Beyond Control and Enthusiasm: A Ten-Phase Model for Pedagogical AI Integration in Academic Writing

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Abstract: The rapid adoption of generative AI among students and faculty has confronted universities with a pedagogical challenge that neither prohibitionist control strategies nor uncritical enthusiasm adequately address. The present paper puts forward the argument that a deliberate, process-oriented framework is required; one that renders the use of AI visible, discussable and educationally meaningful. The present study draws on the cognitive process tradition of Flower and Hayes (1981) and Bereiter and Scardamalia's (1987) distinction between knowledge-telling and knowledge-transforming writing. In this paper, a foundational conceptual distinction is introduced between AI-supported authorship and AI-displaced authorship. On this basis, a ten-phase model of academic writing is proposed. This model functions as a transparency scaffold rather than a prescriptive sequence, thereby making the recursive subprocesses of academic writing explicit. This enables students to reflect on their use of AI within each phase. Seven competence dimensions—including process awareness, AI-related information literacy, evaluative judgment, didactic prompt design, transparency and documentation, ethical and legal awareness, and cooperative AI use—translate the model's logic into teachable and assessable criteria.

1. INTRODUCTION

Over the past two years, generative AI systems such as ChatGPT have become an integral part of student and academic work. Data from the AI Monitor 2025, a nationwide study of German universities (HFD, 2025), illustrates the speed and breadth of this adoption: 91% of students and 68% of faculty report using tools such as ChatGPT, DeepL Write, or Grammarly. This empirical study concludes that students in Germany primarily use generative AI for exam preparation (76%), text production (64%), and information retrieval and research (59%). Faculty members use it primarily to create teaching materials, assignments, and for providing feedback. These figures present universities with a decision that goes deeper than the question of rules or detection mechanisms: How should we respond to a tool that deeply impacts core academic practices—namely, scholarly writing? Two approaches have dominated the discourse so far, and both fall short. On the one hand, there is mistrust and control: the call for reliable “AI detectors,” for stricter examination formats, for institutional bans. This impulse is humanly understandable, but factually problematic. Current research and legal opinions demonstrate that existing detectors are technically unreliable, legally fragile, and epistemically opaque: They produce a significant number of false positives and false negatives, cannot cite verifiable sources in the sense that plagiarism software does, and generally lag behind the latest model generations (Baresel et al., 2025). Even more serious is that an overemphasis on the control function distracts universities from one of their core tasks: fostering critical thinking. On the other hand, there is an uncritical enthusiasm that views generative AI primarily as a productivity tool—and in doing so risks undermining central educational goals: independent thinking, argumentation skills, and the understanding of academic work as a process.

This article takes a different approach. Instead of relying on control or euphoria, we ask: How can we identify the points in an academic writing process where AI can be usefully integrated—and where fundamental debates about authorship, intellectual property, original contribution, and the acquisition of academic competence are absolutely essential? This approach builds on the tradition of critical thinking. It views integration not as a capitulation to a tool, but as a prerequisite for students to make informed, reflective, and responsible decisions when dealing with AI (Weimann-Sandig, 2023). Such an integrative stance requires structured guidance—not despite, but precisely because of the openness and ambivalence that generative AI introduces into academic writing processes.

The strongest objection to the framework proposed here could, of course, be the one that assumes that intensive independent reading and autonomous writing may simply produce better learning outcomes than any form of AI-assisted composition, and the pedagogical energy invested in managing AI integration might be better spent defending and cultivating those practices. This objection deserves to be taken seriously. There is robust evidence that cognitive struggle produces deeper and more durable learning than assisted performance (Shanley, 2026; Klein, 2023). The present framework does not dispute this. It proceeds, however, from a different empirical starting point: the question is no longer whether students *should* encounter AI in academic writing contexts, but how they already do, and under what conditions that encounter can be pedagogically structured rather than left unmanaged.

2. ACADEMIC WRITING MODELS: CURRENT STATE OF RESEARCH

A seminal shift in the field of writing research was initiated by the cognitive process model of Flower and Hayes (1981). Previous literature on academic writing (e.g., Britton, 1977) has typically suggested a predominantly linear progression from literature review to drafting to final revision, thus emphasizing the text as a product. Conversely, Flower and Hayes (1981) conceptualize writing as a goal-directed and recursive process, wherein planning, formulating, and revising interact continuously throughout the composing process. In this view, writers set and adjust goals, monitor the emerging text, and develop ideas through the act of writing itself. This means that composing functions not only as communication but also as discovery and conceptual clarification. Later work (Hayes, 2012) have highlighted the role of goal setting, working memory, and the social-material environment in the regulation of these recursive cycles. The distinction between process and product needs to be clarified, as this is often erroneously interpreted as a dichotomy. This is not the case. The written product is precisely the sedimented form of the process: it bears the traces – visible or invisible – of the planning decisions, the discarded formulations, the revised arguments, and the knowledge transformations that produced it. From a process perspective, the product is not rejected but examined – as evidence of the decisions and reasoning that shaped it. This distinction matters particularly with AI-tools. When assessment focuses exclusively on the submitted text, the question of how that text came to be—which cognitive operations were performed by the student, and which were delegated to a tool—remains systematically invisible. Conversely, a process-oriented lens enables educators and students to formulate more precise inquiries, focusing not on the AI-generated output, but rather on the specific components of the writing process that the AI either supported, reshaped or displaced. This reinterpretation builds on Bereiter and Scardamalia (1987), who drew a distinction between knowledge-telling and knowledge-transforming writing. In knowledge-telling, the writer retrieves and transcribes existing content; in knowledge-transforming, the writer restructures both content and rhetorical goals through the act of composing. Academic writing, as conceived by higher education, exemplifies knowledge transformation (Bereiter & Scardamalia 1987). It demands that the writer formulate research questions, construct and evaluate arguments, integrate and critically assess sources, and revise reasoning under uncertainty. These are not merely incidental features of academic work but precisely the operations that generative AI is capable of performing, simulating, or substituting. This distinction forms the foundation for differentiating between two qualitatively distinct modes of AI involvement in academic writing. We use two terms throughout this paper: “AI-supported authorship” and “AI-displaced authorship”. In the context of AI-supported authorship, generative AI functions as a heuristic aid within a writer's own recursive goal-directed activity (Buck, 2026). This activity may involve asking to suggest counterarguments, seeking help with alternative phrasing, or generally receiving support during the revision process. However, the writer retains executive control over planning, conceptual decisions, and evaluative monitoring (Brommer et al., 2023; Limburg et al., 2023). In contrast, in AI-displaced authorship, the substantive knowledge-transforming operations are outsourced: The use of artificial intelligence in academic research entails the formulation of research questions, the structuring of arguments, and the production of draft text. The student then adopts this draft with only superficial changes (Buck, 2026). The transformative act of writing was not carried out by the learner, but by the tool, and was subsequently merely validated. A process model, however, illustrates the cognitive work expected of students, including goal-setting, planning, and structuring; the translation of ideas into text; and the evaluation and revision of the argument. From this perspective, academic writing is not merely a means of assessing performance, but a central arena where knowledge is organized, questioned, and expanded. This is precisely why generative AI raises not only questions of integrity but also pedagogical questions: If the tool can perform the knowledge-transforming processes that academic writing is actually intended to foster, what purpose does academic writing at universities still serve (Shanley, 2026; Brommer et al., 2023)? A process-oriented perspective facilitates the design of learning and assessment formats that make cognitive work visible and open to discussion (Boud & Dawson, 2023). In the context of writing instruction, these can include, for example, intermediate products such as exploratory notes, outlines, or partial drafts. When generative AI is incorporated, documentation of the process is required regarding the use of AI in the various writing phases. To achieve this, however, students must first be encouraged to break down the academic work process into individual steps. Something that, as shown in the next chapter, is not self-evident for all students.

3. TOWARDS AN INCLUSIVE AI-WRITING MODEL

This paper is founded on the cognitive process tradition and assumes that a stronger orientation towards process models of writing enables students and instructors to integrate generative AI more deliberately and more responsibly (Buck, 2026; Brommer et al., 2023). In the model proposed by Flower and Hayes (1981), the process of writing is not conceived as a linear chain of steps, but rather as a recursive system of interacting processes. These processes, which include planning, drafting, and reviewing (and consequently evaluating and revising), are coordinated through a form of executive control, often described as monitoring. Furthermore, the process of writing is continuously shaped by the task environment, such as the assignment, audience, genre, and constraints, as well as the writer's long-term memory, which encompasses domain knowledge, discourse conventions, and strategies. Later developments (Hayes, 2012) further highlight the role of goal setting, attention and the social-material environment in regulating these cycles. This theoretical lens matters for the AI debate because generative AI tools can intervene in *each* of these subprocesses: they can support planning (e.g., generating options), translation (e.g., producing draft language), and reviewing (e.g., suggesting revisions). The pedagogical question is therefore not whether AI can produce text, but which cognitive steps the writer delegates to the tool – and why. This distinction matters epistemologically: students who outsource certain writing steps out of genuine curiosity or acquired competence engage with AI differently than those who delegate because they lack the underlying tools. In the latter case, it becomes important to further distinguish whether a foundational understanding is missing or whether the student simply lacks practice. AI use that substitutes for underdeveloped competences risks foreclosing the very learning process that academic writing is meant to support (Bereiter & Scardamalia, 1987). The goal, then, is not to prohibit delegation, but to make it legible – to help students recognize which steps they are handing off, and to reflect on what that reveals about their own epistemic position. This is precisely the approach we are taking in the BediRa higher education development project. The empirical and developmental grounding of this paper draws on the BediRa project (*Building Reflexive Professionalism and Relationships in Remote Teaching*), a higher education development initiative located at the University of Applied Sciences for Social Work, Education and Nursing (EHS Dresden, Germany). The project was initiated in response to the experiences of emergency remote teaching during the COVID-19 pandemic, which revealed both the structural limitations of existing digital teaching practices and the largely untapped potential of involving students as co-constructors of learning environments (Weimann-Sandig, 2022). BediRa encompasses three interconnected formats: a student-led ThinkTank that organizes cross-curricular online test labs in a weekly 60-minute format, in which students and faculty jointly explore digital tools and reflect critically on their affordances and risks; a course on Digital Literacy and Academic Writing, in which generative AI has been systematically integrated as an object of critical inquiry; and a service portal on digital teaching and learning, offering didactic teaching-learning scenarios. BediRa operates on the principle that neither students nor teachers hold exclusive expertise in navigating digital transformation: knowledge is understood as co-constructed, and students are positioned as partners rather than recipients (Cook-Sather, Bovill, & Felten, 2014; Weimann-Sandig, 2023). The project thus provides both a practical testing ground and a conceptual reference point for the didactic proposals developed in this paper. In the BediRa test labs, research involving generative AI has consistently been a major focus. Over the course of four semesters, approximately 200 students explored which stages of the research process can be supported by generative AI and why critical thinking strategies help shape interactions with generative AI in line with the human-in-the-loop approach (von Garrel, 2026).

This article argues that both outright bans and uncritical enthusiasm for such tools are inadequate responses to generative AI in academic writing. Three interrelated arguments support a deliberate, pedagogical integration. First, a sociocultural perspective on learning (Vygotsky, 1978) shows that the construction of knowledge is inextricably linked to the cultural tools and symbolic environments in which learners operate. If, as current data on media use consistently confirms (Gonser, 2024; HFD, 2025), students' lived environments are strongly shaped by digital and AI-supported environments, then excluding these tools from higher education does not result in a neutral learning environment; rather, it creates an artificial environment that is disconnected from the lived environment in which students currently find themselves. Second, a critical engagement with any technology requires a well-founded and reflective experience with it, and ideally, this experience should be guided. Universities must therefore increasingly see themselves as spaces for gaining experience in working with generative AI (Cox, 2024). Banning or ignoring generative AI in academic writing instruction means that students will develop their practices informally, influenced by peer networks and commercial platforms rather than by academically grounded judgment. Integrating AI into university curricula also means that we must familiarize ourselves with students' biographical backgrounds. At many universities, the number of first-generation college students has risen sharply—a trend that must be actively promoted as part of efforts to reduce educational inequalities. However, this also means that a large number of students are not automatically familiar with academic standards through family socialization (Lea & Street, 1998). It is precisely these students who, out of a sense of perceived inadequacy, tend to trust the expertise of AI more than their own. Third, prohibitionist strategies reinforce tendencies toward avoidance and defensive regulation, as has already been documented among university instructors in German studies (Weßels, Bils & Budde, 2025; Budde, 2024). This leads to a lack of engagement on the part of instructors with the pedagogical integration of AI into teaching and, consequently, to a role dilemma (Budde, 2024). If students believe that generative AI would have provided them with a more insightful answer than the instructor, how does this affect the relationship and trust between instructors and learners, especially when instructors themselves refuse to engage in such a discourse?

To summarize the argument developed so far: this paper proposes the integration of generative AI into academic writing instruction as a component of critical thinking education – not as a concession to technological inevitability, but as a response to the epistemic realities of students' lived environments. We proceed from the assumption that the capacity to engage reflectively with AI tools is itself an essential academic competence. The didactic goal of the learning formats we propose is therefore not rule compliance, but informed judgment: students should, by the end of such a learning unit, be able to assess for themselves where AI involvement supports their writing process and where it risks displacing the very cognitive work that academic writing is meant to develop. Achieving this requires institutional spaces in which such reflection can take place – spaces that universities, as sites of formation rather than mere credentialing, are uniquely positioned to provide. It also requires, however, a prior and honest inquiry into what students already know about academic writing, how they have engaged with it so far, and where their uncertainties lie. This is precisely the starting point of the BediRa test labs.

4. THE IDEA: A 10-PHASE MODEL OF SCIENTIFIC WORK

The following observation is not merely anecdotal: In BediRa test laboratory sessions on academic writing with AI, 200 first-semester bachelor students who had already completed a mandatory academic writing module were asked to map their own writing process. Over 70% described their process in three stages or fewer—a finding that is striking given that even introductory models in German writing pedagogy operate with at least five steps (Girgensohn & Sennewald, 2012, p. 102). The implication is not that students had forgotten their instruction; it is that the instruction had not produced a workable, differentiated process model that students could carry forward and apply independently. In contexts where generative AI is available, this gap becomes structurally consequential: a student with an underdeveloped process conception has no framework within which to locate AI use, evaluate its appropriateness, or recognize what cognitive work is being displaced. This objection must be taken seriously: if generative AI consistently performs the cognitive operations that academic writing is meant to develop, then integrating it without pedagogical structure does indeed risk foreclosing the formation of core competences. We also provide a platform for them to state that they do not consider the use of AI in academic work to be desirable at all, and to explain why. Consequently, the aim here is not to make AI a requirement, but rather to establish conditions for its use—or even to support the conscious decision to do without it.

In line with the co-constructive learning approach, students developed, discussed, and revised the steps of the academic research process over several phases. In the end, it became clear that, particularly for the integration of generative AI, a granular process model appears practical for students because it helps them break down both work steps and thought processes, thereby enabling them to reflect on them more deeply. This resulted in a **10-phase model**, which is examined in more detail below. We therefore propose this ten-phase model as an inclusive scaffold that translates the abstract recursion of Flower and Hayes (1981) into units that can be taught, discussed, and reflected upon. This should not be misread as a return to linearity. The ten phases are a didactic decomposition, not a sequence: each phase corresponds to a cluster of goals and subprocesses – planning, translation, reviewing – and can be revisited at any point in the writing process. The value of this decomposition is, first, one of inclusivity. Making the phases explicit reduces reliance on the tacit knowledge about how academic writing 'is done' that students from non-academic backgrounds often cannot draw upon. Second, a phase-sensitive scaffold makes it possible to define AI use as guided inquiry rather than product generation, because prompts can be tied to the specific epistemic goals of each phase – challenging assumptions during framing, testing argument coherence during revision. Third, and not least, explicit phases make AI use both documentable and assessable: the relevant question shifts from whether AI was used to how it functioned within a specific phase and in relation to the learning aims associated with it. It is also necessary to provide a terminological clarification prior to the presentation of the phases. Phases 5 (micro-planning and paragraph-level design) and 6 (drafting and initial text production) may appear to be inseparable from a cognitive perspective, and in one sense they are: research in cognitive process (Flower & Hayes, 1981; Hayes, 2012) consistently shows that planning and translating are recursively intertwined rather than sequentially ordered – writers plan as they draft, and drafting reshapes their plans. The distinction drawn here is therefore not a claim about cognitive sequence, it is a didactic one. Students who have previously been exposed to the implicit conventions of academic writing, whether through family socialisation, intensive prior schooling, or extensive academic reading, often exhibit a high degree of automaticity in many micro-structural decisions. These decisions encompass aspects such as the initiation of a paragraph, the indication of an argumentative transition, and the management of the claim-evidence-commentary structure. For students who have not had this access, these decisions remain opaque and effortful precisely because they have never been made explicit (Lea & Street, 1998). The rendering of these elements as a discrete phase does not imply that competent writers treat micro-planning as a separate step. Rather, it is a pedagogical strategy that facilitates the transition from structural planning to the production of a legible and discussable text. This strategy is beneficial for individuals who may not be aware of the expectations at this stage. This design choice is directly consistent with the inclusive rationale previously stated: the ten phases function as a transparency scaffold. The value of these resources lies not in prescribing a particular writing sequence, but in providing a shared vocabulary that students and instructors can use to locate, discuss, and critically evaluate where generative AI was involved—and to what effect.

Ten phases (overview)

We operationalize the recursive writing process as ten phases. The phases are not a prescribed sequence; writers may move back and forth between them as their goals, evidence base, and drafts evolve. The phases are: (1) topic exploration and task clarification, (2) exploratory reading and literature orientation, (3) research question and conceptual framing, (4) planning and macro-structuring the argument, (5) micro-planning and paragraph-level design, (6) drafting and initial text production, (7) revising and evaluating, (8) source integration, citation, and documentation, (9) surface editing and finalisation, and (10) metacognitive reflection on the process. Across all phases, a cross-cutting principle applies: AI outputs are treated as proposals requiring verification, justification, and alignment with disciplinary norms. Students document (minimally) what they used AI for, why in that phase, and how they verified—or decided against—suggestions. **Table 1** summarizes phases 1-9:

Table 1 - Nine phases of Academic Writing with AI-specific writing support. Source: own illustration.

Phase	Process-model link (Flower & Hayes, 1981; Hayes, 2012)	Epistemic purpose (what students should learn/do)	Legitimate AI role (as heuristic aid)
1. Topic exploration & task clarification	Task environment analysis; initial goal setting (planning)	Make constraints explicit (genre, audience, scope, assessment criteria)	Clarifier: generate interpretations of the task; surface hidden assumptions; suggest feasible scopes
2. Exploratory reading & literature orientation	Long-term memory building; planning (knowledge gathering)	Map a field, identify debates, concepts, and search directions (without claiming completeness)	Mapper (verification-heavy): propose keywords, clusters, contrasts based on provided sources/abstracts
3. Research question & conceptual framing	Planning; goal refinement; monitoring (fit of question and evidence base)	Move from topic to investigable question; define terms; select perspective	Socratic framer: critique scope/ambiguity; propose alternative lenses; ask counter-questions
4. Macro-structuring the argument	Planning; goal hierarchy; rhetorical problem solving	Design overall architecture; align sections to the research question	Structure challenger: propose alternative outlines with explicit rationale; identify "burden of proof" points
5. Micro-planning (paragraph-level design)	Planning ↔ translating interface; local goal setting	Turn macro structure into paragraph moves (claims, warrants, evidence placement)	Warrant tester: ask what evidence is needed; stress-test inferences; generate topic-sentence options
6. Drafting & initial text production	Translating; continuous monitoring	Produce a workable draft while preserving authorship of claims and reasoning	Expression support: improve clarity/register; offer alternative phrasing **without** replacing reasoning
7. Revising & evaluating (global/local)	Reviewing; evaluation; revision cycles; monitoring	Test coherence, alignment, and argument strength; revise substantively	Reviewer simulator: generate objections; identify drift/inconsistencies; suggest revision strategies
8. Source integration, citation & documentation	Task environment (integrity norms); reviewing for attribution	Integrate sources with clear function; ensure correct citation; document AI use where required	Source-bound assistant: help with citation formatting and attribution language; never invent sources
9. Surface editing & finalisation	Reviewing at surface level; task constraints	Ensure correctness, consistency, and formatting compliance	Consistency checker: grammar/style, terminology consistency, readability/accessibility checks

Phase 10 (metacognitive reflection) is intentionally excluded from AI support. Reflection serves to consolidate self-regulation and transfer by requiring students to articulate what they learned, where they struggled, and how they will adapt their strategies next time. For this reason, it should be completed independently and assessed as the student's own account of their writing process.

A first empirical indication of the model's pedagogical utility comes from the BediRa writing course itself, where 20 students applied the ten-phase model to an actual term paper and subsequently reflected on the experience. The results, while preliminary, are instructive. More than half of the participants reported that prior to the course, they had engaged with generative AI in a predominantly production-oriented mode – submitting direct instructions such as *"Create a research question for my paper on topic X in module Y"* and adopting the output with minimal revision. Following their engagement with the ten-phase model, several of these students described a qualitative shift in how they formulated their prompts. Rather than requesting a finished product, they began using AI to clarify their own epistemic situation – asking, for instance, what a viable research question might look like for a specific module with a particular thematic focus, and then evaluating the response against their own developing understanding of the subject matter. In essence, what changed was not the tool, but the students' orientation toward it: from output retrieval to process inquiry. At the same time, four of the twenty participants responded to the model with a degree of skepticism that deserves to be taken seriously rather than dismissed. For these students, the ten-phase framework did not feel like a scaffold but like an additional burden: it made visible how much reflexive work a properly conducted writing process actually involves – and how little time the structural conditions of their degree programme allow for it. This is not a weakness of the model, but a systemic observation it enables. If students can now articulate that the problem is not their willingness to reflect but the temporal and institutional conditions under which they write, then the model has already done part of its critical work. The discomfort it produced in these cases is not a failure of the didactic intervention; it is, arguably, one of its more important effects

5. DIMENSIONS OF COMPETENCE FOR USING GENERATIVE AI IN ACADEMIC WRITING

Based on these initial findings, as part of the BediRa project, we have been working with the students to repeatedly discuss and develop the competencies needed to consistently implement such an inclusive 10-phase model—both as learners and as teachers—since our approach is based on co-constructive knowledge acquisition. These competences can be aligned with specific phases of the writing process. The seven competence dimensions outlined below are not intended as a taxonomy for summative grading. The objective is to facilitate discussion and, when deemed pertinent, evaluation of these procedures. For each dimension, we give at least one example from practice, drawn from the BediRa project.

The **first competency is process awareness**, which can be defined as an understanding of academic writing as a multi-stage epistemic and communicative process, rather than as a one-time product to be produced. Students with a high degree of process awareness can distinguish between phases such as topic selection, planning, drafting, revision, and final editing, and articulate the various cognitive and epistemic functions of these phases (Flower & Hayes, 1981; Kieft et al., 2006). In the BediRa writing course, we presented students with a term paper written by AI to help them practice this skill and had them switch roles. They then acted as first and second reviewers to evaluate this paper, meaning they had to work in pairs to examine how the process of topic selection, the logic of the argumentation, and the development of the theoretical framework might have taken place, and how plausible this seemed to them. A student demonstrating low process awareness might describe their writing process in two or three undifferentiated steps and use AI to generate a complete draft. A student demonstrating high process awareness can articulate which specific cognitive goals were at stake in a given phase, explain what they delegated to AI within that phase, and reconstruct the reasoning behind those decisions in Phase 10 reflection. Instructors can assess this aspect by asking students to submit a brief reflection on their work process along with their final paper. In research papers, critical reflection on the research process is an essential component for demonstrating the validity of the research; this approach could be adopted for academic writing as well. The relevant indicator is not the maturity of the report, but its level of detail: For example, a student who can distinguish between a planning decision and a revision decision demonstrates a qualitatively different level of process awareness than someone who views their work as a mere writing and editing process.

The **second dimension concerns AI-related information literacy**, that is, the ability to critically evaluate AI-generated information and sources. Students must understand the potential pitfalls of generative models, including their tendency to invent facts and sources, reproduce biases, and make claims that appear convincing at first glance but are unsubstantiated (Kasneci et al., 2023). The production of so-called fake news or fake facts is a central part of our students' everyday lives. They are inundated with such a flood of information that they often find it difficult to distinguish between reality and pseudo-realities, as recent studies show. In the context of academic work, the BediRa test labs showed that nearly 100% of students trust the scientific facts presented to them by generative AI because they lack the necessary background knowledge to question these facts. In this regard, the focus of skill development here was primarily on demonstrating verification techniques and alternative research methods. Competence in this dimension manifests along a discernible continuum. At a nascent level, students accept AI-generated claims without scrutiny, treating confident prose style as a proxy for factual reliability and making no attempt to verify citations or trace claims to primary sources. At an intermediate level, students demonstrate awareness that AI outputs can be unreliable and apply selective verification – checking sources when they appear implausible or unfamiliar, but still relying on surface plausibility as a first filter. At an advanced level, students treat AI-generated information as a starting point requiring systematic verification by default: they cross-reference claims against primary literature, flag unverifiable assertions in their writing, and can articulate specific mechanisms – such as token-prediction dynamics or training data biases – that explain why a given output may be misleading. This progression from passive reception to active, structurally informed scrutiny is precisely what the model aims to support through its verification-focused phases. Instructors may ask students to document at least one instance in which they verified or rejected an AI-generated claim, including the verification method used. The ability to provide a specific reason—for example, that a cited work does not exist or that the claim misrepresents the source.

As Tai et al. (2018) explain, a **third dimension**

consists of an evaluative assessment specifically applied to AI-generated outputs. Students must assess the suitability of AI-generated texts for academic purposes, evaluating their accuracy, conceptual appropriateness, the appropriate length for the assignment, and compliance with disciplinary conventions. This encompasses not only superficial criteria (e.g., grammar, coherence) but also substantive academic standards, including the quality of argumentation, the use of evidence, and the text's contribution to scholarly debates. In the process of drafting and revising, evaluative judgment is of crucial importance, as students might be tempted to uncritically adopt AI-generated phrasing. Without this competence, the use of AI in education carries the risk of improving the superficial quality of written work while simultaneously undermining students' ability to construct and evaluate arguments independently. In the BediRa project, AI platforms such as POE were used here, which allow for the comparison of different AI agents, so that students can also gain a sense of the different stages of development of generative AI. In addition, AI-generated texts were examined for weaknesses in their argumentation using the Socratic dialogue method (Stavemann, 2008). This dimension is assessable through targeted revision tasks: students are asked to evaluate an AI-generated paragraph against the disciplinary conventions of their field and to justify any changes they make. The relevant indicator is the quality of the justification – whether the student can articulate why a formulation is argumentatively weak or disciplinarily inappropriate, rather than merely substituting their own preferred phrasing

It is also important to consider a **fourth dimension** in policy debates, which is often overlooked. This is the **didactic prompt design**. In contrast to the utilisation of prompts for the primary purpose of saving time or outsourcing cognitive effort, it is imperative for both students and teachers to cultivate the capacity to design prompts that facilitate profound learning. This can be achieved by, for instance, eliciting counter-arguments, alternative theoretical perspectives, or critical questions (Brommer et al., 2023). The ability to competently and promptly design is comprised of the following competencies: In order to formulate effective prompts, it is necessary to consider the phase of the writing process to which they are to be attached. For example, in the context of a discussion section, it is important to suggest possible structures for this section, rather than simply writing it for the reader. In addition, the model should be invited to surface assumptions, limitations, or missing perspectives. Finally, it is important to use AI interaction as a form of scaffolded dialogue that supports conceptual development, rather than replacing it. This dimension is of particular relevance during phases of planning, argument development, and metacognitive reflection, where prompts can be designed to stimulate higher-order thinking. Instructors can ask students to include two or three representative prompts in their AI log, together with a brief reflection on the intent behind each. The performance indicator is whether the prompt is designed to elicit a response that supports the student's own thinking – for instance, by requesting counterarguments or surfacing assumptions – or whether it requests a finished output. The distinction between these two prompt types is itself a teachable and discussable criterion.

The fifth dimension is that of **transparency and documentation of AI use**. This encompasses the capacity to disclose and justify the use of generative AI in the production of an academic text, in accordance with institutional policies and emerging publishing standards (Flanagin et al., 2023). Competence in this area is defined by the following criteria: All students were required to keep records of the phases or stages of the writing process in which AI support was used. In addition, they were tasked with marking where AI had influenced the content and where technical support (e.g., in the form of a grammar check) was provided. Finally, they were asked to create their own AI log for this purpose, the form and scope of which were entirely up to them; the only requirement was that the use of AI had to be traceable from the students' perspective. This is the most directly assessable dimension: the AI log is the artefact. Instructors can evaluate it on three minimal criteria – whether the phase of use is indicated, whether content-level and technical-level AI involvement are distinguished, and whether the student reflects briefly on the decision to use or not use AI at a given point. Completeness is less important than traceability.

The **sixth dimension concerns ethical and legal awareness** regarding the use of generative artificial intelligence in academia. It is essential that students develop a comprehensive understanding of the normative frameworks governing good academic practice, authorship, and the prohibition of deception (Díaz & Nussbaum, 2024). In practice, this means knowledge of institutional regulations, issues of copyright and data protection, as well as the ability to recognize when AI-assisted practices cross the line into plagiarism or contractual fraud. In the BediRa project, we followed the international debates on AI authorship and jointly analyzed the EU AI Act. In particular, the question of what personal data can be fed into generative AI was highly relevant to the students. To this end, the students trained their own AI agents (which is possible on the POE platform) using fictional personal data, while also utilizing local AI models and discussing the training outputs. Assessment here is best embedded in a short reflective question at the end of Phase 10: students are asked to identify one decision point in their writing process where the boundary between AI support and AI displacement was genuinely unclear to them, and to explain how they navigated it. This produces evidence of normative reasoning in context, rather than abstract knowledge of regulations.

Depending on the institutional and disciplinary context, a **seventh**, more advanced **dimension** can be added: the **cooperative and dialogic use of AI**. In this paradigm, the focus is on using generative tools as a third voice in the context of collaborative writing and peer feedback. To illustrate this, consider the use of AI to generate alternative formulations, suggest revision strategies, or model questions from reviewers. These questions were then critically discussed by the group. Competence in this dimension encompasses the coordination of human and AI contributions within groups, the negotiation of differences of opinion between peers and AI suggestions, and the preservation of human authorship and responsibility in multi-author contexts. In collaborative writing settings, instructors can ask groups to document how AI suggestions were discussed and either integrated or rejected, and who took responsibility for the final formulation. The relevant indicator is whether the group can articulate a shared rationale for their decisions, rather than simply noting that AI was consulted.

Over the next few semesters, the task will be to assess whether these competencies need to be supplemented or even rethought in light of the ongoing development of generative AI. It should also be noted that our students primarily come from social sciences and humanities programs. Other disciplines have different competency requirements, and this should not be overlooked. However, as a basic framework, these seven competencies have proven to be extremely robust for both the students and the instructors in our project.

6. CONCLUSION

This paper has argued that the question generative AI poses to universities is not primarily one of detection or permission, but one of pedagogy. Neither prohibitionist control strategies nor uncritical adoption constitute adequate responses to a technology that has become structurally embedded in students' epistemic environments. What is required instead is a deliberate, process-oriented framework that renders AI use visible, discussable, and educationally meaningful. The argument developed across these sections is founded upon three interlocking principles. Firstly, the cognitive process tradition – particularly the recursive model of Flower and Hayes (1981) and its subsequent elaborations – provides a theoretically grounded basis for distinguishing between AI-supported authorship and AI-displaced authorship. This distinction is not merely terminological; it determines whether AI use constitutes a pedagogical resource or a pedagogical risk. Secondly, the ten-phase model proposed here functions as a transparency scaffold rather than a prescriptive sequence. The value of this work lies in its ability to explicate the competencies that are often implicit in the writing process. This explicitness is particularly beneficial for students from non-academic backgrounds, who may lack the familial or social exposure to academic conventions. By associating the implementation of AI with particular epistemic objectives within clearly defined phases, the model shifts the evaluative focus from the mere use of AI to the manner and rationale behind its engagement at a specific juncture. This reorientation gives rise to significant repercussions in the design of assessments. Thirdly, the seven competence dimensions outlined in this paper translate the model's logic into teachable and, where appropriate, assessable criteria. When considered as a whole, these elements portray an academic learner who not only utilizes AI effectively but also engages with it thoughtfully. This involves verifying the outputs of AI, designing prompts that provide support rather than replacing thought processes, transparent documentation of AI involvement, and comprehension of the normative and legal frameworks within which academic AI use is situated. The ten-phase model is not designed for students who have already achieved the competence profile it describes; it is designed for students who are in the process of developing it. The seven competencies do not constitute prerequisites for engaging with the model – they constitute its pedagogical horizon. The model intervenes at the moment of formation, not after it. Framing the competence dimensions as the goal of the intervention, rather than its entry condition, is therefore not a limitation of the approach but its defining rationale.

The preliminary empirical results from the BediRa writing course – while limited in scope – offer an early indication that this approach can produce the intended reorientation. The shift documented in students' prompting behaviour, from direct output requests to epistemic inquiry, reflects precisely the movement from product-oriented to process-oriented engagement that the model is designed to encourage. Concurrently, the scepticism articulated by a minority of participants – their perception that the model illuminates a workload that existing institutional frameworks are unable to accommodate – should not be addressed by diminishing the model's scope. Instead, it should be regarded as a catalyst for introspection regarding the structure of academic writing. When students find it challenging to engage reflexively with their writing process, the constraints are often not due to motivation or capacity, but rather due to limitations in time, the design of the curriculum, and the conditions under which term papers are assigned and assessed. A process-oriented approach to academic writing with AI ultimately gives rise to questions that extend beyond the scope of any individual course. Looking ahead, several lines of inquiry remain open and will require further investigation. The model has thus far been developed and tested within a single institutional context, with students drawn primarily from social sciences and human services programmes. Its transferability to STEM disciplines, to more research-intensive university types, or to contexts with markedly different academic writing conventions has yet to be established empirically. The competence dimensions proposed here must similarly be understood as a working framework rather than a finished taxonomy: they will need to be tested against a broader range of disciplinary practices, learning outcomes, and assessment formats. Most pressingly, the rapid and ongoing development of generative AI models introduces a moving-target problem that any didactic framework must honestly acknowledge. What constitutes a meaningful epistemic contribution from a student writer, and what can be considered routine AI support, is a boundary that will shift as the capabilities of these systems expand. This makes it all the more important that the frameworks we develop now are not built around the limitations of current tools, but around the enduring goals of academic education: the capacity to formulate questions, construct arguments, evaluate evidence, and take intellectual responsibility for one's claims.

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