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Situated AI judgement: A teaching and assessment model for generative AI in higher education

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Abstract

This conceptual design article proposes situated AI judgement as a teaching and assessment model for responsible generative AI use in higher education. It argues that students need to learn not only how to use AI tools, but also how to evaluate, challenge, revise, and refuse AI outputs in relation to disciplinary standards, evidence, and ethical boundaries. Building on evaluative judgement and assessment scholarship, the article presents a four-stage model: pre-AI interpretation, structured AI dialogue, critical comparison, and reflective accountability. The model is developed through an anthropology and heritage studies activity in which students analyse public nomination files submitted under UNESCO's 2003 Convention for the Safeguarding of the Intangible Cultural Heritage, especially the nomination of Momoeria, New Year's celebration in eight villages of Kozani area, West Macedonia, Greece. The article shows how this case can help students examine institutional language, community participation, safeguarding, consent, visibility, and decontextualisation while judging the limits of AI-generated summaries. It contributes to applied learning and teaching by offering an assessment design that makes AI-mediated judgement visible and may be adaptable across disciplinary contexts, with a brief inclusive education example illustrating how the same logic might be adapted beyond heritage studies. The article operationalises responsible AI use not as disclosure or compliance alone, but as an assessable capacity to interpret, verify, critique, and ethically limit AI use within a specific field.

Introduction

Generative artificial intelligence has not created the problem of judgement in higher education, but it has made it harder to ignore. Students have long been assessed through final products that only partly reveal how they interpreted evidence, understood standards, used feedback, revised, or took responsibility for their decisions. Tools such as ChatGPT, Copilot, Claude, and Gemini intensify this problem because they can produce fluent summaries, plausible arguments, and polished prose at speed. Fluency, however, is not a reliable sign of understanding. A coherent final text may conceal weak evidence, generic reasoning, unexamined assumptions, or ethically inappropriate use of material.

The first institutional reaction to generative AI has often centred on cheating, detection, disclosure, and academic integrity. These concerns are legitimate. AI-supported writing raises questions about authorship, plagiarism, assessment validity, and the trustworthiness of submitted work (Cotton et al., 2024). Yet an integrity-centred response is too narrow. It asks whether AI was used and whether the use was allowed. It says much less about whether students can judge AI output, decide when it is useful, notice when it misleads, verify its claims, or recognise when its use should stop.

This article focuses on how AI judgement can be taught and assessed. I use the term *situated AI judgement* to describe students' capacity to evaluate, use, challenge, revise, or refuse generative AI outputs in relation to a specific disciplinary object, evidential standard, and ethical context. The term is deliberately narrower than general AI literacy. It does not mean knowing that AI can hallucinate or learning to write more effective prompts. It means deciding what should be done with AI output in a particular learning situation.

The argument builds on evaluative judgement scholarship. Tai et al. (2018) define evaluative judgement as the capability to make decisions about the quality of one's own and others' work. Bearman et al. (2024) extend this concern to generative AI, arguing that students need to judge AI outputs, AI-supported processes, and AI-mediated judgements while retaining the human role as arbiter of quality. I accept this general argument but place it in a more situated teaching design. Students cannot learn responsible AI use only through abstract rules. They need practice in judging AI in relation to the materials, standards, and responsibilities of a field.

The article develops this model through anthropology and heritage studies. Students analyse public nomination files submitted under UNESCO's 2003 Convention for the Safeguarding of the Intangible Cultural Heritage, with particular attention to the file for Momoeria, a New Year's celebration in eight villages of Kozani area, West Macedonia, Greece. The case is introduced here only as a teaching object: a public policy document whose official language can be compared with student interpretation, AI output, and critical scholarship later in the article.

The proposed activity involves four stages. First, students produce a short interpretation of the nomination file before using the AI. Second, they use AI as a structured interlocutor by asking it to identify actors, assumptions, absences, tensions, and alternative readings. Third, they compare the AI output with their own interpretation, source file, and relevant scholarship. Fourth, they submit a reflective accountability statement explaining what they accepted, rejected, revised, or refused. The sequence is designed to prevent the AI from becoming the first interpreter of the document. Student interpretation comes first; AI is introduced later as a material to be judged.

This article is a conceptual design article and not an empirical evaluation of student outcomes. Its purpose is to define *situated AI judgement* and offer an implementable teaching and assessment model that can be tested and adapted. Although the main teaching case comes from anthropology and heritage studies, the model is proposed as potentially transferable across disciplines. Its core sequence is not tied to UNESCO materials: students first interpret a disciplinary object, then use AI to test or complicate that interpretation, compare AI output with evidence and standards, and finally account for what they accepted, rejected, revised, or refused. A brief example from inclusive education is included later to illustrate how this logic might be adapted beyond heritage studies, while recognising that such cross-disciplinary applicability has not yet been empirically demonstrated. The next sections define the construct, explain the assessment-theory basis for moving from AI use to AI judgement, introduce UNESCO nomination files as a teaching case, present the four-stage model, and discuss assessment, ethics, potential transferability, and future evaluation.

Situated AI judgement as a pedagogical construct

Situated AI judgement names a pedagogical construct rather than technical competence. This refers to students' capacity to decide what to do with AI output in relation to a disciplinary task: whether to trust, challenge, verify, modify, ignore, or refuse the interaction altogether. The construct assumes that AI output has no educational value in itself. Its value depends on the student's ability to evaluate it against evidence, concepts, quality standards, and ethical constraints.

The construct extends evaluative judgement into AI-mediated learning. For Tai et al. (2018), evaluative judgement involves understanding what quality means and applying that understanding in appraisal. Bearman et al. (2024) show that generative AI complicates this process because students must now judge not only their own work and the work of peers but also machine-generated outputs, suggested revisions, and feedback-like comments. Situated AI judgement adds a disciplinary specification: the student is not judging AI in general but an AI-generated response to a particular object, such as a UNESCO nomination file.

The four-stage model draws on several complementary strands of scholarship rather than directly from a single framework. Evaluative judgement provides the central concern by recognising and applying standards of quality (Bearman et al., 2024; Tai et al., 2018). Situated learning adds an important qualification: such judgement develops through engagement with the practices and expectations of a field rather than as a context-free competence (Lave & Wenger, 1991). Feedback literacy is also relevant because externally generated information has to be interpreted and acted upon rather than accepted as authoritative (Carless & Boud, 2018). Recent work on AI-supported assessment further points to the importance of making processes, evidence, and student decision-making visible (Cheng et al., 2024; Fischer et al., 2024). Taken together, these ideas informed the sequence proposed here. Students first establish their own disciplinary reading, then introduce AI as material for scrutiny, compare its output against sources and standards, and finally account for the decisions they made, including decisions not to use or accept AI.

The situated dimension draws on the insight that learning is participation in practice rather than the acquisition of decontextualised knowledge (Lave & Wenger, 1991). Students do not learn responsible AI use through abstract warnings about hallucinations, bias, or disclosure alone. They require criteria to determine whether an AI-generated interpretation is adequate for a specific disciplinary task. In the Momoeria activity, this means asking whether the response treats a nomination file only as a descriptive account or whether it also recognises how the file constructs community, participation, safeguarding, consent, visibility, and transmission as evidence. Such judgement requires familiarity with the object of analysis, the vocabulary of the 2003 Convention, and the disciplinary expectation that institutional texts should be read critically rather than paraphrased (Table 1).

Four components are central. The first is disciplinary anchoring. Students judge AI outputs against field-specific expectations, not against fluency. In the Momoeria case, this means asking whether AI treats the nomination file merely as a descriptive account of a festive practice or whether it recognises it as a policy document that organises claims about community, authority, transmission, participation, and responsibility. The more technical vocabulary of the UNESCO framework is introduced below; at this stage, the point is simply that a good AI response is not one that sounds polished but one that can be judged against the interpretive standards of anthropology and heritage studies.

The second component is evidential evaluation. Students must test claims against the source and relevant scholarship. AI may correctly identify the eight villages, the Pontian background of the practice, or the sections on safeguarding and consent. It may also infer unity where the file offers representation through associations or treat consent documentation as if it settled the question of participation. Situated AI judgement requires the student to distinguish what the file evidences from what AI merely makes plausible.

The third component is ethical discrimination. Students need to know what materials can be used with AI and what should remain outside AI systems. Bearman et al. (2024) argue that students must learn to judge not only AI outputs but also the ethical quality of AI processes, including situations in which privacy, intellectual property, or the nature of the task make AI use inappropriate. This concern has particular force in anthropology, where fieldnotes, interviews, photographs, recordings, and local documents are produced through relationships, permi-

-ssions and expectations rather than as neutral textual inputs (Madden, 2010). In the present activity, a public UNESCO nomination file can be appropriate for classroom AI critique, provided it is used critically and with attention to the Convention framework. An interview transcript, private community document, or unpublished fieldnote usually cannot be treated in the same way. The Operational Directives reinforce this distinction. They link inscription and awareness-raising to participation, free, prior, and informed consent, customary access, and community benefit, while also warning against decontextualisation, misappropriation, over-commercialisation, unsustainable tourism, and violations of intellectual property or privacy rights (UNESCO, 2024, Ch. I.2, para. 2, criterion R.4; Ch. IV.1.1, para. 101(b)–(d), 102(a) & 102(d)–(e); Ch. IV.1.2, para. 104).

The fourth component is reflective accountability. Students must explain how AI shaped their thinking and justify what they accepted, rejected, revised, or refused. A declaration that AI was used is not enough. A short account that identifies a specific AI claim, checks it against the file, and explains why it was kept or discarded offers stronger evidence of learning. The construct therefore shifts the assessment from the amount of AI use to the quality of the student’s decisions about AI-mediated material. A student may use AI minimally and still show strong judgement by identifying unsupported claims, official language, or ethical limits.

Table 1. Situated AI judgement in relation to adjacent concepts

Adjacent concept	Relation to situated AI judgement
AI literacy	Provides background knowledge about AI systems, risks, and uses, but does not by itself show field-specific judgement.
Prompt engineering	May improve the interaction, but the learning outcome is the evaluation of output, not the technical sophistication of prompts.
Academic integrity	Establishes rules and disclosure expectations; situated judgement asks what the student did with AI and why.
Evaluative judgement	Provides the main assessment theory foundation: decisions about quality are extended to AI-mediated work.
Feedback literacy	Frames AI output as feedback-like information that must be interpreted rather than received as an authoritative source.
Responsible AI use	Overlaps strongly, but situated AI judgement includes disciplinary standards and justified refusal.
AI Assessment Scale	Specifies the levels of permitted AI involvement within an assessment task; situated AI judgement instead concerns the quality of students’ decisions about AI-generated material within those boundaries.

From AI use to situated judgement

Having defined situated AI judgement as a disciplinary and ethical extension of evaluative judgement, the next question is how such judgement can be taught and assessed. To teach situated AI judgement, assessments must make students’ decisions about AI-generated material visible. This extends the evaluative judgement scholarship. Tai et al. (2018) define evaluative judgement as the capability to make decisions about the quality of one’s own

and others' work. In AI-mediated learning, the object of judgement expands: students must appraise not only their own draft or a peer's response, but also AI-generated summaries, suggestions, revisions, and feedback. Bearman et al. (2024) argue that generative AI makes this capability newly urgent because students may be able to produce acceptable-looking work before they have developed the standards needed to evaluate it.

Accuracy is necessary but not sufficient. A response may be factually plausible and still be educationally weak. In the case of a UNESCO nomination file, AI may identify the element, list the relevant actors, and reproduce the language of safeguarding or participation, while failing to ask how those categories organise authority, evidence, and representation. Situated judgement concerns the student's capacity to decide whether an output is adequate for the disciplinary task at hand.

Therefore, assessment design is central. Rather than inspecting finished essays for traces of AI, teachers can create conditions in which students compare AI-generated material with explicit standards of quality. Sadler's (1989) account of formative assessment is useful here: students need to grasp standards, compare their work against them, and act on the gap. Boud's (2000) argument for sustainable assessment adds a further point: assessment should prepare students for future judgement, not only certifying current performance. Under AI conditions, these arguments acquire new objects. Students need practice in appraising machine-generated summaries, suggestions, and revisions as provisional material, deciding what can be used, what must be checked, and what should be rejected.

Feedback literacy helps to refine this point. Carless and Boud (2018) define feedback literacy as the capacity to make sense of information and use it to improve work and learning strategies. AI output can function as feedback-like information, but it is not equivalent to that of teachers or peers. It lacks relational responsibility and reliable evidence. Therefore, students must learn to treat AI output as provisional material for interpretation, not as feedback to receive.

Recent work on AI-supported assessment reinforces this need, and the present article should be read as contributing to that active conversation rather than as opening an empty field. Fischer et al. (2024) show that students' claims about AI use do not necessarily correspond to sophisticated sensemaking or critical evaluation. Hu et al. (2025), in a review of digital technologies in authentic assessment, find that digital tools are often built into task design but less consistently into evaluative judgement and feedback processes. Other work has also moved towards process-visible assessment. Cheng et al. (2024), for example, propose an evidence-centred approach to assessing human-AI collaborative writing. The AI Assessment Scale takes a different but complementary approach by helping educators specify the permitted level of AI involvement in an assessment (Perkins et al., 2024), with its pilot implementation suggesting that this can clarify expectations and support assessment redesign (Furze et al., 2024). Situated AI judgement addresses a different question. Rather than specifying how much AI use is permitted, it focuses on what students do with AI-generated material once it enters the task: how they judge it against disciplinary evidence and standards and whether they can explain why they accepted, revised, challenged, or refused it. Recent work on ChatGPT and DeepSeek similarly frames generative AI in higher education around the tension between learning support, dependency, ethical risk, and the possible erosion of critical thinking (Nair et al., 2026). The present article addresses that concern at the level of assessment design: it asks how students can be required to evidence judgement rather than merely use, disclose, or depend on AI output.

Nomination files under the 2003 UNESCO Convention as a teaching case

The teaching case begins with a particular kind of source: a 2003 UNESCO Convention nomination file. For students, such a file is accessible enough to read as a public document, but complex enough to resist simple summarisation. Its pedagogical value lies in the double reading it demands. On one level, students must understand what the file says about an element, its practitioners, its transmission, and its proposed safeguarding. On another level, they must ask how the file makes those claims persuasive within the Convention system: who is authorised to speak, how participation is evidenced, what kinds of risk are acknowledged, and what forms of local complexity become harder to see.

The key terms are deceptively procedural. The 2003 Convention defines intangible cultural heritage as “the practices, representations, expressions, knowledge, skills” and associated “instruments, objects, artefacts and cultural spaces” that “communities, groups and, in some cases, individuals recognise as part of their cultural heritage” (UNESCO, 2003, Art. 2.1). Safeguarding refers to “measures aimed at ensuring the viability of the intangible cultural heritage,” including identification, documentation, research, preservation, protection, promotion, enhancement, transmission through formal and non-formal education, and revitalisation (UNESCO, 2003, Art. 2.3). A nomination file is the formal document through which a State Party proposes an element for inscription. For the Representative List¹, the Operational Directives state that the file must demonstrate that the element constitutes intangible cultural heritage, contributes to visibility and awareness, has safeguarding measures, has been nominated with the widest possible participation and free, prior, and informed consent, and is included in an inventory (UNESCO, 2024, Ch. I.2, para. 2, criteria R.1–R.5).

These criteria make the nomination files pedagogically rich. They provide students with a clear documentary structure to analyse while also inviting more critical questions. What is being called a community? Who is authorised to speak? What constitutes participation? Does consent documentation reveal substantive involvement or only traces of administrative requirements? How does safeguarding relate to promotion, tourism, education, and state oversight? These are not incidental queries. They are central to the anthropology of heritage governance, where nomination files are read not only as sources of information but also as documents that organise authority, representation, participation, selection, and value (Adell, 2015; Bortolotto et al., 2020; Brown, 2005; Hafstein, 2009; Karampampas, in press; Kirshenblatt-Gimblett, 2004; Smith, 2006).

Heritage scholarship has long shown that institutional heritage language is not neutral. Smith’s (2006) work on authorised heritage discourse and Kirshenblatt-Gimblett’s (2004) account of intangible heritage as metacultural production both draw attention to the labour through which practices become legible as heritage. Hafstein (2009) makes this point more specific to UNESCO listings: lists are selective devices that decontextualise and recontextualise practices, give them comparative visibility, and may be used for purposes, such as tourism or competition, that exceed safeguarding. Put more simply, the act of naming a practice as heritage does not merely describe it. It gives that practice a second life as an object to be documented, displayed, evaluated, safeguarded, promoted, and governed. This is why a nomination file should not be read only for what it says about an element, but also for what it does to the element by translating it into policy. Adell (2015) shows how the demand for participation in an ICH dossier can produce a managed polyphony, in which internal differences are translated into a more unified account. Bortolotto et al. (2020) further show how participation can become something that must be demonstrated bureaucratically. Related work on the Greek ICH system shows how this process can also produce an administratively legible version of “community” that does not necessarily exhaust the wider social field from which it is drawn (Karampampas, in press). For students, this means that the nomination file is both a source and an object of critique.

The Momoeria nomination file offers a compact but demanding example. Submitted by Greece and inscribed in 2016, it concerns a New Year celebration practised in eight villages of Pontian origin in the Kozani area of West Macedonia. The file identifies dancing and theatrical teams, village associations, musicians, leaders, craftspeople, local communities, researchers, journalists, municipalities, and state bodies. It includes sections on transmission, social functions, safeguarding measures, community participation, free prior and informed consent, customary access, and inventorying (UNESCO, 2016).

Several tensions make the file especially useful for AI-supported teaching. It presents Momoeria as a living practice transmitted through families, village associations, oral narration, and annual performance, while also translating the practice into the categories required by UNESCO. It describes public meetings, village discussions, association involvement, and the preparation of the inventory and international file. It also records concerns about decontextualisation, tourist display, and alterations designed to make the practice appear more authentic. Students can therefore see participation as a criterion, a documentary claim, and an empirical question.

¹ The Convention establishes two lists and one register: the Representative List of the Intangible Cultural Heritage of Humanity, the List of Intangible Cultural Heritage in Need of Urgent Safeguarding, and the Register of Good Safeguarding Practices. For their purposes, see <https://ich.unesco.org/en/purpose-of-the-lists-00807> (accessed 29 June 2026).

Karampampas (2021) adds a second layer. In his analysis of the Greek implementation of the 2003 Convention, Momoeria appears as a case in which inscription raised the status of a local performative practice, increased visibility among folk dance practitioners, and opened spaces for marketisation, tourism, museum display, and public recognition. The point for students is not simply that inscriptions have effects. The file's language of safeguarding and visibility must be read alongside scholarship on how such recognition changes value and status.

Tsekouras (2026) adds an even sharper post-inscription perspective. Based on fieldwork conducted between 2022 and 2024, he examines how the inscription affects the poetics, economy, and sociality of Momoeria. The article shows that UNESCO recognition does not simply produce visibility. It intensified tensions around popularity, visitor pressure, outsider imitations, authenticity, local ownership, unofficial copyright claims, and fears of folklorisation. Tsekouras argues that the inscription both verifies and unsettles UNESCO objectives, revealing a tension between sustainability as dissemination or commercialisation and safeguarding as local ownership.

This makes Tsekouras (2026) particularly valuable for the present article. It shows what the official nomination file and a likely AI summary of that file may not foreground. A generative AI tool asked to summarise Momoeria may reproduce the nomination's smooth account of community participation, safeguarding, and visibility. It may not notice the later anxieties about popularity, the pressure on households to provide hospitality, the privileging of dance over theatrical improvisation, or the concern that dissemination can become delocalisation. Read alongside Karampampas (2021) and Tsekouras (2026), the nomination file becomes a strong teaching case for why students must compare official accounts, AI summaries, and critical ethnographic analysis.

The situated AI judgement model

The model translates the preceding arguments into teaching sequences. Its governing principle is simple: students should encounter AI after they have begun to form their own interpretations. If AI is used first, it can quietly establish the categories and priorities through which the student later reads the text. If AI is introduced after an initial reading, it becomes a material to test rather than a frame to inhabit.

The four stages are pre-AI interpretation, structured AI dialogue, critical comparison, and reflective accountability. They are presented here through the Momoeria nomination file, but the sequence is not tied to that case alone. Figure 1 summarises the sequence and assessment controls that keep AI use subordinate to disciplinary interpretation.

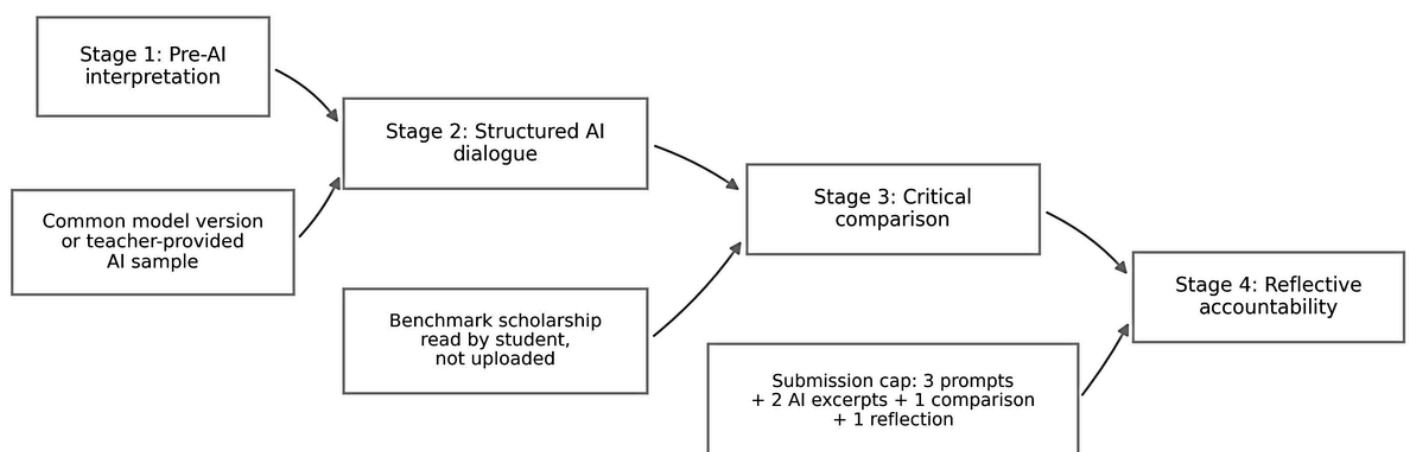


Figure 1. Controlled assessment workflow for situated AI judgement

Stage 1: Pre-AI interpretation

Students first produce a short interpretation of the selected nomination file without the use of AI. In the Momoeria activity, this might be a 400-600 word response identifying the element, the communities or groups represented, the main safeguarding claims, the forms of participation described, and questions about representation, consent, visibility, tourism, decontextualisation, or institutional framing.

The aim is not to produce a complete analysis. It is to establish an interpretive baseline. A student might note, for example, that the nomination presents Momoeria as a living New Year celebration transmitted through families, village associations, oral narration, and annual performance, while also showing the involvement of state bodies, municipalities, researchers, journalists, and UNESCO procedures. This initial position gives the student something to defend, modify, or reject later.

Stage 2: Structured AI dialogue

Students then use AI as an interlocutor. They are not rewarded for the length of the interaction or for prompt sophistication. The point is to ask questions that test disciplinary interpretation. Suitable prompts include: Which actors are made central in this file, and which may be less visible? What assumptions about community, participation, safeguarding, transmission, and consent shape the nomination? Does the file treat the eight villages and associations as unified, or does it reveal differences? What risks of decontextualisation, tourism, or folklorisation are mentioned or implied? Which claims would require further evidence? Does your response reproduce the file's official language? How would the interpretation change if read alongside Karampampas (2021) and Tsekouras (2026)?

These prompts do not turn AI into an authoritative source. They turn AI into a source of provisional answers, some of which are useful and some poor. A response may help students notice the consent section, safeguarding measures, or the role of associations. It may also give generic language about community identity, living heritage, or tradition, and fail to see the politics of documentation. Both outcomes are educationally useful if students are required to judge them.

Stage 3: Critical comparison

The third stage is the analytical centre of the model. Students compare their pre-AI interpretation, selected AI outputs, the nomination file, and relevant critical scholarship. The order matters. In this version of the activity, students use AI to engage with the public UNESCO nomination file, not to process the critical scholarship for them. Tsekouras (2026) is introduced as a benchmark text that students read themselves to evaluate what remains invisible when AI works mainly from the official account.

This design prevents critical scholarship from becoming an object outsourced to AI. The aim is not for students to ask AI to summarise Tsekouras and then reproduce an already critical response. The aim is for students to notice the gap between an AI-mediated reading of the nomination file and an ethnographic analysis of the later effects of the inscription. Tsekouras (2026), for example, allows students to see that official visibility can coexist with local unease about dissemination, ownership, imitation, visitor pressure, and festivalisation. These tensions are not easily recoverable from the nomination file alone.

The comparison should therefore be concrete. Did AI identify what the nomination file actually says? Did it distinguish between documented consent and the wider problem of participation? Did it notice that tourism and decontextualisation appear as risks? Did it treat community as a unified actor? What becomes visible only after reading Tsekouras (2026)? How does the later ethnographic account complicate the official language of visibility, safeguarding, and participation? Did AI invent claims, generalise from the file, or flatten Pontian, refugee, regional, and village-specificities?

This stage teaches the difference between summary, critique, and judgement. AI may summarise a nomination file well. It may list the elements, villages, performers, safeguarding measures, and consent documents. Yet analysis requires a further step: judging how the file produces authority, how it translates practice into UNESCO

categories, and what later scholarship reveals about the effects of inscription. Critical scholarship is therefore not a shortcut to be processed by AI, but a disciplinary standard against which students learn to test AI-mediated interpretation.

Stage 4: Reflective accountability

Finally, students submit a reflective accountability statement. This is not a confession or a generic AI-use declaration. It is an account of judgement. Students explain what they accepted, rejected, revised, or refused, and why. They should refer to specific AI claims, parts of the nomination file, and, where appropriate, scholarly sources.

A strong reflection might state that AI helped identify the file’s safeguarding measures but treated them as neutral, whereas the student’s reading of Karampampas (2021) and Tsekouras (2026) showed that visibility and dissemination could alter value, ownership, and performance. Another student might reject an AI claim of community consensus because the file evidences letters and association involvement, not the full range of views across the eight villages. A third might refuse to upload interview material or photographs, explaining that public policy documents are acceptable for this activity, but relationally produced ethnographic materials are not.

Table 2. Four-stage model for assessing situated AI judgement

Stage	Student work	Evidence of judgement
Pre-AI interpretation	Students read the nomination file and write an initial interpretation without AI.	Establishes a disciplinary baseline before AI performs the task.
Structured AI dialogue	Students prompt AI to test their assumptions, absences, evidence, and alternative readings.	Shows whether AI is used as an interlocutor rather than an authority.
Critical comparison	Students compare their interpretation, AI output, the file, and relevant scholarship.	Identifies accuracy, omission, distortion, official language, and unsupported claims.
Reflective accountability	Students explain what they accepted, rejected, revised, or refused.	Justifies AI-related decisions through evidence, disciplinary standards, and ethics.

The sequence keeps AI subordinate to disciplinary interpretation (Table 2). It also provides teachers with assessable evidence of the process. Instead of trying to infer hidden AI use from style, the teacher evaluates how the student handled AI-generated material.

Assessment design and reflective accountability

The model depends on the assessment design. A conventional essay can show whether a student has produced a coherent final analysis, but it may conceal how the analysis was formed. Under AI conditions, this concealment matters. The same polished essay may reflect careful judgement, uncritical adoption of AI output, extensive AI rewriting, or some mixture of these. The assessment must therefore make the process visible without turning the task into bureaucratic surveillance.

A compact portfolio works well; however, it should be tightly capped. In the Momoeria activity, students might submit the following: (1) a 400–600 word pre-AI interpretation; (2) exactly three prompts; (3) exactly two short AI excerpts, each no more than 120–150 words; (4) a 600–800 word annotated critical comparison; and (5) a 500–700 word reflective accountability statement. Each AI excerpt should be tagged according to its evidential role, for example, accurate summary, unsupported inference, mirrors official language, misses participation issue, ethically refused, or revised by student. This prevents the portfolio from becoming a prompt archive and directs assessment towards judgement.

The AI environment should also be standardised. Where possible, all students should use the same institutionally approved model. In large classes or where equity, access, or data concerns make direct AI use problematic, teachers can provide a common AI response for all students to critique. This route is not a lesser alternative. It allows students to demonstrate situated AI judgement by evaluating AI-generated material without requiring them to use a commercial system. It also reduces the variation caused by subscription level, platform familiarity, or model differences.

Benchmark scholarship should be protected from outsourcing. In this version of the activity, students use AI to engage with the public UNESCO nomination file, not to process Tsekouras (2026) or other critical scholarship. The assignment brief should state that secondary scholarship must be read directly and not uploaded to an external AI system. Students should therefore use Tsekouras (2026) as a benchmark for judging what AI missed, not as another text to be summarised by AI.

The AI transcript is not an achievement in itself. A long interaction should not receive credit unless the student evaluates it well. Conversely, brief AI use may demonstrate strong learning if the student identifies precisely what the AI missed or why a suggestion was rejected. To avoid performative scepticism, each judgement claim in the comparison should be linked to one AI sentence and one source passage. A claim such as “AI flattened the community” is too generic unless the student shows which AI wording produced that flattening and which part of the nomination file or scholarship complicates it.

Reflective accountability should move beyond statements such as “AI helped me think”. Students can be asked to answer: What was my interpretation before AI? What did AI help me notice? What did it miss, flatten, or distort? Did it reproduce the file’s official language? Which claims did I verify against the nomination file or scholarship? Which suggestions did I reject? Did I refuse AI use for any material or purpose? These questions direct students towards specific acts of judgement.

The task should be taught before it is assessed. One workshop can provide all students with the same extract from the Momoeria file and the same AI response. In groups, they identify accurate summaries, unsupported inferences, official vocabulary, missing voices, and ethical risks. A second workshop can compare two AI responses to the same prompt: one fluent but generic, and the other less polished but more attentive to participation, ownership, and decontextualisation. A third exercise can focus on refusal. Students identify materials related to a heritage topic that should not be uploaded to an external AI system: interview transcripts, unpublished fieldnotes, personal correspondence, photographs with identifiable people, consent forms, or local documents not already public. They then explain why refusal is appropriate. This exercise makes a key principle explicit: responsible AI use includes non-use.

A short calibration exemplar should also be provided, either in the manuscript or as an appendix: one student prompt, one AI excerpt, one comparison paragraph, one reflective paragraph, and a brief explanation of why it constitutes strong or middling evidence of judgement. Exemplars reduce ambiguity for students and support more consistent marking processes. The point is not to prescribe a single correct answer but to show what traceable judgement looks like.

The rubric should be shared before the activity and used in teaching, not only for marking (Table 3). Students need opportunities to apply these criteria to examples. This follows a broader assessment principle: criteria become meaningful through use, comparison, and discussion, not by being listed in an assignment brief. Weight-

-ing also makes the priorities of the model explicit. Students are not rewarded for producing long, prompt histories or polished AI-assisted prose. They are rewarded for source-grounded interpretation, disciplined AI dialogue, evidential comparison, ethical discrimination, and accountable judgement.

This approach also changes how academic integrity is evidenced. Disclosure remains necessary, but it is only the beginning. A statement that a student used AI for “ideas” records use; it does not show judgement. Prompt excerpts, source comparisons, annotations, and reflective justifications offer stronger assessment evidence. The teacher assesses documented reasoning rather than guessing from the prose style.

The design is manageable only if students submit selected excerpts rather than full transcripts. Assessors should not be expected to read long prompt histories or evaluate the technical quality of every AI exchange. In large classes, the reflective component can be structured under four headings: initial interpretation, AI contribution, critical evaluation, and accepted/rejected/revised/refused. In smaller seminars, students can discuss selected AI excerpts with peers before final submission. The aim is not to create a paper trail for its own sake, but to provide limited, purposeful evidence of the decisions that matter educationally.

Table 3. Weighted rubric criteria for assessing situated AI judgement

Criterion	Suggested weighting	Strong evidence
Pre-AI interpretation and key terms	25%	The student offers a source-grounded initial reading and uses relevant terms, such as intangible cultural heritage, safeguarding, community, participation, consent, inventory, and Representative List, accurately and analytically.
Quality of AI dialogue	20%	The three prompts test, challenge, or extend interpretation rather than asking only for a summary or writing assistance. The selected AI excerpts are purposeful and appropriately tagged.
Critical comparison and evidential checking	30%	The student compares their own reading, AI output, the nomination file, and critical scholarship. AI claims are checked against evidence; unsupported claims, overgeneralisations, hallucinations, official language, omissions, and distortions are identified.
Ethical discrimination	15%	The student distinguishes public teaching materials from sensitive, copyrighted, personal, or relationally produced materials, and justifies any refusal to use AI.
Reflective accountability	10%	The student clearly explains what was accepted, rejected, revised, or refused, with reasons grounded in evidence, disciplinary standards, and ethics.

Ethical and legal boundaries

Ethical and legal boundaries are part of the judgement students are being asked to practise. A student who can explain why an AI interpretation is weak demonstrates one kind of judgement; a student who can explain why a particular text, image, or transcript should not be uploaded demonstrates another. The activity uses public UNESCO nomination files by design. Public policy documents allow students to examine institutional language, participation, consent, safeguarding, and visibility without using unpublished fieldwork material. Yet, public availability does not remove responsibility. Nomination files may refer to named practitioners, associations, local authorities, photographs, videos, signatures, or consent documents. Students should learn to distinguish legitimate analysis of a public document from unnecessary extraction of personal or decontextualising detail.

This distinction is especially important in anthropology. Fieldnotes, interviews, recordings, photographs, personal correspondence, workshop notes, and local archives are not neutral data. They are produced through access, trust, and expectation. Even anonymised material can carry obligations to the persons and groups through whom it was produced (Madden, 2010). Brown's (2005) discussion of heritage trouble is useful here because it shows that intangible heritage protection raises difficult questions about information movement, public availability, ownership, and control over representation. Work on Indigenous data governance makes this point even more explicit. Although not every heritage classroom example involves Indigenous data, the CARE principles foreground collective benefit, authority to control, responsibility, and ethics as data governance concerns that exceed individual privacy or narrow copyright (Carroll et al., 2020). Students should therefore be instructed not to upload non-public ethnographic material, community-produced materials, or sensitive local documents to external AI systems unless there is explicit institutional approval, suitable consent, and a secure tool approved for that purpose.

The Momoeria file makes this issue concrete. It presents the performance as public and without customary restrictions on access, yet it also notes that transmission involves older narrators disclosing personal information and family stories. Public performance, public nomination, personal memory, and family knowledge are not the same kind of material. A public file may be suitable for AI-supported critique; intimate narratives connected to transmission may not be. The same logic applies to AI outputs. The Operational Directives identify decontextualisation, misappropriation or abuse of knowledge and skills, over-commercialisation, and unsustainable tourism as specific risks of awareness-raising (UNESCO, 2024, Ch. IV.1.1, para. 102(a) & (d)–(e)). They also address intellectual property rights, privacy rights, and other appropriate forms of legal protection in relation to awareness-raising and commercial activities (UNESCO, 2024, Ch. IV.1.2, para. 104). These concerns should shape the AI activity. A response describing Momoeria as a colourful tourist festival may appear harmless, but it risks reducing the practice to spectacle and ignoring the file's own concern with local context. Tsekouras (2026) shows why this matters: popularity can place pressure on households, shift attention from theatrical improvisation to dance display, and intensify anxieties about folklorisation.

Operational guidance should therefore be explicit and lean. Students should know which tools are permitted, whether institutional accounts are required, what must be disclosed, and which materials are off-limits. Personal data, confidential records, unpublished research data, identifiable images, consent forms, signatures, private correspondence, student records, and third-party copyrighted materials should not be uploaded to external AI systems unless the tool, permission structure, and institutional policy clearly allow it. Where direct AI use raises access, equity, or data concerns, students can instead critique a teacher-provided AI output.

Bias should also be treated as a disciplinary issue, not only a technical one. In heritage policy analysis, generative AI may reproduce dominant or highly visible language: treating UNESCO terminology as neutral, state-centred accounts as sufficient, or documented consent as equivalent to settled participation. Students should therefore ask whose language the AI amplifies, which actors become authoritative, and who remains absent or difficult to see.

Refusal is central. In many AI-inclusive assignments, non-use appears as absence. Here, justified refusal counts as evidence. A student may refuse to upload a transcript, refuse an AI suggestion that misrepresents the file, or refuse to let AI supply the first interpretation of a document. These refusals are not failures to engage. They are acts of responsible judgement.

Potential transferability and adaptation across disciplines: An inclusive education example

The model is situated in anthropology and heritage studies, but its design logic is proposed to be adaptable to other disciplinary contexts. What is proposed as transferable is not the Momoeria case or UNESCO framework. The sequence of what travels is as follows: students first interpret a disciplinary object, then use AI to test or complicate that interpretation, then compare AI output with evidence and standards, and finally account for what they accepted, rejected, revised, or refused.

A brief example from inclusive education illustrates how this logic might be adapted beyond the realm of heritage studies. Inclusive education is used here in the broad sense of identifying and removing barriers to participation and learning for all learners, rather than as a narrow synonym for the provision of pupils with formally recognised additional needs (Ainscow, 2020). In a teacher-education or education-studies module, students might analyse a public inclusion policy, a fictionalised classroom scenario, or an anonymised support plan prepared specifically for teaching purposes. Before using AI, they would identify the assumptions the document makes about learners, support, differentiation, teacher responsibility, and institutional constraints. They could then ask AI to generate an alternative interpretation or identify possible exclusions. The critical comparison would not ask whether AI produced fluent inclusion language but whether it recognised the tensions between policy ideals, classroom practice, resource limits, teacher identity, and learner voice. Students would also need to judge ethical boundaries: a public policy document or fictionalised case may be appropriate for AI-supported critique, whereas real pupil records, family correspondence, or identifiable classroom observations should not be uploaded. The same four-stage sequence could be applied, but the standards of adequacy would shift from heritage governance to inclusive educational judgement.

Transferability should not be confused with generic AI literacy. The same prompts and criteria cannot be simply moved from anthropology to law, health education, business, or history. Each field must decide what counts as evidence, what counts as quality, what forms of reasoning are valued, what ethical boundaries apply, and what would count as justified refusal. In law, students may judge whether AI distinguishes binding authority from commentary. In history, they may test AI against source criticism and the risk of anachronism. In education, they may examine whether AI produces generic inclusion language or attends to the complexity of pupils, families, and institutions. In health-related teaching, public or fictionalised material may be appropriate, while real patient data should not enter the activity.

The following questions can guide adaptation: What object will students analyse? What must they do before AI use? What role can AI legitimately play? What claims require verification? Which disciplinary concepts define quality? What material must not be uploaded? What would count as justified refusal? What process evidence will students submit? These questions prevent the activity from degenerating into “ask AI and reflect”. They keep the task anchored in a field.

The model could also be adapted by level. First-year students might critique a teacher-provided AI response to a short extract. Advanced undergraduates might produce their own prompts and comparisons. Postgraduate students might connect AI critique to scholarship and ethical decision-making. Direct AI use is not always required. Students who do not wish to use AI or cannot use a particular platform can still demonstrate situated AI judgement by critiquing pre-generated outputs.

The wider point is that graduates will encounter AI-generated summaries, recommendations, drafts, and feedback in many domains. They will need to judge these outputs rather than consuming them. Authenticity in this model does not mean narrowly reproducing a workplace task. It means asking students to practise a consequential form of judgement: deciding when machine-generated material is useful, when it is weak, and when it should be refused.

Limitations and future evaluation

This article offers a conceptual design model rather than evidence of measured learning gains. It does not claim that situated AI judgement has already improved students' evaluative judgement, disciplinary interpretation, or ethical decision-making. Such claims would require classroom implementation and systematic evaluation. The model should therefore be read as a design proposal grounded in assessment theory and disciplinary practice, not as an empirical validation study.

Several limitations follow. Students may still treat AI as an authority, especially when they lack confidence in their subject matter. Such reflective accounts may overstate critical engagement. Different tools, versions, languages, and access levels may produce uneven AI output. Prompt behaviour will also change over time. The model's durability lies less in any particular tool than in the sequence of interpretation, dialogue, comparison, and accountability.

The case also has limitations. Public UNESCO nomination files are suitable teaching objects, but they are not complete accounts of the practices they describe. Tsekouras (2026) makes this particularly clear for Momoeria: post-inscription effects around popularity, imitation, ownership, and folklorisation become visible through fieldwork in ways that the nomination file cannot fully capture. Students should therefore learn that the file is an object of analysis, not a transparent window onto the whole social life of the practice.

Assessment workload is another concern. Process-based assessment can become burdensome if students submit full transcripts and lengthy reflections. Implementation should be lean: selected excerpts, clear templates, and rubrics focused on judgement rather than tool mechanics. Large classes may require structured forms, while seminars can allow for more open reflective prose.

Future evaluations can proceed through small-scale implementation studies. Data might include pre-AI interpretations, selected AI outputs, critical comparisons, reflective accountability statements, final analyses, and assessor comments. Analysis could ask whether students identify AI errors, verify claims, notice official language, compare sources, and justify acceptance, rejection, revision, or refusal. Comparing student self-reports with assessor judgements would be especially useful, as reported AI use does not necessarily indicate critical engagement (Fischer et al., 2024). Existing AI literacy frameworks may also inform future evaluations, but they should not be treated as direct measures of situated AI judgement. Long and Magerko's (2020) competencies include critical evaluation of AI technologies, communication and collaboration with AI, and practical AI use. Future studies could examine how these general competencies interact with field-specific capacities to verify evidence, notice institutional language, apply disciplinary standards, and justify ethical refusal.

Further studies could examine the changes between pre-AI interpretation and final submission. Did AI dialogue help students ask sharper questions, or did it pull them towards generic phrasing? Did students become better at distinguishing summary from analysis? Did they learn to use scholarship, such as Karampampas (2021) and Tsekouras (2026), to challenge the official account? Ethical discrimination should also be evaluated: can students identify which materials may be used with AI and which should remain outside it?

Longitudinal studies would be valuable in this regard. Situated AI judgement is unlikely to develop through a single assignment. Students may need repeated opportunities across a programme: identifying AI inaccuracies in early courses, evaluating AI-generated arguments later, and justifying ethical refusals in research-based work. Assessor reliability also needs attention. If teachers assess AI judgement, they need shared examples and moderation practices.

Despite these limitations, the model offers a practical starting point. It does not ask teachers to solve every problem raised by generative AI. It asks them to redesign one part of assessment around a more precise educational aim: making students' AI-mediated judgements visible.

Conclusion

Higher education should not merely train students to operate generative AI tools. It should teach them to remain responsible interpreters in AI-mediated environments. This requires more than disclosure policies or detection technologies. It requires assessment designs that show how students interpret, compare, verify, revise, and take responsibility for their decisions.

Situated AI judgement offers one such design. Building on evaluative judgement, it asks students to evaluate AI outputs in relation to a disciplinary object, evidential standard, and ethical context. In the UNESCO intangible heritage activity, students analyse a public nomination file, use AI as an interlocutor, compare its output with the file and critical scholarship, and explain what they accepted, rejected, revised, or refused. The Momoeria case illustrates why this matters. AI can reproduce the official voice of safeguarding, participation, and visibility, while scholarship such as Karampampas (2021) and Tsekouras (2026) reveals effects and tensions that the official file does not fully show.

The model's contribution is both conceptual and practical in nature. Conceptually, it operationalises responsible AI use as a form of situated evaluative judgement. Practically, it offers a sequence, forms of assessment evidence, and rubric criteria that may be adapted across fields, although the effectiveness of such adaptations requires empirical evaluation to be determined. It does not seek to increase AI use for its sake. It seeks to make judgement visible: the judgement to accept, the judgement to revise, the judgement to challenge, and, when necessary, the judgement to refuse. The central educational task in the age of generative AI is therefore not production but judgement. Students need to learn what AI makes visible, what it obscures, whose language it reproduces, and where its use should end. Such work is disciplinary, evidential, ethical, and teachable.

AI use disclosure

An AI-assisted writing tool was used solely for proofreading and improving the clarity of expression. All ideas, arguments, interpretations, and the selection and use of sources are entirely my own. All references were independently verified. No generative AI was used to develop the article's intellectual content or conduct research.

References

- Adell, N. (2015). Polyphony vs. monograph: The problem of participation in a French ICH dossier. In N. Adell, R. F. Bendix, C. Bortolotto, & M. Tauschek (Eds.), *Between imagined communities and communities of practice: Participation, territory and the making of heritage* (pp. 237–247). Göttingen University Press.
- Ainscow, M. (2020). Promoting inclusion and equity in education: Lessons from international experiences. *Nordic Journal of Studies in Educational Policy*, 6(1), 7–16. <https://doi.org/10.1080/20020317.2020.1729587>
- Bearman, M., Tai, J., Dawson, P., Boud, D., & Ajjawi, R. (2024). Developing evaluative judgement for a time of generative artificial intelligence. *Assessment & Evaluation in Higher Education*, 49(6), 893–905. <https://doi.org/10.1080/02602938.2024.2335321>
- Bortolotto, C., Demgenski, P., Karampampas, P., & Toji, S. (2020). Proving participation: Vocational bureaucrats and bureaucratic creativity in the implementation of the UNESCO Convention for the safeguarding of the intangible cultural heritage. *Social Anthropology/Anthropologie Sociale*, 28(1), 66–82. <https://doi.org/10.1111/1469-8676.12741>
- Boud, D. (2000). Sustainable assessment: Rethinking assessment for the learning society. *Studies in Continuing Education*, 22(2), 151–167. <https://doi.org/10.1080/713695728>.
- Brown, M. F. (2005). Heritage trouble: Recent work on the protection of intangible cultural property. *International Journal of Cultural Property*, 12(1), 40–61. <https://doi.org/10.1017/S0940739105050010>

- Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education*, 43(8), 1315–1325. <https://doi.org/10.1080/02602938.2018.1463354>
- Carroll, S. R., Garba, I., Figueroa-Rodríguez, O. L., Holbrook, J., Lovett, R., Materechera, S., Parsons, M., Raseroka, K., Rodriguez-Lonebear, D., Rowe, R., Sara, R., Walker, J. D., Anderson, J., & Hudson, M. (2020). The CARE principles for Indigenous data governance. *Data Science Journal*, 19(1), 43. <https://doi.org/10.5334/dsj-2020-043>
- Cheng, Y., Lyons, K., Chen, G., Gašević, D., & Swiecki, Z. (2024). Evidence-centered assessment for writing with generative AI. In *Proceedings of the 14th Learning Analytics and Knowledge Conference (LAK '24)*, 178–188. Association for Computing Machinery. <https://doi.org/10.1145/3636555.3636866>
- Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 61(2), 228–239. <https://doi.org/10.1080/14703297.2023.2190148>
- Fischer, I., Sweeney, S., Lucas, M., & Gupta, N. (2024). Making sense of generative AI for assessments: Contrasting student claims and assessor evaluations. *The International Journal of Management Education*, 22, 101081. <https://doi.org/10.1016/j.ijme.2024.101081>
- Furze, L., Perkins, M., Roe, J., & MacVaugh, J. (2024). The AI assessment scale (AIAS) in action: A pilot implementation of GenAI-supported assessment. *Australasian Journal of Educational Technology*, 40(4), 38–55. <https://doi.org/10.14742/ajet.9434>
- Hafstein, V. T. (2009). Intangible heritage as a list: From masterpieces to representation. In L. Smith & N. Akagawa (Eds.), *Intangible heritage* (pp. 93–111). Routledge.
- Hu, A., Liu, Q., & Daniel, B. (2025). Digital technologies in authentic assessment in higher education: A systematic literature review and narrative synthesis. *SAGE Open*, 15(3), 1–27. <https://doi.org/10.1177/21582440251357198>
- Karampampas, P. (2021). (Re)inventing intangible cultural heritage through the market in Greece. *International Journal of Heritage Studies*, 27(6), 654–667. <https://doi.org/10.1080/13527258.2020.1844277>
- Karampampas, P. (in press). *The phoenix rising in grey zones of living heritage and avocational individuals*. Cambridge University Press.
- Kirshenblatt-Gimblett, B. (2004). Intangible heritage as metacultural production. *Museum International*, 56(1–2), 52–65. <https://doi.org/10.1111/j.1350-0775.2004.00458.x>
- Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge University Press.
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Association for Computing Machinery. <https://doi.org/10.1145/3313831.3376727>
- Madden, R. (2010). *Being ethnographic: A guide to the theory and practice of ethnography*. SAGE.
- Nair, S., Rasul, T., Arpaci, I., Saadouli, N., Ladeira, W. J., & Santini, F. de O. (2026). ChatGPT and DeepSeek in higher education: Comparing two contrasting generative AI models and their implications for student learning. *Journal of Applied Learning & Teaching*, 9(2). <https://doi.org/10.37074/jalt.2026.9.2.5>
- Perkins, M., Furze, L., Roe, J., & MacVaugh, J. (2024). The artificial intelligence assessment scale (AIAS): A framework for ethical integration of generative AI in educational assessment. *Journal of University Teaching and Learning Practice*, 21(6). <https://doi.org/10.53761/q3azde36>

Sadler, D. R. (1989). Formative assessment and the design of instructional systems. *Instructional Science*, 18, 119–144. <https://doi.org/10.1007/BF00117714>

Smith, L. (2006). *Uses of heritage*. Routledge.

Tai, J., Ajjawi, R., Boud, D., Dawson, P., & Panadero, E. (2018). Developing evaluative judgement: Enabling students to make decisions about the quality of work. *Higher Education*, 76, 467–481. <https://doi.org/10.1007/s10734-017-0220-3>

Tsekouras, I. (2026). From tradition to intangible cultural heritage: Localisation and heritagisation in Pontic Greek Momoeria. *International Journal of Heritage Studies*. <https://doi.org/10.1080/13527258.2026.2689929>

UNESCO. (2003). *Convention for the Safeguarding of the Intangible Cultural Heritage*. UNESCO.

UNESCO. (2016). Nomination File No. 01184 for Inscription in 2016 on the Representative List of the Intangible Cultural Heritage of Humanity: Momoeria, New Year's Celebration in Eight Villages of Kozani Area, West Macedonia, Greece. *Intergovernmental Committee for the Safeguarding of the Intangible Cultural Heritage, Eleventh Session, Addis Ababa, Ethiopia*. UNESCO

UNESCO. (2024). *Operational Directives for the Implementation of the Convention for the Safeguarding of the Intangible Cultural Heritage*. UNESCO.

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