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Mapping Student-GenAI Interactions onto Experiential Learning: The GENIAL Framework

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ABSTRACT

This study proposes a conceptual framework for understanding how generative artificial intelligence (GenAI) affects university students' learning journey. The use of GenAI tools in academic settings left scholars at a lack of theoretical tools to capture the impact of how chatbots impact learning. Current studies rely heavily on self-reports and controlled experiments, missing how students engage with chatbots while learning. Building on literature on experiential learning and styles of student engagement with GenAI as theoretical underpinnings, the GENIAL framework sheds light on the dynamics of AI-human interaction in all stages of the experiential learning cycle, allowing us to identify how the cycle of learning is affected by the use of GenAI tools. Our findings, based on the analysis of 200 course chatlogs at a London-based research-intensive university and two case studies in which we illustrate the use of the GENIAL framework, reveal that GenAI can catalyse or disrupt learning depending on student agency and contextual factors. Our framework reveals how students learn with GenAI and identifies if critical steps are missed. By introducing a diagnostic notation that maps GenAI interactions onto Kolb's learning stages, the framework enables educators to mark whether each stage is catalysed (+), disrupted (-), or skipped entirely. We contribute to the literature by turning vague concerns about 'AI cheating' into precise diagnostic evaluation that enables educators and policymakers to address the negative impacts of GAI usage on learning as well as the curriculum.

Keywords: Generative artificial intelligence, Higher education, Learning processes, Educational technology, Learning analytics.

1. INTRODUCTION

This article positions the research on GenAI in teaching and learning within traditional learning theories and the cycle of experiential learning. The widespread use of chatbots in higher education has sparked discussions about academic integrity and the wider impact of technology on students' learning outcomes(Chan, 2023a; Luo et al., 2025). The current debate centres on whether GenAI's benefits – personalised learning or real-time feedback – outweigh its risks around content accuracy, academic integrity, or the potential to widen educational inequalities (Pallant et al., 2025). Research indicates that students attain superior learning outcomes when employing GenAI for the construction and augmentation of knowledge, while the more procedural use of GenAI devoid of critical engagement results in lower-level learning outcomes (Du et al., 2025; Hu & Chan, 2025; Pallant et al., 2025). Chatbots are especially useful in contributing to enhancing students' creativity in marketing and management (Fisher et al., 2025), even though there is a risk that without support students might use these tools to bypass rather than enhance their learning (Sallai et al., 2024; Verboom et al., 2025).

Despite the growing number of studies in the field, scholars have called for more empirical evidence on how learning processes unfold in authentic contexts and how GenAI can be integrated in education in an equitable way (Alfredo et al., 2025; Chan, 2023a; O'Dea, 2024). Current research approaches provide complementary but partial insights: surveys capture reported behaviours but not actual practice (Abbas et al., 2024; Delcker et al., 2024; Schutte & Li, 2025) and experimental studies allow us to measure outcomes reliably (Bastani et al., 2025; Fan et al., 2025; Zhang et al., 2024) but without illuminating the processes that lead to them.

What remains underdeveloped is the direct observation of authentic student-GenAI interactions in naturalistic settings. This gap is particularly concerning given emerging evidence that GenAI's impact on learning may be more complex than initially assumed. While some studies suggest potential benefits (Handa et al., 2025; Li et al., 2024), others highlight reduced critical thinking (Gerlich, 2025), "metacognitive laziness" (Fan et al., 2025), and potential harm to long-term knowledge acquisition despite short-term performance gains (Bastani et al., 2025). What remains unanswered is how students interact with GenAI during their learning journey and how these interactions shape their educational development.

Our paper addresses this gap by providing empirical and theoretical insights into how GenAI influences the cycle of learning. Based on the empirical analysis of student chatlogs, GitHub histories, and survey responses of 200 students on a selection of undergraduate and postgraduate courses, we provide unprecedented temporal insight into how GenAI assistance integrates into the learning process.

We argue that understanding GenAI's impact on learning requires us to ground our investigation in classical pedagogic theories and to consider how a student's learning cycle is influenced by their use of the technology, as well as the context in which it occurs. We map students' learning journey in a way that allows us to understand where GenAI catalyses or disrupts learning. By examining both productive uses and potential pitfalls through direct observation of student-AI interactions, we provide empirical evidence to inform educational practice and policy in the GenAI era.

2. THEORETICAL FRAMEWORKS AND RELATED WORK

Experiential Learning Theory (ELT) provides an effective theoretical foundation for understanding how GenAI affects student learning processes. Building on traditional constructivist principles, ELT conceptualises learning as "*the process whereby knowledge is created through the transformation of experience*" (Kolb & Kolb, 2013, p. 59), sometimes expressed as "learning by doing".

This aligns with foundational educational theories, stating that education is a "*continuing reconstruction of experience*" where process and goal are inseparable (Dewey, 1897) and in which individuals construct knowledge through experiences that create conflicts with prior beliefs (Piaget, 2005). Learning is contextual. It involves integrated functioning through thinking, feeling, perceiving and behaving, emerging from the interaction between an individual and their environment (Follett, 1924; Piaget, 2005) and individuals can realise

their creative function by integrating personal meaning and community life (Whipps, 2014, p. 421).

Learning is challenging because it requires the resolution of conflicts as we adapt to the world as we learn. Conflict, differences, and disagreement drive the learning process. These tensions are resolved through repeated cycles as the student goes through conflicting modes of reflection, action, feeling, and thinking (Kolb, 1984).

This perspective on learning as a transformative process extends beyond individual cognition. Early management and education scholars argued that learning requires collaborative skills and reflective practices that connect with and expand meaning in students' lives (Follett, 1924). By integrating personal meaning and community life, individuals can realise their creative function (Whipps, 2014: 421). Learning, therefore, is not just the result of cognition but involves the integrated experience of the individual through thinking, feeling, perceiving and behaving (Kolb, 1984) and emerges from the interaction between the individual and their environment. Consequently, learning occurs through the process of integrating our new experiences into our existing worldview and consequently changing our perceptions of the topic at hand (Piaget, 1950).

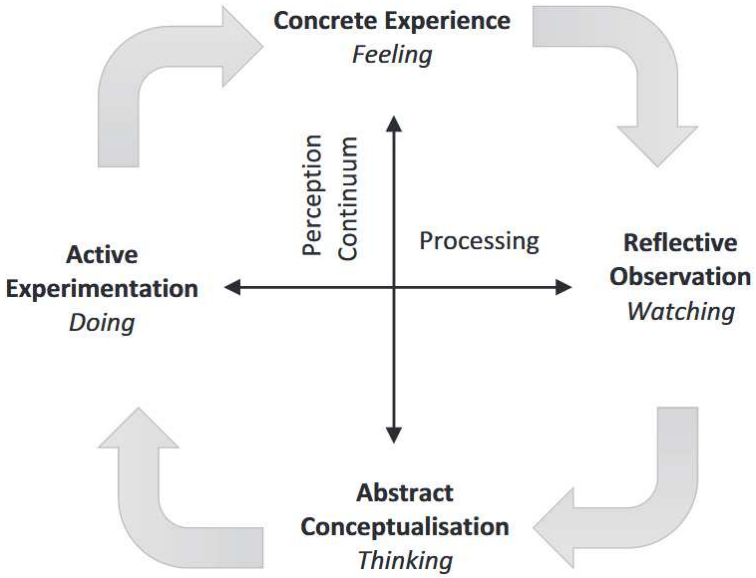


Figure 1. Kolb's idealised learning cycle. Source: (Chan, 2023b).

Kolb argues that students need to go through a learning cycle that has two related modes for grasping experience: concrete experience (CE) and abstract conceptualisation (AC); and two modes for transforming experience: reflective observation (RO) and active experimentation (AE). According to Kolb, learning arises through the resolution of the creative tension among these four learning modes, which he describes as an idealised learning cycle (see **Figure 1**). The learning cycle involves learners progressing iteratively through experiencing, reflecting, thinking, and acting, driving meaningful knowledge creation. The creative tension between these modes drives meaningful learning through the continuous cycles of the opposing modes of reflection, action, feeling, and thinking. Knowledge emerges through the transaction between social knowledge (co-constructed in

socio-historical context) and our personal knowledge (subjective learner experience) (Kolb & Kolb, 2013, p. 7).

When applying these ideas to students' engagement with GenAI, we can assume that students who use AI for learning should go through iterative processes of conflict and resolution, action and reflection. Hence, students, students may even find the learning process uncomfortable, frustrating and challenging, as it requires not just their cognitive but also their emotional and social engagement with the content and the context.

If we accept that learning is a conflictual and emotional process requiring us to understand our existing knowledge, reflect on new experiences, and relinquish our current understanding in favour of new insights during the learning journey, we can then test whether our students undergo the same iterative process while learning with GenAI.

To understand how GenAI affects learning, we need to explore how chatbots affect students' learning cycle and whether they disrupt it in a way that prevents students from going through the whole cycle. In our proposed framework, we investigate whether students complete this cycle or bypass critical stages when using GenAI tools. Students who unquestioningly accept GenAI responses may skip crucial reflection and experimentation stages, allowing chatbots to "steal" the learning process. Kolb's framework helps identify when GenAI prevents progression through experience transformation stages.

Current frameworks for GenAI engagement

While Kolb's framework reveals whether students complete learning cycles, it does not explain how different students interact with GenAI tools. Research into student-GenAI interactions has built upon previous analytic approaches to understand these interaction patterns.

Research into student-GenAI interactions has produced various analytical approaches. Mishra and colleagues considered how to think of the TPACK framework in the age of GenAI, identifying several characteristics that distinguish it from previous educational technologies: its protean nature (shape-shifting across multimodal interfaces and interacting via natural language processing), opacity (outputs unexplainable even by creators), instability (produces unpredictable errors, often called "hallucinations", in a way not seen in other digital technologies) (Mishra et al., 2023). They also highlight two other important novel factors: GenAI's generative capacity to produce whatever a user requests and its social quality. GenAI systems are set up to make it feel as if you were interacting with a "psychological other". The TPACK framework, with its notion of ConteXtual Knowledge (**XK**) - encompassing all the Content Knowledge (CK), Technological Knowledge (TK), Pedagogical Knowledge (PK) involved in teaching and learning – as well as the overlaps between and the combination of these, remains unaltered. These attributes fundamentally alter how educators and students engage with this particular technology in learning contexts.

Exploring student agency, Yang and colleagues argue that students engage with GenAI in four different ways (2024). They define student agency as active engagement in and control over the learning process. Consequently, only providing access to GenAI does not guarantee

positive learning outcomes. Students need to develop strong agency to critically evaluate, guide, and meaningfully integrate AI into their learning process.

From this perspective, agency has two dimensions: 'knowledge' that the students create through collaborative activities and 'process', referring to the quality and originality of the outputs co-created with GenAI (Yang et al., 2024). The different levels of student agency can lead to diverse learning experiences and outcomes. As shown in (**Table 1**), resourceful and reflective learners, who actively engage with and shape AI outputs, demonstrate higher academic performance compared to students who take a resistive or receptive engagement.

Table 1. Yang et al.'s (2024) Typology of GenAI Engagement

Engagement Type	Key Characteristics	Approach to GenAI
Resistive	Avoidance of GenAI	May be driven by ethical concerns, scepticism about AI capabilities, or preference for traditional methods
Receptive	Acceptance of GenAI outputs with minimal critical assessment	Involves incorporating AI-generated content with limited evaluation or modification
Resourceful	Active guidance of GenAI through strategic prompting	Involves iterative refinement and critical evaluation of AI-generated content
Reflective	Critical reflection on the interaction process itself	Involves high levels of intentionality and critical thinking about both the technology and the learning process

Learning disruption versus enhancement

Empirical studies reveal that GenAI impacts learning in different ways. Some argue that unstructured GPT-4 use improved performance but decreased exam scores, suggesting short-term gains mask long-term learning loss (Bastani et al., 2025). Others found that time pressure can lead to GenAI dependency, arguing that procrastination may lead to lower performance (Abbas et al., 2024). Scholars have also found evidence for reduced critical thinking (Gerlich, 2025; Singh et al., 2025), metacognitive laziness (Fan et al., 2025) and reduced cognitive load (Stadler, 2024).

Some go further, distinguishing substitutive use (replacing effort) from complementary use (supporting thinking), arguing that substitution increases coverage of topics while decreasing depth of understanding (Lehmann & Cornelius, 2024). Outside the field of education, we also encounter similar findings in workplace settings (Lee et al., 2025).

In contrast, some studies found positive impacts when GenAI interactions are framed differently. Students who were asked to teach concepts to ChatGPT improved their programming knowledge and self-regulated learning strategies (Chen et al., 2024). Vanzo et al. (2025) showed that a GPT-4 setup as an interactive homework tutor improved student engagement, particularly for students who were falling behind.

The role of the educator in GenAI-mediated learning

Decisions made by educators also influence how students use GenAI tools. According to the TPACK framework, teachers' Contextual Knowledge (XK) is shaped by institutional policies, assessment design, and faculty attitudes, amongst other factors. These forces therefore also affect students' learning context (Mishra et al., 2023). For instance, teachers' TPACK has a positive impact on their willingness to integrate AI (WIAI), even though their negative emotions, such as their fears, may moderate this effect (Yang et al., 2025). It is worth remembering however that these negative emotional effects can be buffered by supportive institutional environments.

3. DATA & METHODOLOGY

Research design and context

We conducted this study at the [UNIVERSITY] during the 2023-2024 academic year, following a phased approach. We ran a pilot study in autumn 2023, testing data collection methods with limited engagement (see **Appendix A**), and started the main study in January 2024 with an extended pool of subjects, covering multiple disciplines and educational levels. The data collection ran until March 2024, focusing on the naturalistic observation of students' authentic GenAI use.

We followed an iterative analytical approach, grounded in empirical observation. We began by applying Yang et al. (2024)'s four-category typology as a sensitising framework whilst remaining open to emergent patterns. Through the iterative analysis of chat logs and temporal data, we identified behaviours that both confirmed and extended existing categories.

After identifying the emerging themes, we mapped our findings on Kolb's learning cycle and developed the Genial Framework by identifying how students' learning is affected at each stage of the learning journey.

Participants and courses

Table 2. Courses in the main study (January–March 2024). The 'Study Participants' column shows students who engaged with at least one component of the study. (UG – undergraduate; PGT – postgraduate)

Department	Level	Code	Title	Study Participants
[DEPT A]	UG	[COURSE A]	[ENTRY-LEVEL DATA SCIENCE COURSE]	48 (out of 52)
	UG	[COURSE B]	[INTERMEDIARY-LEVEL DATA SCIENCE COURSE]	30 (out of 43)
[DEPT B]	PGT	[COURSE C]	[ADVANCED COMPUTING COURSE]	52 (out of 89)
[DEPT C]	UG	[COURSE D]	[MANAGEMENT COURSE - UG]	8 (out of 18)
	PGT	[COURSE E]	[MANAGEMENT COURSE - PGT]	18 (out of 65)
[DEPT D]	PGT	[COURSE F]	[PUBLIC POLICY COURSE]	8 (out of 18)

The main study involved 200 students across six courses spanning undergraduate and postgraduate levels in data science, statistics, management, and public policy (**Table 2**). All participating courses explicitly permitted GenAI usage at varied levels of permitted engagement and requirements for acknowledgement.

Our participants represented a convenience sample, with students who were willing to share their GenAI interactions. Whilst our sample skews towards GenAI-positive students and may not represent typical UK higher education attitudes, even among these enthusiasts, we documented counterproductive usage patterns that compromised learning outcomes.

Data collection procedures

We employed multiple data sources to capture both observable behaviours and student perceptions:

- **Surveys and focus groups**: Initial/final surveys tracked attitudes and demographics; weekly surveys captured learning ratings and GenAI helpfulness and focus groups sessions (one per course) explored motivations and contextual factors.
- **Chat logs**: Our primary behavioural data. Students created dedicated ChatGPT or Bard conversations for coursework and share them with us weekly. These provided complete interaction histories with timestamps, enabling temporal correlation with assignment deadlines.
- **GitHub records (COURSE A only)**: Students were asked to track the evolution of their data science projects with Git, a professional version control tool. The timestamps of git logs allow us to see precisely how GenAI suggestions influenced their programming decisions.

In total, 200 students engaged with at least one component of the study. If we break it down per component, 163 unique students completed the initial survey, 155 submitted at least one chat log during the eleven-week term, 44 completed the exit survey and 15 attended a focus group session.

We collected interactions with ChatGPT v3.5 (free), ChatGPT v4.0 (only available to paid users then) and the first version of Google Gemini (renamed from Google Bard halfway during the study) because those were the only products at the time that allowed one to share their full chat logs with others. Importantly, these versions did not have persistent memory, web browsing, or advanced reasoning capabilities that are present in the GenAI chat bots of 2025.

Our process of analysis

A high-level view of participants' self-reports from the surveys revealed that most students had a positive view of GenAI usage and that they reported having a dominant conscientious approach to studying, with most saying they like to prepare ahead of a teaching session. When they needed to seek clarity for something in class, participants reported reading the course materials, using search engines and asking questions to the class teacher above GenAI tools. More information on these findings can be found in **Appendix B**.

Chat log analysis confirmed Yang et al. (2024) typology while exposing its limits. We found evidence of all four engagement styles, but we also observed students brainstorming alternative analytical approaches or seeking different perspectives on work they have completed in a way that the Resourceful and Reflective categories did not seem to fit these particular cases, so we added a fifth style we termed "Riffing." A discussion of interesting examples of these 5R's can be found in **Appendix C**.

Critically, we also noted how contextual factors such as time pressure, prior knowledge, task complexity, and institutional policies profoundly influence how students engaged with GenAI. The same student can exhibit different engagement patterns depending on circumstances, indicating contextually determined behaviours rather than fixed traits.

A COURSE C student's chat logs revealed this complexity: during the Assignment 1 of the course, they typed fragmented Receptive searches like "*log-transformed Mel spectrograms*" without follow-up. Yet within the same chat, they demonstrated sophisticated metacognitive engagement by seeking validation for their assignment proposals rather than direct solutions. By Assignment 2, this student persistently challenged ChatGPT ("*You're still treating them the same way still*") yet could not develop independent solutions due to limited domain knowledge and likely due to being on a tighter deadline.

This initial analysis and early attempts at categorisation led us to revisit Kolb's established experiential learning theory to examine how these different engagements styles with GenAI mapped onto Kolb's learning cycles, considering all observable contextual influences. This work led us to our integrated framework, presented in **Section 4**.

Limitations and Ethics

The voluntary participation design naturally created a potential selection bias towards GenAI-positive students, though concerning patterns emerged even within this sample. Students controlled which chat logs to share, potentially curating submissions. The study period captured early ChatGPT versions, which did not have the interactive features currently available in these tools. The study received ethics approval from [UNIVERSITY] Research Ethics Committee. All participants provided informed consent for analysis of anonymised data. Students could withdraw without affecting course standing.

4. THE GENIAL FRAMEWORK: A PROCESS-BASED MODEL FOR UNDERSTANDING GENAI-MEDIATED LEARNING

Yang et al.'s framework proves helpful in labelling interactions with GenAI chatbots, but the analysis of GenAI-mediated learning can be more meaningful if we incorporate other aspects that are relevant for the student's learning process: where they are in their learning journey (as expressed by Kolb's learning stages), what was happening in the course at that moment, and other contextual factors that might be impacting their GenAI usage. Context matters because the same student will approach GenAI differently depending on their position in the learning cycle.

In this section, we introduce the GENIAL Framework that maps contextual influences and students' GenAI use onto Kolb's experiential learning stages to understand not just how students learn with GenAI, but why they use it as they do. GENIAL is an acronym for Generative AI (flipped) as Catalyst for Learning.

The Framework

The framework approaches the concept of learning as a continuous process of knowledge transformation, in which one resolves creative tensions that arise from moving through the cycle of four experiential learning stages. The framework captures how the learning cycle is catalysed when GenAI tools are used purposefully and with high student agency and it also depicts how the process can be disrupted when students delegate control to GenAI. These two dimensions, student agency and nature of the use of GenAIcan be defined as:

- **Agency**: represents the student's capacity for self-directed learning and autonomous decision-making across all learning contexts. High agency manifests through deliberate questioning, critical evaluation of responses, and strategic use of tools and knowledge aligned with learning objectives. Low agency appears as passive acceptance (e.g.: mindless copy-pasting from online sources or the course materials) and surrender of decision-making to external sources.
- **GenAI Use**: distinguishes between purposeful and reproductive engagement. Purposeful use involves strategic prompting, iterative refinement, and contextual adaptation of GenAI outputs. Reproductive use manifests through direct copying and wholesale adoption without critical evaluation.

In the framework, these dimensions form a four-quadrant assessment for each learning stage of Kolb's cycle (see **Figure 2** and **Table 3.** Stage Assessment Notation), where each stage can be catalysed (+), disrupted (–), unchanged or skipped. We posit that agency and GenAI use are normally correlated, as students with strong self-direction typically develop effective AI interaction strategies. The top-left quadrant of **Figure 2** (low agency + purposeful GenAI use) might not exist in practice, as purposeful GenAI engagement requires the intentional control that defines high agency. The bottom-right quadrant (high agency + reproductive GenAI use) likely occurs when motivated students lack GenAI literacy training, demonstrating clear learning intentions but resorting to basic copying due to limited prompting skills.

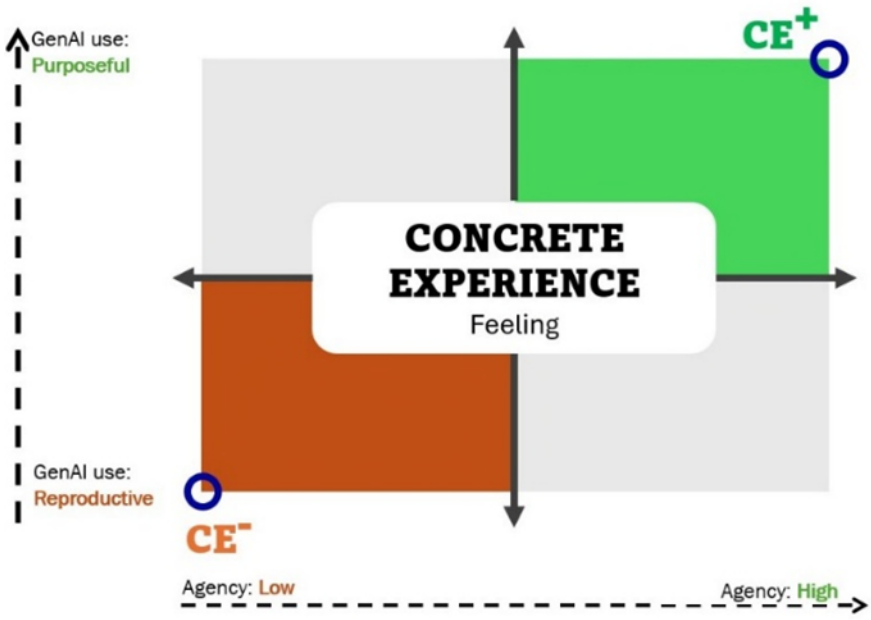


Figure 2. The expanded Concrete Experience (CE) stage. In the GENIAL Framework, each of Kolb's learning stages is defined as a continuum between two axes: student agency and GenAI use. Green shading indicates the catalysed region of the learning stage, and orange indicates disruption of the stage.

Table 3. Stage Assessment Notation

Notation	Characteristics | Impact	Example Evidence
Stage+	High agency + Purposeful use	Strategic prompting, iterative refinement, critical evaluation of GenAI outputs
	GenAI catalyses learning	
Stage–	Low agency + Reproductive use	Direct copying of GenAI suggestions, wholesale adoption without modification
	GenAI disrupts learning	
Stage	Mixed patterns	Some strategic use combined with occasional passive acceptance
	Neutral impact	
~~**Stage**~~	Stage skipped	Temporal compression, absence of characteristic cognitive work, direct progression to outcomes
	Learning phase bypassed	

The complete framework (**Figure 3**) maps all stages of a student journey through the learning cycle as mediated by GenAI use and student agency. The centre of the framework depicts the contextual factors that might influence how learners traverse the cycle. Teacher and institutional influences include curriculum and assessment design, institutional norms and culture, faculty stance towards Generative AI, as well as the teacher's contextual knowledge (TPACK) and course policies on GenAI usage. Individual and social factors include prior knowledge of the content, time pressures, AI literacy, peer-to-peer dynamics, student culture, job market pressures and current events (such as the release of new GenAI chatbot versions).

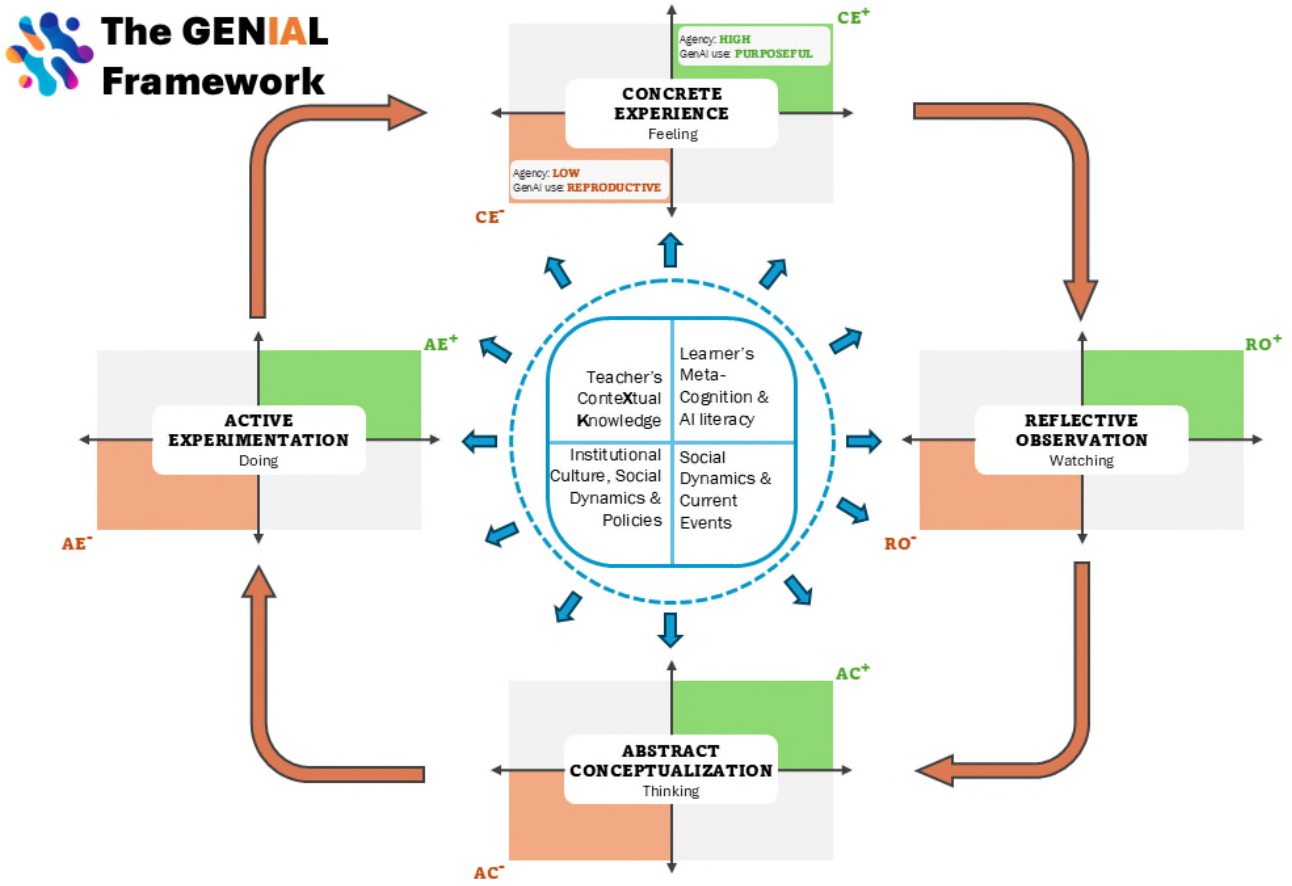


Figure 3. The GENIAL framework shows how each of Kolb's learning stages can be catalysed or disrupted through the interaction of student agency and GenAI use. The central contextual factors influence learning journeys.

The framework's diagnostic power emerges from mapping the student learning journeys, categorised by Kolb and extended by the GENIAL framework according to the interaction with GenAI, to the engagement patterns of Yang et al.'s (2024). In **Table 4** we revisit and extend these engagement patterns as described.

How to apply the framework

A useful application of the framework requires educators and researchers to select a specific learning task or assignment either in class or one spanning multiple sessions, then collect appropriate temporal data that capture how a student progresses through the learning stages. This could be a combination of chat logs, reflection diaries, digital analytics data, intermediary versions of a piece of work (such as Git logs or a MS Word or Google Docs document with version history enabled). The process involves mapping observable behaviours onto the learning cycle using evidence from these artefacts, using the researcher's contextual knowledge of the learning environment to infer agency levels and GenAI use patterns at each stage. Once a cycle has been identified and mapped, one can speak of the overall engagement pattern that emerged. **Figure 4** provides a visual illustration of this process of analysing student data with the GENIAL framework.

Table 4. Typical learning journeys characteristics of the 5 GenAI engagement styles. We incorporate Yang et al.'s (2024) four engagement patterns plus the fifth pattern we term 'Riffing', characterised by creative exploration and ideation with GenAI.

Engagement Pattern	Typical Journey	Key Characteristics
Resistive	Nonspecific	Learner has a sceptical or negative stance towards GenAI use: if present, is limited or likely to be part of a learning activity mandatory in an educational setting. The learning journey will, therefore, not show any (**–**) or (**+**).
Receptive	**CE- → ~~RO~~ → ~~AC~~ → AE-**	Acceptance of GenAI output without much reflection or attempt to think through concepts revealed via the exchange with GenAI. We see the presence of at least 2 disrupted stages. The other stages are most likely skipped but if present, they are never in their catalysed form. The combination **CE–** and **AE–** might be common in coding activities where learner can try an initial solution (CE) and adapt it straightaway (AE) given the instant feedback from the computer without having to reflect.
Resourceful	**CE+ → RO → AC → AE+**	Usage of GenAI with the purpose of serving their learning needs as a priority. Strategic prompting and iterative refinement evident throughout. Learner might also choose to validate information and confront the GenAI chat bot when output produced by the tool is deemed inaccurate or unhelpful. We see catalysed **CE+** and/or **AE+** and no disruption/skipping of the other stages.
Reflective	**CE → RO+ → AC+ → AE**	Deep metacognitive engagement with both learning process and GenAI interaction. Learner uses GenAI tool to ask why something is the way it is (RO) or to solidify concepts they are grappling with. Strong enhancement of the reflection and conceptualisation stages, **RO+** and **AC+** and no disruption/skipping of the other stages.
Riffing	**CE+ → RO → AC+ → AE+**	Creative exploration and ideation with GenAI. Brainstorming of alternative ideas, different ways to solve a problem or to think about a concept. Enhancement of both **AC+** and the experimental stages (**CE+**, **AE+**). RO may or may not play a big role, but it certainly is not disrupted/skipped.

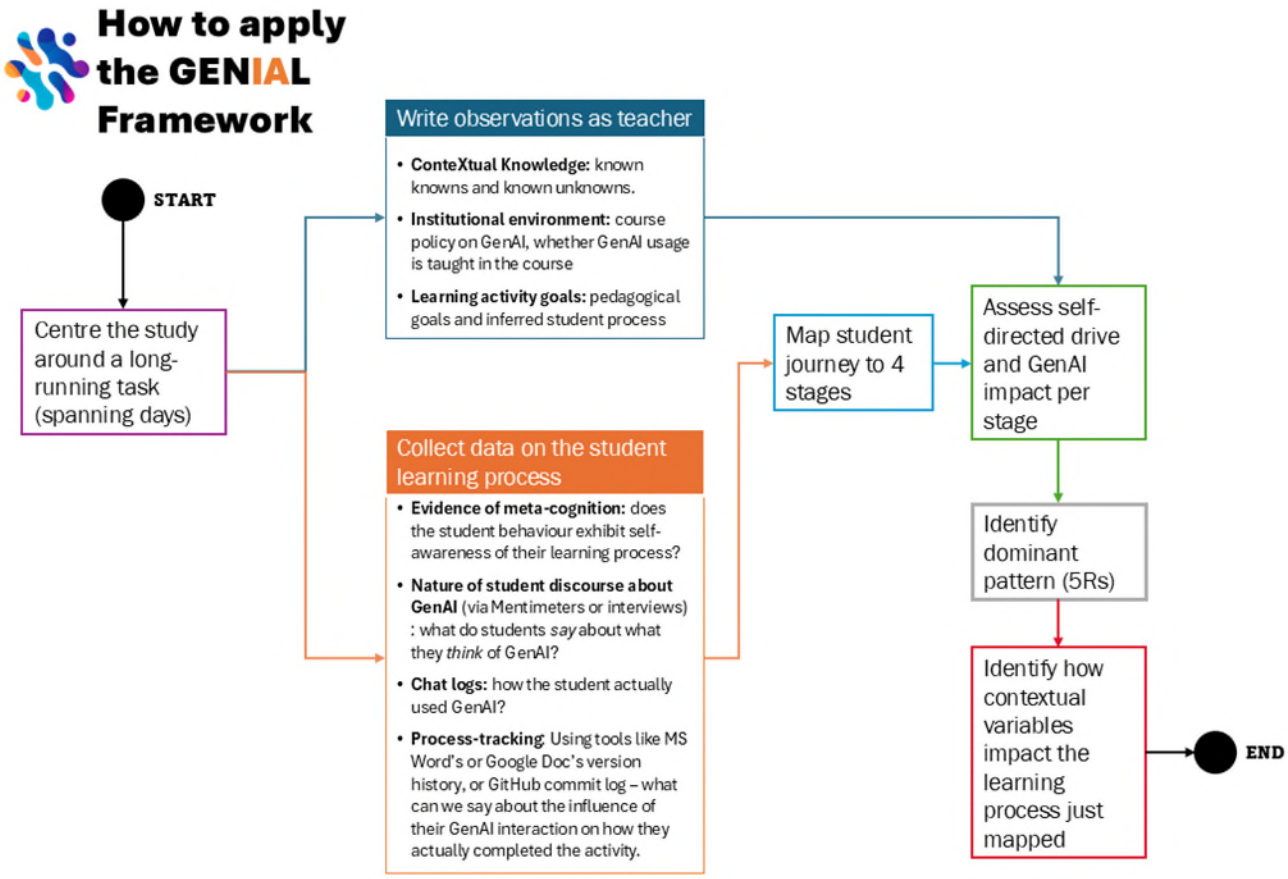


Figure 4. Flowchart describing how to apply the GENIAL framework to study GenAI-mediated learning

5. FRAMEWORK APPLICATION: CONTRASTING LEARNING JOURNEYS

We demonstrate how the GENIAL framework illuminates GenAI-mediated learning through analysis of COURSE A students with contrasting learning journeys. Student A, a second-year in International Social and Public Policy, had no programming experience, while Student B, also a second-year but studying Economics, had previously coded in Python. COURSE A taught students to collect and manipulate real-world data through Python programming, with a key assignment (30% of the final grade) requiring them to scrape a designated university website. The course deliberately used Scrapy instead of BeautifulSoup (ChatGPT's default) to gauge student engagement depth. Students tracked their work through Git commits, which contains temporal timestamps that allows for correlation with ChatGPT interactions. Both students used ChatGPT for the same web scraping assignment with dramatically different results. Student A's reliance on the tool prevented understanding of the core automation principles emphasised in the course, while Student B's strategic use of ChatGPT enabled them to master the concepts and develop sophisticated programming intuition.

The sections below highlight the major insights from both students. A comprehensive breakdown of Student A's learning cycles can be found in **Appendix D**. For the sake of brevity, we move the analysis of Student B's catalysed case to the Appendix.

5.1 Starting Point

The assignment ran in February 2024, giving students ten days to complete the web scraping tasks.

Student A: Direct Task Engagement

Student A opened their first ChatGPT conversation at 20:28 on 15 February asking "what is scrapped data" [sic], then immediately moved to questions about producing JSON files. Their initial web scraping code resembled course materials, suggesting they worked without AI assistance at first. However, their next code block revealed a fundamental misunderstanding. Instead of building on their web scraping work, Student A manually copy-pasted links from websites and typed out information that the code should have collected automatically. This manual approach demonstrated a complete failure to grasp automation principles – the core concept of the assignment. While this breakdown occurred before significant GenAI engagement, it established a pattern of task completion without conceptual understanding that would persist throughout their AI interactions.

Student B: Preparation Before Action

Student B's first ChatGPT interaction on 10 February had nothing to do with the assignment itself. For two hours, Student B worked through practice exercises from the previous week, using ChatGPT to explain concepts they'd already encountered in lectures. Despite possessing solutions for these exercises, they queried the syntax of the Scrapy library, data structures, and error handling. This preparation revealed multiple iterations of the experiential learning cycle. Student B used GenAI when experiencing confusion applying concepts to code (**CE+**), reflecting on gaps in their understanding (**RO+**), clarifying conceptual models (**AC+**), and testing comprehension through practice problems (**AE+**).

Only after two hours of exploration did they turn to the actual assignment, completing both tasks within 30 minutes using clean, iterative code that demonstrated genuine understanding of automation principles. Their foundation proved decisive when ChatGPT suggested incorrect libraries. After receiving BeautifulSoup code, Student B immediately confronted the chat bot with a copy of a much simpler piece of code they had seen in the course: "*sel.css('title') worked when the other stuff didn't.*".They recognised the mismatch with course materials and steered ChatGPT back to appropriate solutions. This correction required both technical knowledge and confidence to challenge the authoritative tone of GenAI.

Unlike Student A who shared only assignment-related exchanges, Student B proactively shared chat logs throughout the academic term, revealing consistent patterns of strategic GenAI use. **Figure 5** shows bursts of ChatGPT interactions coinciding with assessment periods, yet these exchanges maintained the same resourceful qualities evident in their initial preparation. This pattern of high agency and purposeful GenAI use was present throughout their entire learning journey in this course, and it is safe to say that GenAI helped this student get more out of the course.

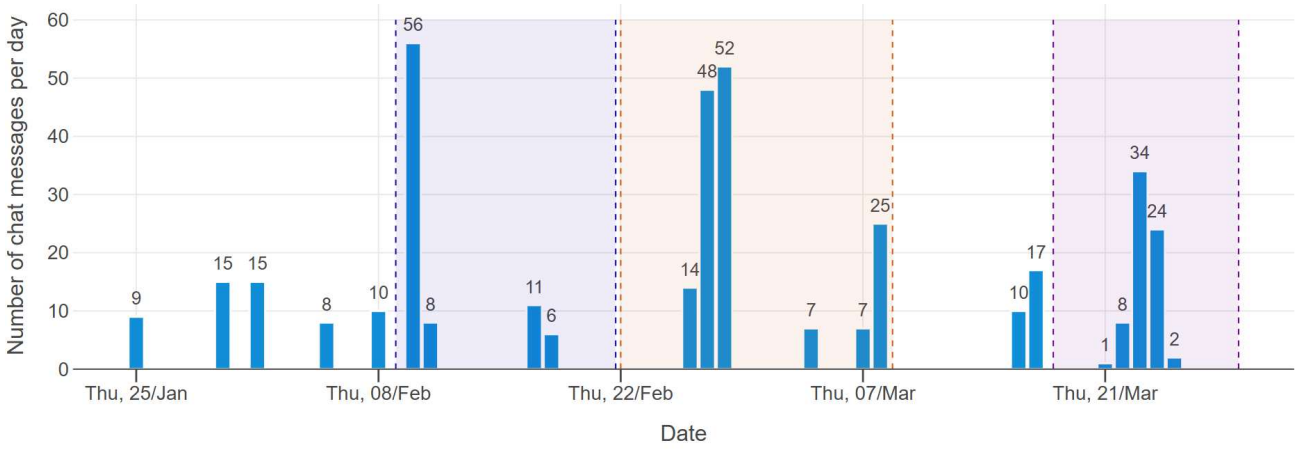


Figure 5. Student B's usage of ChatGPT over time. Their use intensified during periods of assessments (hashed areas).

The students' Git commit messages provide additional evidence of their contrasting approaches. Git, a version control system that tracks code evolution, requires users to describe each saved version with a message. Student B wrote meaningful descriptions like "*complete task 1*" and "*finish task 2*," demonstrating metacognitive awareness. These Git practices align with Chen et al.'s (2024) finding that teaching-oriented interactions with GenAI, where students maintain agency through critical evaluation, correlate with improved self-regulation. Student A, however, used the identical message "*setting up my assignment*" for every commit until submission, suggesting they learned the mechanics of saving work but not the reflective practice of documenting their learning process. These seemingly minor differences in tool usage reveal fundamental disparities in how students conceptualised their own learning journey.

5.2 Deterioration: How GenAI Compounded Learning Gaps

Student A's journey through Tasks 2 and 3 demonstrates how GenAI can systematically deepen conceptual confusion when students lack foundational knowledge and the necessary AI literacy training. **Table 5** summarises how the student tackled the assignment, with examples of good, complete learning cycles along with cycles disrupted by the direct influence of GenAI and low agency in the process, influenced by the lack of prior knowledge.

The chronological analysis reveals Student A's systematic deterioration from initial awareness to complete learning bypass. Early cycles showed capacity for reflection and partial conceptual understanding, but ChatGPT's confident responses gradually eroded critical evaluation skills. The critical turning point occurred during Task 3, when vocabulary imprecision ("using selector") enabled ChatGPT to steer Student A toward fundamentally flawed approaches. Most concerning, Student A retroactively corrupted previously working solutions, demonstrating how GenAI can not only prevent new learning but actively degrade existing understanding when foundational knowledge is insufficient.

Table 5. Learning cycles observed in Student A's work on Tasks 2 and 3 of the W06 assignment

Task	Cycles	Brief retelling of the story of this cycle
Task 2 Fri 16 Feb 20:49 – 21:53	CE- → RO → returns to CE → RO → AC → AE	Student copied assignment verbatim to ChatGPT, received BeautifulSoup code. Recognising the mismatch with course materials, they re-prompted same message with "using scrapy" at the end to which ChatGPT output was of code that was much more complex than necessary. Here, the student seemed to know how to extract the useful syntax from there and apply to their code. Student achieved partial learning but missed automation principles that would have prevented later repetitive coding. The chatbot's output had some automation principles involved which had the student inquired about it, they would not have produced highly repetitive manual code.
Task 2 Sat 17 Feb 16:21 – 19:30	CE → RO → AC → AE	After repeating the manual work, seemingly without GenAI assistant, they asked ChatGPT operational questions about data structures. Code is still inefficient and below standards expected in the course, but works as a good first draft which could be fixed in future cycles. Nonetheless it is a positive and complete learning journey.
Task 2 Sat 17 Feb 16:30 – 23:25	CE- → ~~RO~~ → ~~AC~~ → AE-	Simple assembly of manual work, seemingly treating Task 2 as complete. No evidence (in project documentation, code, git logs or chat logs) of any reflection on repetitive patterns or recognition of task completion as distinct from setup.
Task 3 **(+edits to Task 2)** Sat 18 Feb 13:55 – 14:55	CE- → RO → returns to CE- → ~~RO~~ → ~~AC~~ → AE-	A clear example of receptive engagement and bypassing of learning stages. When working on Task 3, student realised they had to go back to Task 2 and write the scraping code to collect links to the images on the websites. Student seems to recognise that ChatGPT once again gave them code with an incorrect library (BeautifulSoup) and tried to fix this by adding "using selector" to the same previous query, which is an unfortunate choice of words. The term 'selector' is too generic in this context and is interpreted by the ChatGPT as to still mean BeautifulSoup. From here on, student accepts BeautifulSoup code and no longer questions library suggested. More concerning is what followed. ChatGPT's output contained mock data with examples of how the image data would look like when collected from a website's HTML. Student A then seems to understand from this that one is supposed to copy the relevant HTML snippets by hand themselves – rather than have the script automatically collect it for them. Here, they skipped RO and AC completely, performing the computer job themselves without conceptualising about web scraping concepts.
Task 3 Sat 18 Feb 15:39 – 19:15	CE → ~~RO~~ → AC- → AE	Asked relevant file operations questions after manually copying HTML and understood individual operations (file I/O, requests). Failed however to reflect on the quality of the code provided and only seemed to have grasped the abstract concepts produced by the chat bot (disrupting AC), never consulting the course material.
Task 3 Sat 18 Feb 19:25 – 21:24	CE- → ~~RO~~ → ~~AC~~ → AE-	Assembled fragmented knowledge into submission over multiple hours. No recognition of inefficiency despite hundreds of lines of repetitive code. Believed manual approach was legitimate programming technique.

Student B's contrasting approach to the same tasks reveals how prior knowledge and strategic GenAI use produce fundamentally different learning trajectories. Rather than accepting ChatGPT's suggestions wholesale, Student B maintained consistent patterns of verification, testing each solution against course materials before implementation. When encountering errors, they engaged in detailed diagnostic conversations with ChatGPT, using the tool as a debugging partner rather than a solution provider. This Resourceful engagement pattern demonstrates how the same GenAI tool can either catalyse or disrupt learning depending on student agency and contextual factors.

5.3 Framework Diagnostics: Supporting Student Learning Through Process Analysis

Applying the GENIAL framework to these cases reveals the learning processes that usually go unnoticed in traditional assessments which are focused on the final outcome. In our case studies both students produced code that met assignment requirements to different degrees, yet their learning processes diverged fundamentally. The framework exposes these differences through temporal patterns, metacognitive indicators, and interaction quality that traditional output-focused assessment would miss.

Halfway through the study, after a Week 6 open lecture where we shared preliminary GENIAL findings with students and we allowed all teaching staff to advise on GenAI usage, Student A received detailed feedback including specific observations about how their ChatGPT use let them bypass critical learning stages. The student started to attend office hours and drop-in sessions regularly, benefiting from targeted teaching support. Their performance improved markedly through subsequent assignments, rising from 42/100 to 60/100 marks in Week 8 (considered solid average performance in the [UNIVERSITY] undergraduate setting), and later contributing high-quality code to group work achieving distinction-level performance (70+ marks). The pedagogical design of COURSE A which emphasised continuous assessment with multiple submission checkpoints and timely actionable feedback proved essential for Student A's recovery by disrupting unproductive learning cycles early on and fostering genuine skill development.

The framework's diagnostic power extends beyond individual interventions. Without these process-level insights, Student A might have continued bypassing critical learning stages, potentially failing the course despite producing superficially functional code.

DISCUSSIONS AND CONCLUSIONS

The GENIAL framework emerged from the empirical analysis of authentic student interactions with GenAI tools during the 2023-2024 academic year. Through the systematic examination of chat logs, version control histories, and learning outcomes across multiple disciplines, we identified how GenAI can catalyse or disrupt learning depending on student agency and contextual factors. The framework transforms vague concerns about "AI cheating" into precise diagnostic categories. These temporal patterns remain invisible in traditional assessment methods yet prove essential for distinguishing between sophisticated task completion and genuine understanding.

Assessment practices must evolve from product-focused to process-aware evaluation when GenAI enables task completion without learning. Our case study showed that Student A produced functional code that matched assignment requirements only at a surface level while bypassing fundamental principles taught in the course. An assessment strategy focused solely on outcomes would capture performance differences but miss the critical absence of reflective observation and abstract conceptualisation stages. While currently resource-intensive, the framework enables us to identify how, precisely, GenAI is influencing students' learning journeys and helps to spot problematic patterns before they become entrenched. An example of this is the success of the early intervention that allowed Student A's recovery from almost failing to distinction-level performance in the course.

Our findings come with important caveats. The majority of participants had already used GenAI for learning, with eighty percent of those finding chatbots helpful for their studies. Ultimately, students chose which chat logs to share, potentially curating submissions to look better. Still, we saw disruptive patterns to the learning process within this GenAI-positive cohort. In fact, receptive engagement appeared across all quantitative and qualitative courses in this study. The framework revealed that while most students reported satisfaction with AI assistance, some showed clear evidence of skipping learning stages because of it.

Future research should validate the application of the framework with broader samples across disciplines beyond programming contexts. As the framework's first introduction, we focused on how observational data shaped its development and demonstrated its application through detailed case studies. Automated diagnostic tools could scale process analysis without overwhelming researcher or educator workloads, perhaps through integration with learning management systems that already track student interactions. Longitudinal studies tracking students through multiple courses could also reveal whether early interventions produce lasting improvements in learning agency and metacognitive awareness.

GenAI integration requires careful calibration and embracing of relevant, existing pedagogical practices. Our evidence demonstrates these tools genuinely enhance learning when students possess sufficient foundational knowledge, critical evaluation skills, and AI literacy. As seen in the case study, Student A's experience reveals how GenAI systematically degrades learning processes without appropriate guidance, whereas Student B's strategic ChatGPT use accelerated concept mastery while maintaining learning agency through consistent metacognitive reflection. Our findings and new theoretical framework highlight how good pedagogical mechanisms that include timely feedback, a learning-focused curriculum design andassessment strategies that are process-driven, can mitigate the disruptive patterns of students’ GenAI usage in higher education.

The framework provides educators with practical diagnostic tools for navigating this complexity. Process-based assessment becomes not merely preferable but essential for maintaining educational integrity in the GenAI era. As one student observed during one of the focus groups, "*If a professor can't make an assignment that is too difficult for ChatGPT to answer, then it is not a good assignment*." This challenge requires us to design learning experiences that harness GenAI's capabilities whilst preserving the cognitive struggle essential for genuine understanding.

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Use of Generative AI: [AUTHOR] used Cursor IDE as a purposeful copilot when writing code for data manipulation and analysis. The authors also used the Claude chatbot (Sonnet 4 and Opus 4.1 on an Enterprise account) as a writing aid to help better elaborate the ideas that were in his mind. While Claude was also used to generate initial drafts or to paraphrase several paragraphs, they always felt the need to extensively edit those as the output frequently misrepresented the intended meaning.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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APPENDIX A

The Pilot: Autumn Term (September-December 2023)

The three courses included in the pilot were aimed at undergraduate students. All stemmed from data science. Please refer to **Table A1** below for the titles and enrolment numbers. At the time, we were particularly interested in testing a methodology for capturing how, precisely, students use popular GenAI chatbots, OpenAI's ChatGPT or Google's Gemini (at the time called Bard) when faced with coding challenges.

Table A1. List of courses in the pilot study (September 2023 to December 2024). The column 'Engaged Students' displays the count of students who engaged with the study surveys at least once.

Department	Level	Code	Title	Engaged Students
[DEPT A]	UG	[CODE]	[ENTRY-LEVEL DATA SCIENCE COURSE]	6 (out of 60)
	UG	[CODE]	[INTERMEDIARY-LEVEL DATA SCIENCE COURSE]	17 (out of 56)
[DEPT B]	UG	[CODE]	[COMPUTING COURSE]	7 (out of 71)

Our study setup reflects our initial interest in understanding the influence of these tools in learning and developing computer programming skills. Lecturers and class teachers refrained from giving any guidance on using AI for the first half of the course (Weeks 01-05). On Week 06, we sent a newsletter to all participants with contrasting sets of resources to delineate a new study phase. The newsletter included text and links about a) the common criticisms of generative AI tools in education and b) 'prompt engineering' tricks to get the most out of generative AI tools for coding. After this point, instructors would now be free to support students who wished to use GenAI tools more efficiently. This strategy determined the pacing of the course and the moments when we would run observational studies, but the data collection only occurred during the 90-minute computer classes and on specific weeks: weeks 3 & 4, when tips and assistance on AI usage were not allowed, and then on weeks 7 and 9.

During the days when we conducted the observational experiments, the class was divided into two parts. In the first half, all students – regardless of whether they were participants – engaged in the tutorial exercises as usual, as planned by the respective course convenors. In the second half, students worked independently on a more challenging task; however, unlike the rest of the class, participants were instructed not to use the web freely. They could only use their chosen chatbot (either ChatGPT or Gemini) and were prohibited from using search engines or seeking help on forums or Q&A sites (such as Stack Overflow, frequently used for programming assistance). Class teachers were still allowed to provide clarifications on the task. We aimed to isolate the experience of using a general-purpose GenAI tool as a learning assistant and to capture participants' views on its usefulness and effectiveness for learning. After the session, participants completed a brief survey and submitted their chat logs.

In the end, our data consisted of:

- An initial survey at the start of the academic term captured participants' attitudes towards learning and domain-specific skills such as coding and using GenAI for learning.
- Brief surveys from Week 03 until Week 11, except Week 06 (Reading Week). This survey asked students to rank how much they *felt* they had learned from the session and, if using GenAI,

their perceived usefulness of these tools. There was also a free text field for any other reflective notes.
    - In the key weeks we ran experiments, students were also asked to submit a link to their chat logs.
- A final survey at the end of the academic term captured participants' attitudes towards learning and AI.

We learned more from our participants' attitudes towards GenAI tools than from the capture of their chat logs during experiment days. The engagement with the study waned considerably over time, as can be seen in **Figure A1** below.

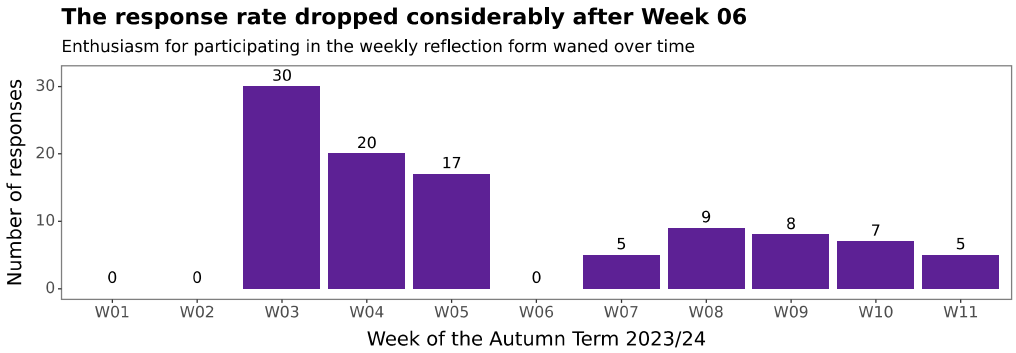


Figure A1. The response rate of the short weekly surveys during the pilot study (Autumn Term 2023/2024) dropped considerably after Week 06. Whereas we got 30 responses in Week 03, only 5-9 students responded to the weekly surveys on Weeks 7 to 11.

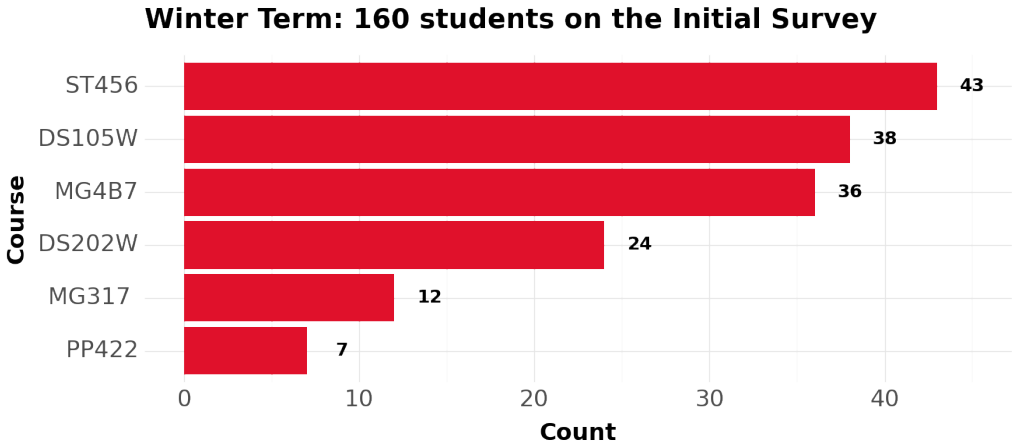


Figure A2. Breakdown of the number of students who filled out our initial survey on Winter Term

APPENDIX B

This appendix presents some of the participants' general perceptions of learning and GenAI tool use in the GENIAL study, drawn from initial surveys, exit surveys, and focus groups.

Note that he academic disciplines of participants of the main study (Winter Term) of GENIAL differed from the pilot (**Appendix A**) due to the inclusion of courses in management, public policy and additional course on deep learning. The inclusion of COURSE D + COURSE E (Same [MANAGEMENT COURSE] offered at UG and PG levels), COURSE F ([PUBLIC POLICY COURSE]) and COURSE C ([ADVANCED COMPUTING COURSE]) meant we expanded the study to include MSc students with extensive programming experience as well as mature students from non-technical courses.

Attitudes towards the use of GenAI for learning

All participants of the main study who engaged with our initial survey[1] had used GenAI chat bots before (**Figure B1**). ChatGPT was by far the most recognised and widely used GenAI tool, with Grammarly coming second and Google Gemini (then called 'Bard') coming third. At the time of the study, [UNIVERSITY] had already granted all students free access to Microsoft Copilot – which had just been rebranded from Bing AI – but even though ~50% of participants knew about it, only a small fraction of them had used the tool. Similarly, around half of students in quantitative courses were aware of GitHub Copilot, a coding assistant tool, when they entered the study.

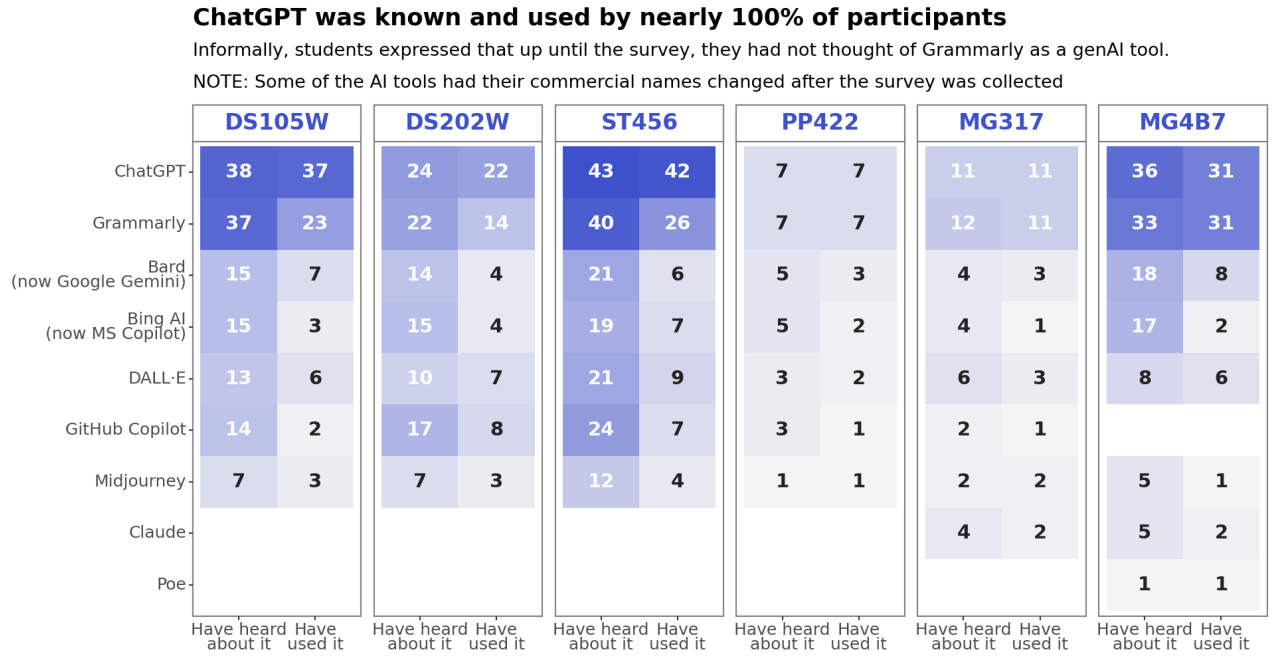


Figure B1. Awareness of participants about the popular GenAI tools at the time of the main study (Winter Term, Jan-March 2023/24)

Most participants said they had used a Generative AI tool to learn something (**Figure B2**). Of those, the majority perceived the tools as useful for their learning (**Figure B3**).

[1] Note that the number of participants who engaged with the initial survey is slightly smaller than of the total number listed in the main text. Some participants came to focus groups and shared chat logs without ever engaging with the survey.

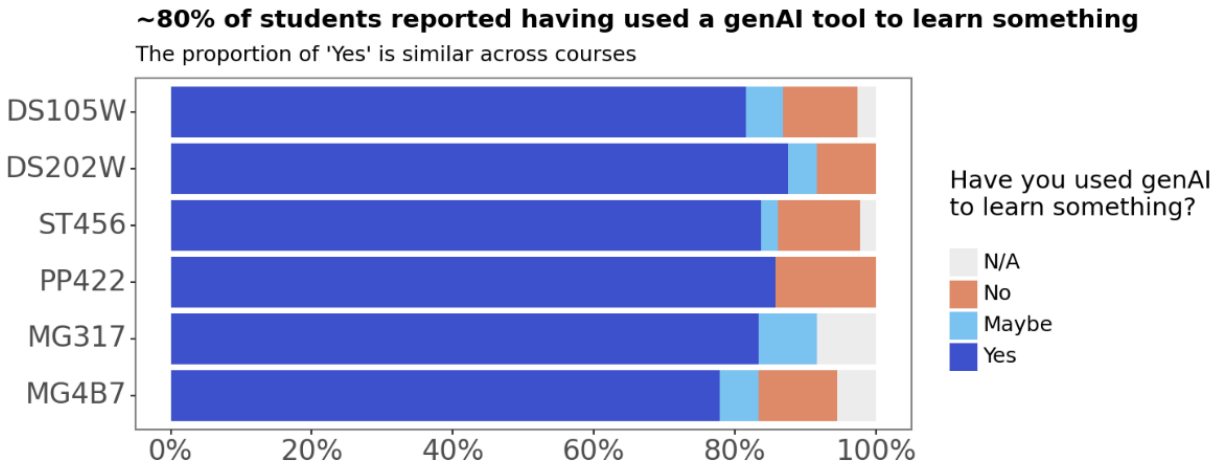


Figure B2. Breakdown of responses to the question "Have you used a Generative AI tool to learn something?" amongst participants of the main study during [UNIVERSITY] Winter Term 2023/2024 (Jan-March 2024)

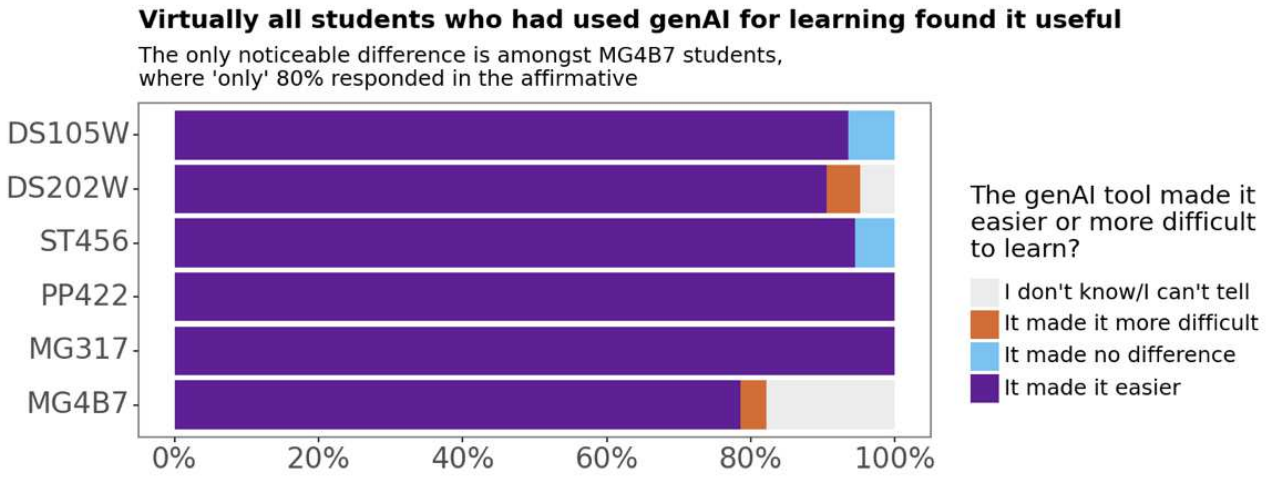


Figure B3. Breakdown of responses to the question "Thinking of [your use of GenAI for learning], do you feel the generative AI tool made it easier or more difficult to learn the topic, as opposed to not using any generative AI tool?"

Attitudes towards learning in general

Participants' willingness to prepare for class

We asked our participants how frequently they tend to prepare ahead of a small-group class teaching (computer class, seminar). Only 10% of participants claim to 'Rarely' prepare ahead of a class, ~49% do some preparation 'Sometimes' whereas ~41% claim to do so 'Always'. **Figure B4** summarises the and categorises the answers.

Management students prepare most consistently, with 58% (COURSE D, UG) and 67% (COURSE D, PG) always preparing versus 40% in COURSE A (UG), COURSE B (UG), and COURSE F (PG). Only 16% always prepare in COURSE C (PG), which also had the highest "rarely prepare" rate at 21%. See Figure B4 for a breakdown of the motivations in each category.

Most participants like to prepare for classes in advance

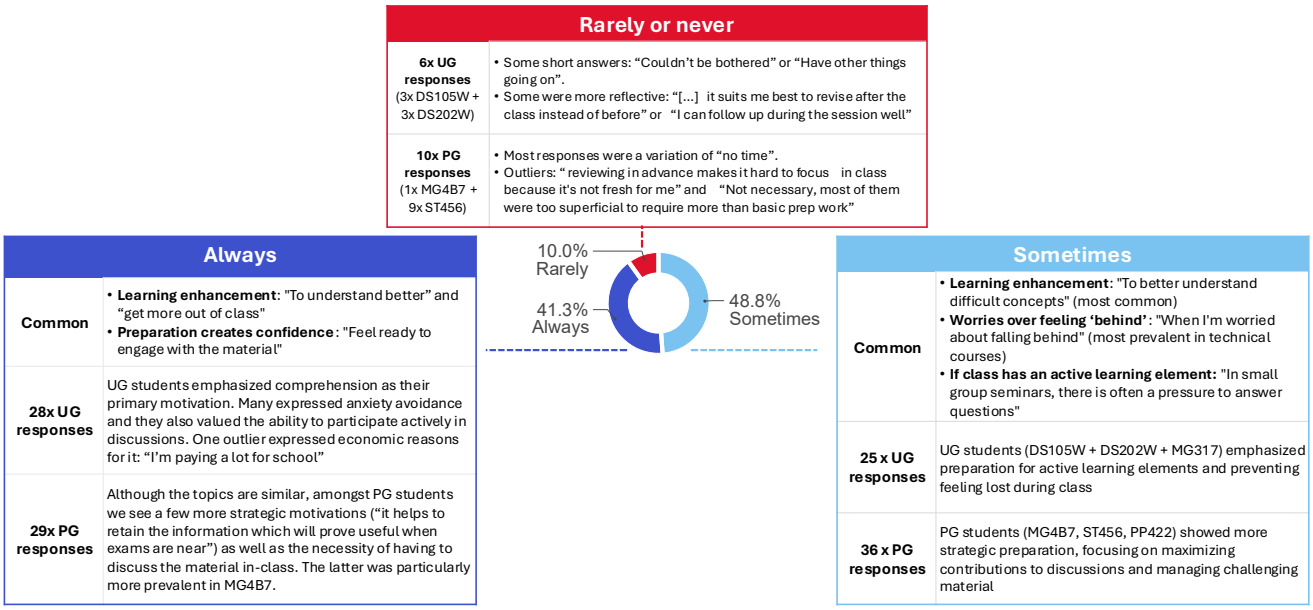


Figure B4. Pre-class preparation patterns among students: When and why undergraduates and postgraduates prepare for class (n=160 total survey responses, with 133 providing justifications)

Effective learning behaviour during the classroom

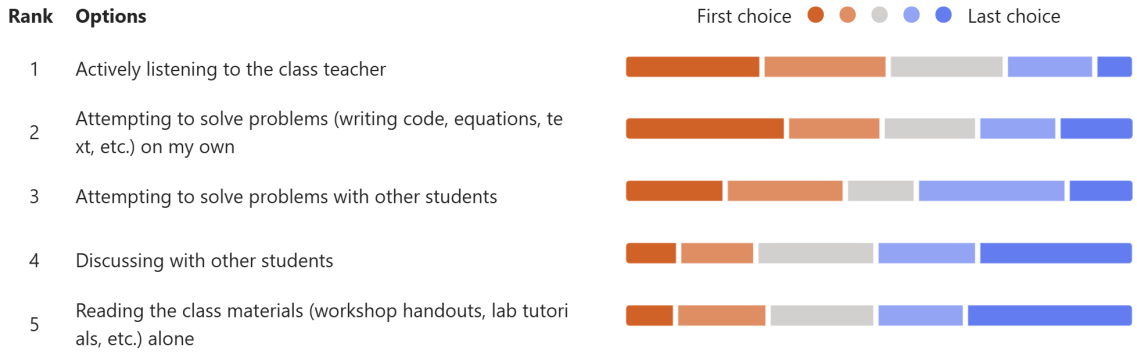


Figure B5. Summary of answers to "Thinking back to your most recent experiences during small group classes, which of the following methods did you find to be more effective for your learning during the session?".

When asked to rank what participants found most effective for their learning in the classroom, '*Actively listening to the class teacher'* and '*Attempting to solve problems on my own*' where the most popular first or second choices whereas '*Discussing with other students*' and '*Reading the class materials alone*' featured more frequently as last choices. **Figure B5** shows a visual summary of these responses and in **Table B1** one can find all (70) answers from those who wanted to express which other things were more effective for them in class. Interestingly, ChatGPT featured in a few answers such as '*Asking* Chat GPT for explanation on some topics*'* from a postgraduate student enrolled in COURSE C and '*In classes that don't use maths, I do like to use ChatGPT to ask the same question the class is discussing*' from a COURSE D undergraduate student.

course	num	response
DS105W	1	some youtube video may also help
	2	Asking the class teacher questions and the actively guiding me in my coding.
	3	Having an assessment element such as a hand in question that was marked. This was very motivating.
DS202W	1	Making us follow the professor as he is actively coding, so we understand the code as we are writing it ourselves and can ask questions if it does not work. This is sometimes difficult as the professors tends to go very quick.
	2	Above methods are fair enough
ST456	1	small group classes don't help much. I also attained a master's in Georgia Tech (US) and they do not have such things. Only hands-on experience helps with programming ability.
	2	Asking Chat GPT for explanation on some topics
	3	small mini-tasks that are done and then discussed directly after in class\nlarger projects
	4	Questions from lecturer to the audience
	5	I think all of those methods into a loop - start by quick individual reading and then trying individually, then checking with group and discussing and getting feedback from the teacher. Also, students bringing different possible applications and then discussing how we could implement x code to make it work
	6	ask questions to the seminar teacher
	7	I think the most effective method is listed above.
	8	Professor coming to discuss exercises you must do in your own.
PP422	1	Watching small explanatory videos.
	2	Teacher asking questions which I then had to understand. Getting set something to read or think about before hand and then discussing it in more detail in the class
MG317	1	I can't think of any other methods
	2	Projects are important that are hands on
	3	In classes that don't use maths, I do like to use ChatGPT to ask the same question the class is discussing.
	4	Best method\n- attempting an exercise alone\n- collaborating and discussing results with partner if stucked\n- going through the exercise once again with teacher
	5	the teacher explaining how to answer the questions in quantitative classes with workings and calculations
MG4B7	1	Playing games/scenarios.
	2	I also found it helpful when teachers asked us to prepare a plan for a past exam paper. It's really helpful for us to prepare and understand how to answer the question properly
	3	debate
	4	homework
	5	Having other students who also participated and were motivated to participate, as it created an environment that encouraged me to join in discussion and collaborate.
	6	Making succinct answer plans
	7	Interactive case solving
	8	interdisciplinary discussion

Table B1. Response to Item 16 of the Initial Survey (free text) which asked: "*Were there any other methods, not mentioned in the previous question, during a small group class that you believe were even more effective for your learning?*"

The next question asked students to rank their preferred methods for revisiting concepts during small group classes, and included GenAI as one option. The AI option ranked notably lower than traditional resources in the aggregate responses. See **Figure B6**.

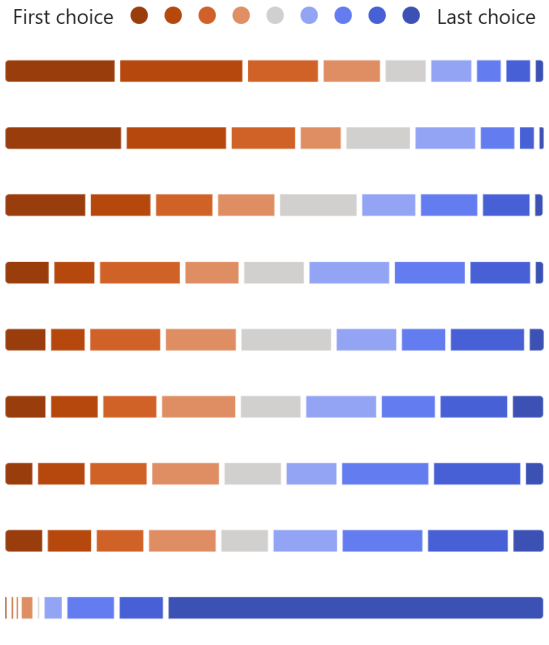


Figure B6. Student rankings for Question 17 of the initial survey, which asked: "Thinking back to your experiences **during a small group class**, when you felt the need to revisit a concept or gather more information about a topic, what were you most likely to do? Rank these options from most likely (top) to least likely (bottom)." Consulting class materials and using search engines emerged as the top two choices, whilst using an GenAI chatbot ranked fourth.

APPENDIX C

In this document, we show selected examples that help us confirm and extend Yang et al.'s (2024) framework. We demonstrate how context shapes both how students used GenAI and how we interpret their behaviour. The same student can shift between patterns based on task requirements, time constraints, and disciplinary setting, and only by relating their interactions to what was happening in the course can we better distinguish if they are acting in a 'receptive' or 'resourceful' mode.

For context, it is important to notice that our initial survey revealed widespread GenAI adoption among our participants. ChatGPT emerged as the most recognised and used tool, followed by Grammarly and Google Gemini (then called Bard) (**Figure B1**). Approximately 80% of respondents reported using GenAI tools for learning purposes (**Figure B2**), with the vast majority indicating these tools had facilitated their learning (**Figure B3**). Yet, even among these enthusiasts, we observed counterproductive patterns where GenAI use systematically bypassed learning processes, particularly when students lacked foundational knowledge or faced time pressures.

Confirming Yang et al categories

Our analysis identified all four of Yang et al.'s (2024) engagement patterns across all courses, though their manifestation varied considerably by discipline and context. Each pattern emerged through distinct behavioural indicators in chat logs, temporal data, and student reflections.

Resistive engagement

We found evidence of resistance mainly in surveys and focus groups, not chat logs. This is natural and expected as students avoiding GenAI provide minimal interaction data. Within our GenAI-positive sample, resistive patterns proved particularly revealing. Two distinct forms emerged: **procedural resistance**, where monitoring concerns inhibited engagement, and **principled resistance**, rooted in pedagogical concerns about learning integrity.

One COURSE C student articulated the vulnerability inherent in authentic learning:

> *"Personally, I found that I used GenAI tools somewhat more selectively in my GENIAL course than in my other courses, because when I knew that I would have to submit my chat logs, even anonymously, I felt embarrassed about asking stupid questions or requesting extremely elementary code. This is a warning about selection effects!"*

As Kolb (1984) noted, learning requires working through discomfort and conflict. The student's self-consciousness reveals sophisticated understanding that meaningful learning involves exposing knowledge gaps through questioning processes.

Principled resistance reflected deeper pedagogical concerns. As another COURSE C student noted:

> *"I'm happy I conducted most of my studies prior to the emergence of ChatGPT. Despite huge gains in efficiency, I feel it takes away some of the learning opportunity/outcome. Also, it makes it VERY easy to produce medium/decent results, which for groupwork can be very counterproductive, if people contribute merely the ChatGPT output to their respective part (e.g. for a report). If that is done, the engagement with the topic goes close to 0 and learning progress is probably negligible."*

This response demonstrates an intuitive grasp of experiential learning principles, recognising that knowledge creation requires active participation rather than consumption of pre-formed solutions.

Another worried that AI takes away the experiential elements of learning:

> *"[…] although it might not be perfect it still takes away actually writing code line-by-line and understanding it. Same for some concepts, when the first reflex is always to use ChatGPT instead of using own notes, lecture material, seminars and searching google to find a solution – this is less time-efficient but potentially slightly more worth-while."*

This recognition that learning requires practice aligns with Dewey's (1897) view of education as reconstructed experience.

A COURSE A student put it bluntly: "*I feel not every course should especially those in humanities courses because it sucks away the ability to think by yourself.*" Another COURSE C student found AI unhelpful for new concepts, noting that crafting precise prompts proved "*just as demanding as simply writing clear and concise text myself.*" These responses collectively demonstrate sophisticated understanding that learning requires productive cognitive struggle, not technological shortcuts.

Receptive engagement

Receptive patterns appeared across all courses, proving particularly significant given our sample's positive orientation towards the technology. Students exhibiting this engagement accepted the chat log outputs with minimal critical evaluation, systematically bypassing essential learning stages. Favourable attitudes toward GenAI do not automatically translate into effective learning practices.

One of the clearest pieces of evidence emerged from a COURSE F student's approach to a text analysis assignment designed to build statistical reasoning through progressive exploration with instructor scaffolding. The instructor provided a seven-question sequence to help guide students through conducting a full analysis rather than present the task or goal in a single step. The student's chat logs, time stamps, and final submission are consistent with simply copying and pasting problem text into GenAI and subsequently the chat bot response for the submission with no modifications. While it is possible for students to read and study GenAI output, the timestamps reveal only two-minute intervals between complex statistical and coding questions, which barely allow time to execute code, let alone comprehend outputs. The rushed timeline eliminated reflection and conceptualisation stages both essential for learning in the sense of Kolb's ELT. The temporal compression, under the light of Kolb's framework, suggests the elimination of reflective observation and abstract conceptualisation stages essential for knowledge creation.

The chat log in general was being used 60 hours before the problem set submission deadline. A first query during the student session was "*how to filter dataset to showing 5 random index*", which focused on helping to solve a problem set question but did not directly copy the text of the question. Later queries, however, move away from this strategy and do not demonstrate any input or rephrasing from the student.[2]

The two tables that follow outline the pedagogical intent and establish the timeline of the interactions of this COURSE F student with ChatGPT.

[2] Given the nature of the data collection, we cannot determine the extent to which the student may have gone back and revised or studied the AI generated code. While the student may have studied and reflected on this code after querying all the problems, the final assignment submission did not change the GenAI produced code.

Table C1. Context Matters: analysis of the chat log of a COURSE F student as they went through a reflective assignment.

Pedagogical Intent	Student Reality
Task Overview: Course leader devised seven-question sequence covering text preprocessing, statistical analysis, and interpretation. Students were expected to create code but ultimately, the goal is to engage with theoretical principles behind natural language processing and statistical reasoning concepts progressively to build a deeper understanding.	**Observed Method**: Direct transfer of complete assignment questions to ChatGPT without preliminary analysis or concept exploration. Student progressed through all seven questions within minutes using wholesale copy-paste approach.
Learning Trajectory: Multi-session exploration allowing students to experiment with statistical parameters, compare analytical outputs, and build understanding through iterative engagement with textual data processing techniques.	**Actual Timeline:** Single evening session with 2-8 minute intervals between complex statistical queries, insufficient time for code execution, output analysis, or conceptual processing of results.
Expected Engagement: Students would test different parameter values, interpret statistical outputs, compare results across approaches, and develop analytical insights about textual data characteristics through hands-on experimentation.	**Observed Engagement**: No evidence of parameter experimentation, output interpretation, or comparative analysis. Student proceeded sequentially through questions without modification or testing of generated solutions.
Assessment Goals: Evaluate statistical reasoning capabilities, analytical interpretation skills, and methodological understanding rather than code production. Focus on demonstrating comprehension through comparative analysis and contextual reasoning.	**Final Submission**: Technically accurate computational solutions with superficial analytical responses. Questions requiring statistical interpretation received brief, generic answers lacking the reasoning development the assignment was designed to assess.

Table C2. Description of how the ChatGPT interactions of the student described in Table C1 unfolded

Problem Set Text Copied to ChatGPT Log	Time Stamp
Instead of relying on a pre-existing list of stop words, we could instead eliminate words based on the amount of documents which contain a given word at least once. Using the `min_df` and `max_df` arguments of the CountVectorizer()function, calculate and report the number of unigrams if we remove words that appear in fewer than 1% of documents or greater than 99% of documents. How does this number to compare to the number of unigrams calculated earlier?	Mar 9, 2024, 10:11:42 PM
Using unigrams and eliminating words in fewer than 1% or greater than 99% of documents, create a document term matrix for this data frame.	Mar 9, 2024, 10:15:03 PM
Using the document term matrix above, for each token (column) calculate the percentage of documents where the token appears at least once. Which words are represented in the highest proportion of documents? Which words are represented in the least proportion of documents?\n\nNotes: you may find it easier to work with a pandas representation of the data for this step. This matrix is small enough where you can make this conversion. Further, recall that the document term matrix representation includes the term frequency (the count of how many times a word appears in a document). For this calculation, you will instead need to determine if an entry is zero or non-zero.	Mar 9, 2024, 10:26:08 PM
For each document in your data frame, calculate and report the percentage of words which appear in the document at least one time. Summarize this information for all the documents. On average, what percentage of the total words appear in any given document?	Mar 9, 2024, 10:33:18 PM
Examine the word count of each document in your matrix. How many words are in an average paragraph? Create a histogram of the length (in words) of the paragraphs in these speeches.	Mar 9, 2024, 10:34:39 PM
To estimate the model, complete the following steps. Isolate the president variable from the original data frame and save this as a variable y. Perform a training testing split on the original data frame (use random_state=422, and set the testing size to 50%) Create a bag of words representation of the training data where you calculate and store TF-IDF using the TfidfVectorizer() function. Consider an n_gram range of (1,1) and keep tokens that appear in at least 10% and fewer than 90% of documents, but do not remove any additional words. Fit a Random Forest Model to your training data. Report the accuracy of your	Mar 9, 2024, 10:36:24 PM

model's classifications within the training data. Predict and report the accuracy of your model's classifications on the testing data. Set any other needed random_state arguments to 0. Note. Your bag of words representation should be created only based on examining the training data. You can then call the .transform() method on your TfidfVectorizer() object to apply this transformation to the testing data. It is convenient to do this by creating a sklearn Pipeline.	
Comment on the overall accuracy of your model in the testing data. Answer the following questions.\n\n1. Do you think this accuracy is relatively small, medium, or large? Justify your decision.\n2. Display a plot of the confusion matrix for your predictions.\n2. Is the classification accuracy approximately even across the `president` labels in the data? If not, explore the data and explain why the accuracy may be higher or lower for certain labels.	Mar 9, 2024, 10:43:08 PM

Similar patterns emerged in the other courses. COURSE A students copied entire problem specifications into ChatGPT, advancing through multiple programming concepts faster than comprehension allows. COURSE D submissions retained example company names and templated analysis structures in case study analysis in a way that revealed wholesale adoption of ChatGPT responses without contextual adaptation or critical evaluation. In COURSE C, students requested complete neural network implementations without conceptual exploration, progressing from basic architecture requests to hyperparameter optimisation within minutes.

One particularly striking example, described in depth in **Section 6** with a forensic analysis in **Appendix D**, involved a COURSE A student whose receptive engagement led to complete conceptual breakdown. This student spent hours manually copying the source code of websites after misinterpreting ChatGPT's example code as literal instructions, demonstrating how receptive patterns can corrupt understanding when foundational knowledge is absent.

The psychological mechanisms underlying receptive engagement align with recent research. Abbas et al. (2024) link time pressure to GenAI dependency, while Fan et al. (2025)’s "metacognitive laziness" explains reduced self-regulation when chat bot assistance is available. Students confuse completing tasks with understanding them, creating illusions of competence. Submissions might be technically correct, but students miss the underlying concepts.

Resourceful engagement

We found evidence of resourceful engagement in our chat logs, where students demonstrated active control over AI interactions through strategic prompting, iterative refinement, and critical evaluation of outputs. These students challenged GenAI suggestions, adapted solutions to specific contexts, and maintained agency throughout their learning process. To appreciate these patterns, we need disciplinary and pedagogical context. Without understanding what was taught in class or knowing domain-specific concepts, one might mistakenly label these interactions as receptive (students copying answers) or reflective (students examining their learning process). We present curated examples from COURSE F and COURSE C, showing how students critiqued GenAI outputs, pre-empted problems with strategic prompts, and used chatbots for genuine revision.

The COURSE F examples (**Table C3**) reveal students who bring sufficient domain knowledge to contradict ChatGPT and awareness that GenAI suggestions can be wrong. Without contextual knowledge about statistical measures or data structures, these exchanges might appear as basic troubleshooting rather than critical engagement.

The COURSE C examples (**Table C**) reveal a different style of resourceful engagement, in which students were voluntarily exploring complex subjects recently taught in the course. These queries were done in a period of quiet revision, and with the intent to fill gaps the lectures left unfilled. They sought understanding of mechanisms and design principles rather than quick solutions for

assignments. Without knowing course boundaries, this self-directed learning might be misread as deadline-driven work.

Yet context also reveals limitations. The coauthors who taught in COURSE C observed students persistently demanding better solutions from ChatGPT rather than developing their own: "*You're still treating them the same way still.*" While showing clear goals and persistence, this pattern suggests dependence on GenAI for insights students might discover through direct struggle with problems and may turn into receptive patterns.

Table C3. Examples of exchanges with resourceful GenAI engagement shows COURSE F students challenging GenAI outputs.

Student query to chat bot	Disciplinary knowledge	Learning evidence
"Can I achieve this another way with a .query function?"	There are many ways to filter rows using Python, the query() function from the pandas library is more professional as the code tends to be cleaner, more readable and more efficient.	ChatGPT produced valid code before but here the student pushes back, using their own knowledge, to direct the chat bot to produce a response with the better method.
"all of my Rsme scores are the same what does this mean?"	RMSE is a measure of the prediction errors for a machine learning model which should vary with resample.	The student recognises there is something unusual about the result and is asking for further clarification. The student is critically engaging with the substantive meaning of their code and is identifying a problem even though there is no formal 'error' that stops the calculation.
"This line of code won't work whether I use X_test or X_train, and X_test is DEFINITELY a pandas dataframe so I don't know why it isn't working"	If the structure of data does not conform to a specific format, the Python code might generate errors. The most typical format is a pandas DataFrame, the default data structure used in the course.	When feeding such an error to the chat bot, the output would instruct the student to fix the DataFrame. Here, the student is fully aware of what they are doing and that the data is already in the right format. They use their own knowledge to direct the chatbot's output towards more useful recommendations.

Table C4. COURSE C students demonstrating resourceful engagement through self-directed exploration

Student query to chat bot	Disciplinary knowledge	Learning evidence
"Explain the mathematical details behind GloVe in more detail"	GloVe (Global Vectors) is a word embedding technique that captures semantic relationships through co-occurrence statistics. The lecture introduced the concept but not the mathematical foundations.	Student voluntarily seeks deeper mathematical understanding beyond course requirements. Shows self-directed learning during revision period, not deadline driven.
"For multi headed self-attention in transformers, how is it possible that each head learns a different relationship? How do we make sure that no two heads learn the same?"	Transformer models use parallel attention mechanisms that somehow specialise without explicit constraints. This architectural mystery wasn't explained in lectures.	Student questions the underlying mechanism, not just implementation. Shows curiosity about potential redundancy in model design - a sophisticated concern.
"Explain why we need residual connections in transformers"	Residual connections allow gradients to flow through deep networks by creating shortcuts. Essential for training stability but often presented as given fact.	Student seeks understanding of architectural choices rather than accepting them as prescribed.

The same behaviour might indicate receptive copying under deadline pressure but resourceful exploration during revision. Understanding timing, prior teaching, and disciplinary norms distinguishes surface behaviours from underlying learning processes.

Reflective engagement

Reflective engagement emerged when students used GenAI to examine their own learning processes and synthesise knowledge across contexts. Unlike resourceful engagement, which focuses more on strategic task completion or to review concepts, reflective patterns showed students questioning their understanding, examining contradictions, and using GenAI to explore the boundaries of their knowledge. Yang et al. (2024) describe these students as embarking on "*a thought-provoking exploration process where they deeply engaged with* [a GenAI tool] *by reflectively asking what, how, and why questions*", demonstrating higher-level metacognitive awareness about both content and process.

The clearest evidence came from a COURSE F student who noticed that different statistical methods they had learned in separate courses seemed to contradict each other (**Table 6**). Rather than accepting this confusion or ignoring it, the student turned to ChatGPT to resolve the conceptual tension.

Student query to chat bot	Disciplinary knowledge	Learning evidence
"If I have split all my categorical variables into dummy variables do I need to get rid of one of the dummies in each case so I don't have an issue with the dummies equalling each other out if I want to make a decision tree?"	In statistics, when you have categorical data (like red/blue/green), you convert them to numbers. Some methods require special handling of these conversions, others do not.	Student noticed that two different statistical methods they learned in handle the same type of data differently. Instead of memorising rules, they are trying to understand why the rules differ.
"Why is this code not dropping the first dummy variable?"	Some statistical software has options that need to be turned on or off depending on which method you are using.	Student wants to understand why their code is not doing what they expected, not just how to fix it. They are reflecting on the gap between theory and practice.
"i want to do sklearn.inspection.permutation_importance, the result from importances_mean has 30 feature, but the initial feature that I have is 56.. how to match those feature to get feature importance?"	Some analysis methods automatically ignore information that does not help with predictions, which can cause confusion when numbers don't match up.	Student chose to explore an optional technique during class time. Rather than interrupt to ask about something off-topic, they used ChatGPT to learn independently, then approached the instructor afterwards for deeper discussion.

Table 6. Examples of reflective GenAI engagement exchanges seen in chat logs from COURSE F students.

Survey responses revealed students' awareness of how AI interaction itself constitutes learning. One COURSE B student articulated a pedagogical insight:

> *"To be honest, I feel like the process of someone training their ChatGPT or other AI tools is actually a process of them learning or revising the knowledge again. It's true that people need to feed everything they know about the topic to ChatGPT first before asking the specific questions, otherwise ChatGPT will just give you some really random or abstract answers. So isn't the training process another way of revising the knowledge again?"*

This recognition that effective GenAI use requires articulating one's understanding echoes Chen et al.'s (2024) findings on learning-by-teaching, where explaining concepts to GenAI chat bots enhances metacognitive awareness.

Another COURSE B student described a deliberate two-phase approach: "*When learning, I copied the codes from teacher/teaching materials and asked ChatGPT to explain them for me. In writing assessment, I wrote most of the codes myself and copied them to ChatGPT to correct them when they had errors.*" This strategy shows conscious reflection on when to seek GenAI assistance versus independent practice, demonstrating the metacognitive control that distinguishes reflective from resourceful engagement.

These examples demonstrate that reflective engagement requires sufficient foundational knowledge to recognise conceptual tensions and the metacognitive sophistication to examine one's own learning process. Students exhibiting this pattern used GenAI not just to complete tasks efficiently but to interrogate their understanding, explore disciplinary boundaries, and consciously shape their learning trajectories. They also point out to the importance of instructing students in the appropriate use of these tools and the importance of priming the chat log with context. Learning which context produces the most helpful GenAI responses is a form of learning about the topic itself.

'Riffing' with AI: a fifth engagement type

Beyond Yang et al.'s (2024) four categories, we observed instances where students used GenAI for creative exploration and ideation that felt distinct from reflective engagement. While reflective students examine their understanding, these students used the chatbots as a brainstorming partner to generate alternative approaches and explore possibilities.

A COURSE A student gave ChatGPT their code which contained a method to extract insights from data they had collected for an assignment and then asked: *"look at the insights I have made here and give me similar ideas"*. The student was not seeking error correction or reflecting on why they had solved it in that way but seeking creative expansion. The response from ChatGPT suggested six alternative analytical directions, the student took up on one (association rule mining) and later returned to the chat bot for more brainstorming on that method.

In focus groups and surveys, students expressed divergent views about GenAI's value for such creative exploration and brainstorming. One COURSE B student argued it was unnecessary "*especially for social science courses, which require brainstorming and debates between students rather than having thoughts immediately from AI tools.*" A COURSE D student took the opposite view, finding it "*useful for using it like a search engine, or brainstorming ideas for a presentation/case recommendation.*" A COURSE D student was more nuanced: "*I think it works good as a fast and basic "second opinion". It helps polish ideas, drafts, and it helps a lot with mindless, mechanical tasks such as organising information, changing formats, or basic coding. I don't think it provides good "enough" responses to use it for "cheating" assessments (perhaps I don't use it well enough).*"

Beyond the categories

Our analysis revealed that engagement patterns are not "fixed student characteristics" but "contextually determined behaviours" that shift even within single assignments. The clearest evidence emerged from a COURSE C student whose interactions with ChatGPT demonstrated multiple engagement styles across two assignments, revealing how task complexity, time pressure, and conceptual understanding dynamically shape GenAI use.

During Assignment 1 (spectrograms analysis), this student began with receptive queries - typing fragmented searches like "*log-transformed Mel spectrograms*" and "*what's the mel scale*" without

context or follow-up. Yet within the same session, they shifted to a reflective (or even 'riffing') engagement when grappling with the core challenge of disentangling time and frequency components. Their query "*my idea is to use asymmetric pool sizes, horizontal rectangles or vertical rectangles in order to better capture the time variation of the musical features*" demonstrates metacognitive awareness of their own conceptual approach, seeking validation rather than solutions.

Assignment 2 showed further evolution. The student attempted a resourceful engagement, persistently challenging ChatGPT's suggestions: "*You're still treating them the same way still.*" However, their limited domain knowledge prevented effective critique and did not allow them to develop their own solutions.

This variation challenges static categorisation. The same student who proposed sophisticated ideas for their assignment later accepted flawed explanations uncritically - shifting engagement styles not from personality but from conceptual familiarity and task demands. Such fluidity demands a process-based framework that maps not just which patterns emerge, but how and why they manifest throughout the learning journey.

APPENDIX D

Subject: Forensic Analysis of a COURSE A student with dominant receptive pattern (Student A)

This appendix contains a detailed application of the GENIAL framework to analyse Student A's learning journey during the W06 Summative Assignment in COURSE A. The analysis reveals how foundational knowledge gaps and poor GenAI literacy led to a complete learning process bypass, where Student A exhibited a mostly Receptive pattern.

Context of the Assignment

The W06 Summative was the first graded assignment of COURSE A, involving web scraping from a designated [UNIVERSITY] website. Students had ten days to complete three tasks of increasing complexity, with drop-in support sessions available (which Student A did not attend). The assignment was designed to develop automation principles and systematic thinking through iterative coding practice.

Notes: Teacher's Contextual Knowledge (XK) & other institutional factors

> Here are some notes about the content taught in the course and the context in which the assignment took place.
>
> *Relevant pedagogical aspects*
>
> COURSE A was taught over a period of 11 weeks during [UNIVERSITY]'s Winter Term of 2024, 15 January 2024 – 28 March 2024. The course focuses heavily on computer programming and is designed to be "hands-on" and therefore very experiential in nature. It covered topics on data collection and the data manipulation skills necessary to convert the data collected into insights. At the time of the study, web scraping was covered in the Weeks 04-05 of the course[3]. There were no pre-requisites to enter the course and those who did not have prior knowledge of programming could enrol in a pre-sessional Python course.
>
> *W06 Assignment Learning Objectives:*
>
> This assignment which accounted for 20% of the final grade of students in this course was released in Week 04. Students had two weeks to submit their work directly via GitHub. The assignment consisted of three tasks that were covered similar topics they encountered in Week 05:
>
> - **Task 1 (20%):** Systematic data collection using programmatic web scraping.
> - **Task 2 (50%):** Iterative processing across multiple web pages with automated extraction
> - **Task 3 (30%):** Batch file operations and systematic data organisation
>
> Assessment of submissions focused on checking if students internalised automation principles and efficient coding practices taught (orally) in the classroom, as well as checking if they made meaningful use of version control software (Git) and produced well-structured and well-documented Jupyter notebooks.
>
> *Technology & Pedagogical Knowledge context*
>
> **Python web scraping package:** I intentionally adopted `Scrapy` instead of the widely popular `BeautifulSoup` package. ChatGPT will always default to `BeautifulSoup` code when you ask it to write a web scraping script in Python so, by adopting an alternative (more professional) tool, this would make it more likely for students to check GenAI-produced code against the coding style adopted in the course.

[3] Web scraping was removed from the syllabus of this course the following year, as it proved too complex to coding beginners.

Institutional Environment

- **GenAI Policy:** The course explicitly permitted the use of GenAI for assessment, with mandatory disclosure.
- **GenAI use in teaching:** Up until Week 06, GenAI had not been incorporated in the course and teaching assistants were advised not to give any advice to students on the use of the tools.

Notes: about the student

Background of student

Student A was a second-year International Social and Public Policy student. They did not have a prior knowledge of Python or computer programming and had enrolled in the pre-sessional course, so it was natural to expect they would struggle with the task and seek help from teaching staff. However, student never attended any of the 3h/week drop-in support sessions or booked any office hours with me or any other class teacher up until the submission of the W06 assignment.

Data sources

- ChatGPT chat log shared by student at the time of submission of their W06 Assignment.
- Git commit history, with timestamps.

First impressions about the work

- **Git Messages:** Student used the same commit message, "Setting up my assignment", every time they committed a new intermediary version of their work, suggesting low awareness of the version history processes taught since Week 03.
- **Code Structure:** Jupyter Notebooks had scattered imports throughout (telltale signs of copy-pasting from chat bots), reliance on absolute paths – against the reinforcement of relative paths as taught in the course.

Because the course required students to use Git for version control, each time they "committed" their code, students were required to write a descriptive message about changes made. These messages provided insight into their metacognitive processing. Student A saved six versions of their project, each labelled identically as "*Setting up my assignment*," revealing no reflection on what they had accomplished or what remained incomplete. Student B's fourteen commit messages, by contrast, demonstrated clear awareness of their journey: "complete task 1" (Sat Feb 10 21:41:51), "*submit first draft (can probably just treat it as finished) of assignment*" (Sun Feb 11 18:20:01), and "*update for list comprehension and other edits*" (Sat Feb 17 12:38:29). Each message shows Student B reflecting on their progress, evaluating completeness, and identifying specific improvements. This metacognitive engagement, as represented in the GENIAL framework, directly influenced Student B's ability to challenge ChatGPT's suggestions rather than accepting them wholesale, maintaining learning agency throughout the assignment.

Task 1: Cycle 1 (16 Feb 20:28-20:48 GMT)

I believe the first exchanges of this student with ChatGPT up until their first committed version seem to indicate a fully complete cycle.

ChatGPT Exchange:

A few short prompts sent to ChatGPT in connection to Task 1:

- `16 Feb 2024 20:28` - "what is scrapped data" → Basic terminology clarification
- `16 Feb 2024 20:29` - "how to save a python dictionary to a JSON file" → Standard coding question
- `16 Feb 2024 20:35` - "how to save a JSON file to a specific path" → Path specification follow-up

Notes on the code:

Committed: at timestamp 20:48:15 GMT, message "Setting up my assignment"

The first block of code shows the correct use of the Scrapy package (see below). As there are no chat exchanges about this, it is possible that the student copied code snippets from the course material and discovered the CSS selector by themselves without any GenAI:

```
sel = Selector(text=respone.text)
methodolgy_menu = sel.css('div > nav > ul > li ::text').extract()
```

However, this is immediately followed by a completely manual data collection disregarding the content of that code block:

```
# Second cell: Complete abandonment of programmatic extraction
menu = {
  "About us": 'https://<redacted>/About-us/About-us',
  "Alumni": 'https://<redacted>/Alumni/alumni',
  # ... 8 more manually entered menu items with full URLs
}
```

It is likely that the student did the manual curation above by themselves without the use of GenAI. Had the student followed up with a prompt like *"how to get this [code block 1] to produce this output [code block 2]",* they would have triggered a fresh new learning cycle leading them to eventually recognise that using `.extract_all()` in the place of `.extract()` would have reached the same output they desired.

Four-Stage Assessment

Stage	Student Actions	Agency	GenAI Use
CE-	Wrote correct Scrapy selector syntax but then immediately abandoned it for manual typing. Copy-pasted the code for writing JSON files.	Low	Reproductive
RO-	There is an attempt at reflecting on the task, with the prompt "what is scrapped data" but student did not seem to have properly reflected on it.	Low (no connection between prompt and following actions)	Intentional but not purposeful
~~**AC**~~	The two contradictory code blocks suggest no abstract conceptualisation of the concept of (automated) scraping of website links seems to have taken place.	-	-
AE	Even though the output was undesirable, an active experimentation stage took place here, with the manual curation of the links.	Medium	None seen

Stage Progression: **CE-** → **RO-** → ~~**AC**~~ → AE
(Somehow but not fully Receptive, as some stages were not mediated by GenAI)

Task 2: Cycle 1 (16 Feb 20:49-21:53 GMT)

Following completion of Task 1, the student immediately moved to Task 2. This cycle reveals both strategic thinking and fundamental conceptual gaps in their approach to web scraping automation.

ChatGPT Exchange

The student sent these prompts in sequence:

- `16 Feb 2024 20:49` - "how to read a json file you created" → File handling preparation
- `16 Feb 2024 20:50` - "how to read a json file you created as a dictionary" → Refinement for Python data structures
- `16 Feb 2024 20:55` - "how to sprape [sic] all content boxes from each link in your menu dictionary. Extract the title, subtitle, text, image URL, and alt title from each box using Python data structures." → Direct copy of assignment instructions
- `16 Feb 2024 20:57` - Same prompt but adding "using scrapy" → Strategic correction
- `16 Feb 2024 21:26` - "how to scrape the contents of a dictionary" → Conceptual confusion
- `16 Feb 2024 21:48-21:52` - Series of basic dictionary operations

Notes on the code

The Saturday commit reveals the student successfully extracted Scrapy's Selector syntax from ChatGPT's complex spider class implementation. They wrote:

```
sel_About_us = Selector(text=About_us.text)
about_us_dict = {
    "title1": sel_About_us.css('div:nth-child(2) > a > div.component__details > h2 > span ::text').getall(),
    # ... etc
}
```

This demonstrates understanding of the selector mechanism taught in class. However, they repeated this structure manually for every menu item rather than using iteration. The student created separate variables and dictionaries for each page (About_us, Alumni, etc.), writing hundreds of lines of repetitive code.

Four-Stage Assessment

Stage	Student Actions	Agency	GenAI Use
CE-	Copied assignment verbatim to ChatGPT, received BeautifulSoup code	Low	Reproductive
RO	Recognised BeautifulSoup wasn't the library used in course	Medium	None
CE	Re-prompted with "using scrapy" to steer response	Medium	Somewhat purposeful
RO	Filtered ChatGPT's spider class to extract useful Selector syntax	High	None
AC	Understood selectors extract data but missed iteration principle	Medium	None
AE	Produced working but highly repetitive code	Low	None

Stage Progression: CE- → RO → returns to CE → RO → AC → AE

Task 2: Cycle 2 (17 Feb 16:21-19:30 GMT)

After a 19-hour gap suggesting overnight manual work, the student returned to construct the `DataFrame` required for Task 2 submission.

ChatGPT Exchange

The student asked focused `DataFrame` questions:

- `17 Feb 2024 16:21` - "how to create data frame in python"
- `17 Feb 2024 16:22` - "how to create a data frame with multiple dictionaries"

- `17 Feb 2024 19:25` - "how to save the data frame"
- `17 Feb 2024 19:25` - "how to save data frame as a csv file python"
- `17 Feb 2024 19:30` - "how to specify the path where you want your data frame saved"

Notes on the code

he student created `df_boxes` as a list of dictionaries, manually entering each box's data:

```
df_boxes = [
   {'department': 'Methodolgy',
    'page_title': 'About_us',
    'page_url': menu['About us'],
    'box_title': about_us_dict["title1"],
    'box_subtitle': about_us_dict["subtitle1"]},
   # ... 40+ more manual entries
]
```

They successfully saved this to CSV using pandas, completing the task requirements through brute force rather than programmatic generation.

Four-Stage Assessment

Stage	Student Actions	Agency	GenAI Use
CE	Asked appropriate `DataFrame` creation questions	Medium	Somewhat purposeful
RO	No reflection on why manual approach was inefficient. To observe RO, we would need evidence of the student questioning their approach, such as "Is there a way to automate creating these dictionary entries?" or "Why do I have so many similar lines?"	-	-
AC	Understood `DataFrame` structure but implemented manually	Low	None
AE	Successfully created and saved `DataFrame` to CSV	Medium	Purposeful

Stage Progression: CE → RO → AC → AE

Task 2: Cycle 3 (17 Feb 19:30-23:25 GMT)

The final cycle before submission involved assembling the manual work into the required format. No ChatGPT interactions were recorded during this period.

Notes on the code

The commit at 23:25 shows the final assembly of all manual work. The student consolidated their individually created dictionaries into the `DataFrame` structure and ensured file paths were correct. The commit message remained "Setting up my assignment", indicating no recognition of task completion as distinct from setup.

Four-Stage Assessment

Stage	**Student Actions**	**Agency**	**GenAI Use**
~~**CE**~~	Assembled manual work into final submission format	Low	None
~~**RO**~~	No reflection on repetitive code patterns	-	-
~~**AC**~~	No abstraction of automation principles	-	-

Stage	Student Actions	Agency	GenAI Use
AE-	Committed functional but inefficient solution	Low	None

To observe RO, we would need evidence of the student recognising inefficiency, such as commenting "this could be shorter" or attempting any loop structure. To observe AC, we would need attempts at pattern recognition or code generalisation.

Stage Progression: CE- → ~~RO~~ → ~~AC~~ → AE-

Overall Assessment of Task 2

The student learned several concepts through experience: JSON file manipulation, `Scrapy` selector syntax, `DataFrame` creation, and CSV file operations. They demonstrated problem-solving ability by recognising incorrect libraries and extracting useful patterns from unhelpful AI responses.

However, they failed to learn the core principle of automation through iteration. The evidence shows no attempt at loops, no questioning of repetitive code, and no conceptual understanding that programming eliminates manual repetition. The 19-hour overnight gap combined with hundreds of lines of repetitive code indicates the student completed Task 2 through manual labour rather than programmatic thinking.

This, so far, represents a receptive engagement pattern where task completion occurs without internalising intended learning objectives. The student achieved functional results whilst bypassing the fundamental automation principles the assignment was designed to teach.

Task 3: Cycle 1 (Sat 18 Feb 13:55-14:55 GMT)

This cycle documents Student A's complete conceptual breakdown in web scraping. They abandoned their working Scrapy implementation for an absurd manual process using BeautifulSoup.

ChatGPT Exchange

The student's technical vocabulary deteriorated from their successful work on 16 February when they correctly specified "using scrapy" to correct ChatGPT's suggestions. By 18 February, their queries degraded:

- `18 Feb 2024 13:55` - "how to extract an image alt" - No mention of `Scrapy` despite using it throughout Task 2. ChatGPT defaulted to `BeautifulSoup`, its most common web scraping library.
- `18 Feb 2024 13:57` - "how to scrape image url and image alt separately" - ChatGPT continued with BeautifulSoup examples.
- `18 Feb 2024 14:00` - "how to scrape image url and image alt separately using selector" - Student attempted to redirect ChatGPT, but "selector" exists in both BeautifulSoup and Scrapy. Without library specification, ChatGPT interpreted this as requesting CSS selectors within BeautifulSoup.
- `18 Feb 2024 14:03` - "how to scrape attributes" - Student abandoned specific terminology entirely.
- `18 Feb 2024 14:24` - Student copied this exact HTML from the [UNIVERSITY] website: `<img src="<redacted>/Images/PromoImages/Campus-Welcome-page.png" alt="Campus Welcome page">`. ChatGPT responded with standard programming forum convention, creating a simplified example with `html_content = '<img src="...">'` as a variable.
- `18 Feb 2024 14:55` - Student provided three more manually copied HTML tags.

Notes on the code

On this day there was a commit at 21:08 which exposed some catastrophic misunderstanding. The version committed included code for Task 3 (download of images) but we also see that Student A went back to Task 2 and added code blocks like the one shown below:

```
anniversary1 = '<img src="/Methodology/Assets/Images/PromoImages/30-Year-History.png" alt="30 Year - History">'
anniversarysoup1 = BeautifulSoup(anniversary1, 'html.parser')
img_selector1 = 'img'
anniversary_tags_1 = anniversarysoup1.select(img_selector1)

for img_tag in anniversary_tags_1:
   anniversary1URL = img_tag.get('src')
   anniversary1alt = img_tag.get('alt')
```

Here we see that Student A manually copied HTML from the browser's inspect element feature, hard-coded these as Python strings, then used BeautifulSoup to parse them. They performed the computer's job manually, then used automation tools to process their manual work.

This repeated for every single image across all ten menu pages.

Four-Stage Assessment

Stage	Student Actions	Agency	GenAI Use
CE-	Asked ChatGPT for code to extract links to all images.	Low	Reproductive
RO	Recognised that ChatGPT returned `BeautifulSoup` code	Medium	-
CE-	Adds "using selector" in follow-up prompt, instead of "using scrapy" which they had used the day before. Selector is a concept that exists in all web scraping libraries and as such, ChatGPT still returns `BeautifulSoup` code.	Low	Reproductive
~~**RO**~~	No questioning why ChatGPT suggested different library than course materials. To observe RO: Student would ask "Why BeautifulSoup when we use Scrapy?" or "What's the difference between these libraries?"	-	-
~~**AC**~~	Interpreted ChatGPT's mock data literally as instruction to hard-code HTML. To observe AC: Student would recognise `html_content = '<img …>'` as example format, not actual implementation.	-	-
AE-	Created BeautifulSoup parsers for manually copied HTML strings across dozens of code blocks.	Low	Reproductive

Stage Progression: **CE-** → ~~**RO**~~ → ~~**AC**~~ → **AE-**

The corruption mechanism worked as follows: ChatGPT provided standard Stackoverflow-style responses where questioners include minimal reproducible examples. When ChatGPT wrote `html_content = '<img src="/example.jpg">'`, it demonstrated how to use `BeautifulSoup` with simplified data. Student A interpreted this as instruction to manually copy HTML from websites and hard-code it into Python. They never questioned why they were parsing strings they had already extracted by hand.

Task 3: Cycle 2 (18 Feb 15:39-19:15 GMT)

After 44 minutes manually copying HTML from browser inspection tools, Student A returned to learn file operations. They acquired individual programming skills without developing systematic thinking.

ChatGPT Exchange

The queries shifted to implementation mechanics:

- `18 Feb 2024 17:53` - "how to read a file in python" - Basic file I/O question
- `18 Feb 2024 17:58` - "how to create a file" - File creation syntax
- `18 Feb 2024 18:02` - "how to create folders and subfolders python" - Directory structure creation

- `18 Feb 2024 18:11` - "how to Use the requests library, download the images from the box_image_url column of the df_boxes dataframe" - Direct paste of assignment instructions
- `18 Feb 2024 18:13` - "how to download images from a data frame" - Simplified version of previous query
- `18 Feb 2024 18:24` - "how to download a specific image from a data frame" - Focused on single operations
- `18 Feb 2024 18:30` - "how to download a specific image from a specific column" - Further specification
- `18 Feb 2024 18:51` - "how to use Python to concatenate the paths" - URL construction
- `18 Feb 2024 19:10` - "how to save full url to a specific folder" - Final storage questions

Notes on the code

The implementation revealed complete absence of programmatic thinking. Student A created folders manually:

```
subfolder1 = os.path.join(main_folder, '/Users/<redacted>/github-repo-folder/data/images/About us')
subfolder2 = os.path.join(main_folder, '/Users/<redacted>/024-w06-summative-<redacted>/github-repo-
folder/data/images/Alumni')
# ... repeated for all 10 menu items
os.makedirs(subfolder1, exist_ok=True)
os.makedirs(subfolder2, exist_ok=True)
# ... repeated for all 10 folders

They downloaded each image individually:
# ABOUT US - downloading images - TWO
index0 = 0
column = 'box_image_url'
subpath = df.loc[index0, column]
full_url = base_url + subpath
response = requests.get(full_url)
if response.status_code == 200:
    file_path1 = os.path.join(target_folder, f'image{0}.jpg')
    with open(file_path1, 'wb') as file:
        file.write(response.content)

index1 = 1
column = 'box_image_url'
subpath = df.loc[index1, column]
# ... exact same code repeated with different index
```

No loops. No iteration. Every operation specified manually for many images.

Four-Stage Assessment

Stage	Student Actions	Agency	GenAI Use
CE	Asked relevant questions about file operations and HTTP requests.	Medium	Somewhat purposeful
~~**RO**~~	Never recognised repetitive patterns. To observe RO: Student would notice "I'm writing the same code repeatedly" or ask "How can I avoid repetition?"	-	-
AC-	Understood individual operations (file I/O, requests) but failed to abstract into reusable patterns.	Low	None
AE	Successfully executed each operation in isolation. Files created, images downloaded.	Medium	Purposeful

Stage Progression: CE → ~~**RO**~~ → **AC-** → AE

Student A learned programming operations as isolated procedures. They understood "download an image" and "create a folder" but never grasped "download all images" or "create all folders". They acquired syntax without understanding programming logic.

Task 3: Cycle 3 (18 Feb 19:15-21:24 GMT)

Student A assembled their fragmented knowledge into a submission that met surface requirements whilst demonstrating complete failure to understand automation.

ChatGPT Exchange

No ChatGPT interactions during this implementation period.

Notes on the code

The 21:08 and 21:24 commits contained hundreds of lines of manual specifications. Student A's README Markdown file revealed their perception of success:

```
Task 2: Collecting boxes
- I used selector CSS to extract the title and text (when available)
- I used selector xpath to extract the subtitle
- I used a HTML parser (beautiful soup) to extract images (image URL + alt)

Task 3: Collecting the images
- I used Python to concatenate paths as the box_image_URL was a subpath
- I then downloaded the images into the correct folders
```

They described `BeautifulSoup` as a deliberate technical choice. They showed no awareness that parsing manually copied HTML strings violated fundamental programming principles.

Four-Stage Assessment

Stage	Student Actions	Agency	GenAI Use
CE−	Wrote hundreds of lines of repetitive code over multiple hours.	Low	None
~~RO~~	No recognition of inefficiency. To observe RO: Comments acknowledging repetition or attempts at simplification.	-	-
~~AC~~	Believed different data types required different libraries (`Scrapy` for text, `BeautifulSoup` for images). To observe AC: Recognition that one library could handle all scraping tasks.	-	-
AE−	Produced functional outputs (images in folders) through manual specification.	Low	None

Stage Progression: **CE−** → **~~RO~~** → **~~AC~~** → **AE−**

Student A achieved the assignment's surface requirements (images were downloaded to separate folders) through manual labour that took hours instead of the minutes a proper solution would require.

Wrap Up Cycle (20 Feb 19:32 GMT)

Student A polished their submission according to course presentation standards, demonstrating ability to follow procedural instructions whilst fundamental conceptual failures remained hidden.

ChatGPT Exchange

No ChatGPT interactions recorded.

Notes on the code

The commit modified presentation without touching logic. Student A:

- Re-ran all cells (execution count rose from 300s to 537)

- Removed debugging print statements
- Converted comment-only code cells to Markdown cells
- Ensured clean notebook execution

These changes complied with explicit course instructions about submission formatting.

Four-Stage Assessment

Stage	Student Actions	Agency	GenAI Use
CE	Reviewed submission against formatting checklist.	Medium	None
RO	Identified presentation issues requiring correction.	Medium	None
AC	Understood distinction between debugging output and final presentation.	Medium	None
AE	Implemented all formatting improvements correctly.	Medium	None

Stage Progression: CE → RO → AC → AE

This cycle demonstrates Student A could successfully learn and apply explicit procedural requirements. They understood "remove print statements" and "convert comment cells to Markdown". This surface compliance masked their complete failure to understand web scraping automation.

Overall Assessment of Task 3

Student A's Task 3 represents comprehensive learning failure disguised as functional success. They downloaded all required images to correctly structured folders through manual specification of every operation. What should have been a 20-line loop became hundreds of lines of repeated code.

The GenAI corruption proved decisive. When ChatGPT's code responses followed the conventions of Q&A forums like StackOverflow where it’s good etiquette to produce simplified mock data for clarity, those were interpreted as literal instructions. Student A believed they should manually copy HTML strings and parse them with `BeautifulSoup`. They spent hours performing the computer's job by hand.

The temporal evidence confirms this interpretation: 44-minute gaps for manual HTML collection, followed by hours writing repetitive code. Student A worked harder than any student who understood the assignment, yet learned nothing about automation.

Most damaging, Student A remained unaware of their failure. Their README demonstrated pride in using "a HTML parser (beautiful soup)" to extract images. They submitted believing they had successfully learned web scraping, when they had actually learned to use programming languages as elaborate manual tools.

These last cycles of Task 3 represents receptive engagement at its most destructive: functional outcomes achieved at a surface level through complete bypass of learning objectives.