critical: strategic AI collaboration requires explicit goal setting, monitoring of AI outputs, and reflective evaluation. SRL provides the foundation for process-oriented assessment, where planning, monitoring, and reflection become observable indicators of genuine competency that AI cannot simulate.

### 3.5. Theoretical Integration

These four perspectives are integrated to address the research question. KSD provides the competency model - what to assess. Bloom's Taxonomy identifies where AI capability is high versus low. OULDI maps activities to AI appropriateness. SRL provides process orientation showing how metacognitive behaviours reveal authentic learning. Together, these theories enable shifting from output-based to process-based competency evaluation, from detecting AI use to assessing strategic AI collaboration, and from theoretical frameworks to actionable assessment design.

## 4. Framework for Process-Oriented Competency Evaluation

The framework comprises three interconnected components (**Figure 1**). Component-1 defines what competencies should be assessed through a KSD model adapted for AI-assisted learning. Component-2 specifies how learning processes can be systematically captured and analysed. Component-3 provides educators with practical tools and guidelines. Ethical principles are embedded throughout.

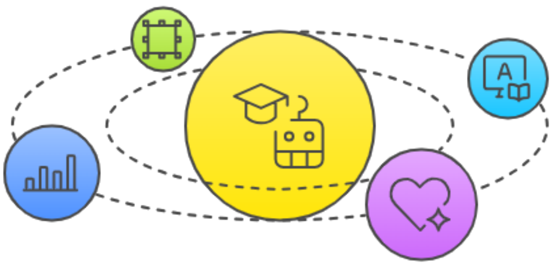


**Figure 1:** Integrated framework for evaluating learner competency

### 4.1. Component 1: KSD Competency Alignment Model

This component addresses what competencies should be assessed when learning involves AI collaboration, adapting the KSD model to distinguish genuine competency from AI-dependent performance (Table 1).

**Table 1: Knowledge-Skills-Dispositions (KSD) Dimensions for AI-Augmented Learning**

| Dimension | Sub-themes | Guiding questions | AI capability | Observable indicators |
|---|---|---|---|---|
| K1: Conceptual Understanding | Domain principles, theories, relationships | Can learners explain concepts in their own words beyond surface definitions? | Moderate - can explain but may lack nuanced understanding | Explains concepts without AI support; identifies relationships; corrects AI misconceptions |
| K2: Procedural Knowledge | Methods, techniques, application | Do learners understand when and how to apply procedures, not just execute them? | High for standard procedures; Low for context-specific application | Justifies procedure selection; adapts methods to context; identifies when AI procedures are inappropriate |
| K3: Conditional Knowledge | Contextual judgment, trade-off reasoning | Can learners justify why specific approaches suit specific contexts? | Low - struggles with nuanced contextual judgment | Evaluates trade-offs; considers stakeholder impacts; provides context-grounded rationale |
| K4: AI Literacy | AI capabilities, limitations, appropriate use | Do learners recognise when AI information may be inappropriate? | Inherently metacognitive - AI cannot assess itself | Identifies AI biases/limitations; verifies AI claims; articulates when AI helps/hinders |
| S1: Domain Performance | Executing core disciplinary tasks | Can learners perform independently and refine AI suggestions with domain expertise? | High for standardised tasks; Low for creative/contextual work | Performs without AI scaffolding; improves AI outputs; demonstrates independent capability |
| S2: Problem Analysis | Breaking complex problems into parts | Do learners frame problems themselves or rely on AI framing? | Moderate - can help structure but needs human direction | Decomposes problems independently; generates analytical frameworks; guides AI rather than follows |
| S3: Critical Evaluation | Assessing quality, validity, evidence | Can learners critique AI outputs using disciplinary standards? | Moderate - can help evaluate but lacks disciplinary depth | Identifies AI errors/omissions; applies domain standards; provides justified critique |

| Dimension | Sub-themes | Guiding questions | AI capability | Observable indicators |
|---|---|---|---|---|
| S4: Strategic Collaboration | Prompt engineering, iterative refinement | Does engagement show strategic thinking or passive acceptance? | Meta-skill about AI use itself | Sophisticated prompting; iterative refinement; strategic tool selection; reflective adjustment |
| S5: Communication | Constructing arguments, authentic voice | Is communication genuinely theirs or AI-templated? | Moderate for drafting; Struggles with authentic voice | Original phrasing; audience adaptation; coherent argumentation; distinct personal voice |
| D1: Self-Regulation | Planning, monitoring, reflecting | Do learners approach work strategically or reactively? | Inherently human - AI cannot demonstrate genuine SRL | Sets goals; monitors progress; adjusts strategies; documents decision evolution |
| D2: Critical Thinking | Questioning assumptions, verification | Do learners verify AI outputs or accept uncritically? | Inherently human - AI cannot have genuine critical stance | Questions claims; seeks verification; identifies assumptions; considers alternatives |
| D3: Professional Ethics | Honest representation, transparency | Are learners transparent about AI collaboration? | Inherently human - AI cannot have genuine ethical stance | Honest AI disclosure; appropriate attribution; acknowledges limitations; maintains integrity |
| D4: Growth Mindset | AI as learning tool not replacement | Is AI enabling learning or replacing it? | Inherently human - AI cannot have genuine motivation | Views challenges as opportunities; embraces struggle; uses AI strategically for learning |

For evaluating performance levels, for each KSD dimension, the framework defines observable indicators at three levels: *Basic* (threshold competency - minimal engagement, surface understanding), *Competent* (solid capability - strategic engagement, clear understanding), and *Sophisticated* (advanced expertise - nuanced understanding, strategic mastery). These descriptors enable rubric development distinguishing surface from deep engagement.

The KSD model is deliberately generic for transferability. Educators adapt by: (1) mapping disciplinary competencies to KSD dimensions, (2) identifying where AI capability is high versus low in their domain, (3) defining discipline-appropriate observable indicators, and (4) creating aligned rubrics. Embedded ethics acknowledges varying AI literacy levels, avoiding disadvantaging students with limited AI access, and recognises cultural diversity in AI interaction patterns.

## 4.2. Component 2: Learning Analytics Integration

Component 2 addresses how learning processes can be systematically captured and analysed. Process analytics capture the how of learning including iterations, decisions, evaluations, strategic choices, making visible the previously invisible dynamics of human-AI collaboration (Table 2).

**Table 2: Data Sources and Analysis Methods for Process Analytic**

| Data Source | Learning processes Captured | Example Indicators | Analysis Method | Insights |
|---|---|---|---|---|
| VLE/ LMS Analytics | Behavioural traces of engagement | Access patterns (frequency, timing), time-on-task (duration), resource navigation (sequences), submission patterns (timestamps, iterations, versions) | Quantitative: Correlation analysis (engagement → outcomes), temporal analysis (progression patterns), clustering (engagement profiles) | Engagement intensity, resource exploration breadth, temporal distribution, iteration frequency, persistence patterns |
| AI Interaction Data | Human-AI collaboration processes | Prompts (specificity, sophistication), AI outputs (what generated), accepted | Quantitative: Prompt sophistication scoring, acceptance rate calculation; Qualitative: | Strategic vs passive collaboration, prompt sophistication devel- |

| Data Source | Learning processes Captured | Example Indicators | Analysis Method | Insights |
|---|---|---|---|---|
| | | vs rejected (usage decisions), iteration sequences (refinement patterns) | Prompt sequence analysis (evolution coding) | opment, critical filtering capability, AI dependency patterns |
| Process Documentation | Metacognitive and decision-making processes | Reflective logs (thinking, decisions), version histories (evolution), problem-solving approaches (strategies), learning narratives (challenges, breakthroughs) | Qualitative: Thematic analysis (5-7 themes in reflections), critical incident analysis (turning points), case study development (6-8 representative learners) | Metacognitive awareness depth, learning evolution patterns, strategic thinking quality, challenge navigation, self-regulation evidence |
| Assessment Artifacts | Evidence embedded in deliverables | Process annotations (decision points), AI transparency statements (tool use disclosure), self-assessments (KSD mapping), comparative analyses (AI vs human work) | Mixed methods: Content analysis of annotations, rubric-based assessment of transparency quality, triangulation across artifact types | Authentic vs AI-dependent contribution, transparency and integrity, self-assessment accuracy, learning transfer evidence, competency integration |

In the integration approach, triangulation validates findings across data sources (e.g., VLE engagement patterns confirm or challenge self-reported reflection quality), mixed evidence confirms or challenges interpretations (e.g. high iteration counts combined with shallow reflection signals AI dependency not strategic collaboration); rich narratives combine quantitative breadth (patterns across all students) with qualitative depth (detailed understanding of individual learning journeys).

Embedded ethics include informed consent, no disciplinary use of process data (analytics inform support), student access to their own analytics data, anonymisation, secure storage with access controls, and GDPR compliance.

### 4.3. Component 3: Actionable Guidelines for Teaching, Learning and Assessment

Component 3 addresses what practical frameworks enable implementation, translating insights into actionable tools that directly address the adoption-to-actionability gap (Table 3).

**Table 3: Actionable Implementation Guidelines**

| Guideline Area | Components | Purpose | Implementation Example |
|---|---|---|---|
| Assessment Design | • Process-based rubrics (Basic/Competent/Sophisticated levels per KSD dimension)<br>• AI-transparent structures (process documentation, visible thinking, reflection prompts)<br>• Authentic task design (higher-order Bloom's, OULDI mapping per Table 5, contextual constraints) | Distinguish surface from deep engagement; ensure thinking is visible; target cognitive levels and activity types where humans retain advantage | Three-part assessment: (1) Research documentation with logs (40%)—Productive + Experiential OULDI types targeting K3, S2-S3, D1-D2; (2) Analytical report with decision logs (50%)—Productive + Communication types targeting K1-K3, S5, D2; (3) AI transparency statement (10%)—Experiential + Assessment types targeting K4, S4, D3-D4 |
| Learning Activity Design | • Scaffolded progression (guided → independent → strategic)<br>• Process-oriented tasks (iteration requirements, decision documentation, critical evaluation exercises, comparative analysis)<br>• Explicit AI boundaries per OULDI type (where appropriate vs | Develop AI literacy and strategic collaboration skills progressively; maintain focus on disciplinary competency; align activities to appropriate OULDI types | Weeks 1-4 (Assimilative + Finding): Guided prompts, required reflection, structured logs; Weeks 5-8 (Productive + Interactive): Independent prompting, decision documentation, mid-point feedback; Weeks 9-12 (Communication + Experiential + As- |

| Guideline Area | Components | Purpose | Implementation Example |
|---|---|---|---|
| | where independent performance essential) | | sessment): Strategic synthesis, comparative analysis, critical self-evaluation |
| Educator Support Tools | • Ready-to-use templates (process log structures, AI-use frameworks, reflection prompts, KSD-aligned rubrics)<br>• Implementation guides (module integration roadmaps, scaffolding plans, feedback strategies, common pitfalls)<br>• Professional development (AI literacy resources, rubric calibration, evidence interpretation, ethical considerations) | Bridge adoption-to-actionability gap; provide concrete tools not abstract principles; build educator capacity for process-oriented assessment | Learning Activity Planner toolkit (Supplementary Figure 1): systematic weekly documentation linking KSD competencies → OULDI activity types with AI appropriateness → pedagogic intentions → LA markers → analysis methods; enables coherent design from module outcomes through activities to process analytics |
| Continuous Improvement | • Mid-cycle adjustments (analytics dashboards, early warning indicators, formative feedback, task refinement)<br>• Post-cycle evaluation (component validation, intervention effectiveness, iterative refinement) | Enable responsive teaching; validate framework effectiveness; adapt to evolving AI capabilities and educational contexts | Dashboard showing iteration patterns by student, reflection depth scores, early identification of Passive Acceptors or Dependent Users requiring differentiated intervention; post-cycle analysis validates whether rubrics reliably distinguish competency levels |

Embedded ethics include equal access to AI tools and training, accommodations for diverse needs, clear expectations, consistent rubric application, appeals mechanisms, and transparent boundaries distinguishing legitimate collaboration from problematic substitution.

## 4.4. Framework application walkthrough

To demonstrate the framework's operationalisation, this draws on assessment design for a Level 4 Computer Science module, addressing technology trends and societal impacts, where the framework was applied to a group case analysis (50% of module mark, 4–5 students per group) comprising five components. Table 4 maps each to KSD targets, OULDI types, AI capability, and process evidence.

**Table 4: Example Assessment Structure - KSD and OULDI Integration**

| Deliverable | KSD Targets | Dominant OULDI Types | AI Capability | Process Evidence |
|---|---|---|---|---|
| Podcast-style video on Case study analysis | **S1** (domain performance),<br>**S5** (communication),<br>**D1** (self-regulation),<br>**D2** (critical thinking) | **Communication** (oral synthesis for audience),<br>**Assessment** (live demonstration of understanding) | Low — AI can script but cannot perform; live delivery is irreducibly human | Oral performance under pressure;<br>AI supports script only - voice and adaptability are human |
| Evidence-based collaborative article | **K1**–K3 (knowledge breadth/depth),<br>**S3** (critical evaluation),<br>**S5** (authentic voice),<br>**D2** (verification stance) | **Productive** (synthesising across sources),<br>**Communication** (presenting arguments),<br>**Finding** (source evaluation) | Moderate — AI drafts structure via RACE-framework prompting;<br>lacks analytical depth and authentic voice | Decision log (5–7 analytical choices);<br>student supplies critical synthesis and individual voice |
| Supporting pitch | **K3** (context adaptation),<br>**S3** (evaluation),<br>**S5** (audience-appropriate communication) | **Communication** (professional value proposition),<br>**Productive** (creating recommendations),<br>**Assessment** (demonstrating synthesis) | Moderate — AI supports argument framing;<br>lacks disciplinary judgment and strategic insight | Concise persuasive output requiring professional clarity AI cannot supply |
| GenAI Usage Log (re- | **K4** (AI literacy),<br>**S4** (strategic collaboration), | **Experiential** (metacognitive reflection on AI interaction), | Inherently Human — AI is the object of study; | Documents prompts, techniques (e.g., RACE, |

| Deliverable | KSD Targets | Dominant OULDI Types | AI Capability | Process Evidence |
|---|---|---|---|---|
| quired appendix, individual) | **D1** (self-regulation), **D3** (professional ethics) | **Assessment** (transparency demonstration) | students document interactions critically | decomposition), integration decisions, and rejections;<br>transforms AI from risk into assessable metacognitive evidence |
| Workload Matrix (individual contribution %, group) | **D1** (self-regulation), **D3** (professional ethics), **S4** (strategic collaboration) | **Assessment** (individual accountability within group), **Experiential** (contribution reflection) | Independent Required — documents individual versus group contribution | Individual contribution percentages;<br>separates individual from group grade;<br>prevents free-riding |

The design targets competencies where AI capability is limited (K3, S3, D2) through components explicitly mapped to OULDI types. The podcast is irreducibly human—AI can script but cannot perform live synthesis or adapt under pressure. The article invites RACE-framework prompting (Role, Action, Context, Evaluate) whilst requiring analytical voice AI cannot replicate. Crucially, the GenAI Usage Log is not a compliance check but an assessable learning artefact, operationalising K4, S4, and D1 in a form that distinguishes strategic collaboration from passive acceptance. A Tutorial Worksheet and Submission Checklist scaffold this process, making documentation a weekly habit rather than a last-minute addition. All three framework components are operationalised simultaneously: Component 1 targets KSD dimensions where human competency is essential; Component 2 captures process evidence through logs and VLE patterns; Component 3 delivers educator tools adaptable across disciplinary contexts (Supplementary **Figure 2**).

## 5. Discussion

This framework makes three primary contributions. First, it establishes process-oriented assessment methodologies shifting focus from unreliable outputs to authentic learning processes, capturing iteration, critical evaluation, and strategic decision-making that provide more reliable competency indicators. Second, it provides systematic criteria for evaluating learner competencies in AI-augmented contexts, with the KSD model distinguishing surface engagement from strategic collaboration through observable indicators enabling rubric-based evaluation. Third, it bridges research to practice through concrete tools providing actionable guidance for structuring assignments, collecting process evidence, and evaluating engagement quality, directly addressing the adoption-to-actionability gap.

### 5.1. Implications

This framework highlights fundamental shifts in learning analytics from measuring outcomes to capturing how learning happens through metacognitive, strategic, and evaluative processes. For GenAI in education, the KSD model operationalises productive collaboration, using AI strategically whilst maintaining critical evaluation and genuine understanding, enabling evidence-based integration that prepares learners for AI-augmented futures.

### 5.2. Limitations and Future Directions

The framework requires empirical validation to address key questions: what iteration thresholds constitute sufficient evidence, and can process-based assessments reliably distinguish collaboration from substitution? The sample module walkthrough is a preliminary instantiation rather than a validated study; systematic data collection from GenAI Usage Logs and prompt sophistication scoring is planned for the subsequent delivery cycle. Resource-constrained contexts may require simplified adaptations, and future work must validate effectiveness across disciplines and institutional contexts whilst addressing equity in AI access.

## 6. Conclusion

GenAI integration creates both crisis and opportunity for assessment. This framework addresses how authentic competency can be evaluated through process-oriented methodologies that distinguish productive human-AI collaboration from problematic substitution. The three-component framework (KSD Competency Model, Process Analytics Integration, and Actionable Guidelines) provides theoretically grounded and practically actionable foundations for responsible GenAI integration. By capturing learning processes rather than outputs, and embedding ethical principles ensuring equitable implementation, this framework establishes pathways for thoughtful integration developing authentic competencies in AI-augmented learning environments.

## Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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## A. Appendices - Supplementary Material

| | |
|---|---|
| **Module Code** | |
| **Module Name** | |
| **Module ILOs** | |
| **Other lesson specific ILOs** | |

| # | Activity ID | Lesson Topic | Week | Knowledge competency | Skill competency | Disposition competency | Pedagogic intention | Learning Design Activity type | Learning Activity/ Task options | Learning Task/s on TLA platform | learning analytics markers on learning platform | learning analytics Analysis method | learning analytics Analysis method details |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | | | | | |
| 2 | | | | | | | | | | | | | |
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| 4 | | | | | | | | | | | | | |
| 5 | | | | | | | | | | | | | |
| 6 | | | | | | | | | | | | | |

**Figure 2 - Learning Activity Planner**

**Table 5:** OULDI Learning Design Activity Types - KSD Development and AI Appropriateness

| OULDI Activity Type | Description | Primary KSD Developed | AI Appropriateness | Design Considerations for GenAI Contexts |
|---|---|---|---|---|
| Assimilative | Attending to information (reading, watching, listening) | K1 (conceptual), K2 (procedural) | **High** - AI can summarise and explain | Require learners to generate own summaries and verify AI-provided information against sources. |
| Finding & Handling Information | Searching, gathering, selecting sources | K2 (procedural), S2 (problem analysis), S4 (strategic collaboration) | **Moderate** - AI helps find, critical selection needed | Require annotated bibliographies documenting search strategy, source selection rationale, and critical evaluation of quality. |
| Communication | Discussing, debating, collaborating | S5 (communication), D2 (critical thinking), D3 (ethics) | **Moderate** - AI drafts but authentic voice essential | Assess oral or synchronous communication requiring genuine dialogue, audience adaptation, and authentic voice. |
| Productive | Applying learning to create outputs (reports, solutions, designs) | K3 (conditional), S1 (domain), S3 (critical eval.), S5 (communication) | **Moderate to Low** - Depends on task complexity | Target higher-order cognitive levels with contextual constraints AI cannot handle; require process documentation showing decision evolution. |
| Experiential | Reflecting on experience, connecting to practice | D1 (self-reg.), D2 (critical thinking), D4 (growth mindset), K4 (AI literacy) | **Low** - Requires genuine personal reflection | Require specific examples from personal experience and assess depth of metacognitive awareness — AI cannot authentically reflect. |
| Interactive/ Adaptive | Practicing with feedback, rehearsing, applying concepts repeatedly | S1 (domain performance), S2 (problem analysis), K2 (procedural) | **Moderate** - may enable surface learning | Use novel problems outside AI training data and require explanation of reasoning to verify transfer beyond procedure execution. |
| Assessment | Demonstrating achievement, being assessed | All KSD dimensions depending on assessment design | **Independent Required** - evaluates learner not AI | Design process-oriented tasks capturing iteration, decisions, and metacognition with AI transparency statements; target dimensions where AI capability is limited (K3, S3, D1–D4). |