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Deepfake Literacy in Higher Education: Assessing Cognitive, Technical-Analytical, and Ethical Competencies

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Abstract: Generative artificial intelligence (GenAI) produces realistic synthetic images that create new challenges for higher education. This exploratory study examines how aspects of cognitive, technical-analytical, and ethical competencies are reflected in students' judgments and reflections concerning authentic and AI-generated images. The study proposes a deepfake literacy framework derived from a qualitative analysis of scientific literature and explores selected aspects through a classroom-based pilot conducted at Polimoda in Florence on 13 July 2026. Fifteen international Master's students completed a structured online questionnaire containing six images, three authentic and three AI-generated, each displayed for five seconds. Classification responses were analysed descriptively, while written justifications, ethical reflections, and scenarios for 2036 were examined thematically. Across 90 judgments, 68 were correct, corresponding to 75.6% accuracy. Participants recognized synthetic images more successfully than authentic photographs and frequently relied on lighting, anatomy, texture, and composition. Since the findings highlight a gap between perceptual recognition and systematic verification, the educational objective is to help learners move from intuitive visual judgment toward transparent, reproducible, and evidence-based verification.

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Keywords: deepfake literacy; higher education; visual verification; cognitive competencies; synthetic media

1. Introduction

Generative artificial intelligence (GenAI) produces synthetic images that are highly realistic and difficult to distinguish from authentic content (Weigelt et al., 2026). This development creates an educational challenge (Tang et al., 2026; Xue, 2026). On the one hand, synthetic media can support engaging forms of education through immersive simulations, avatar-based teaching, and more accessible learning materials. On the other hand, realistic but misleading images can make it harder to assess the authenticity and credibility of visual information, weaken trust in authentic sources, reproduce social and cultural biases, and raise concerns about privacy, student well-being, and academic communication (Iufereva & Mozelius, 2026; Fitriyah et al., 2026). Therefore, students need to recognise possible signs of manipulation, explain the basis for their judgments, verify images through reliable procedures, and understand the ethical and social consequences of synthetic media (Mazhar et al., 2026; Tang et al., 2026; Weigelt et al., 2026). These competencies form the basis of deepfake literacy.

In this study, deepfake literacy is understood as an integrated set of skills and competencies for recognising generated content through verification strategies, analysing its ideological and social context, and understanding the ethical implications of creating and distributing media materials (Iufereva & Mozelius, 2026). Deepfake literacy should therefore include critical interpretation, metacognitive awareness, technical verification, and responsible judgment. The empirical task focuses on still images and examines recognition of AI-generated imagery within this broader educational understanding of deepfake literacy. It does not assess all forms of deepfake manipulation or all competencies included in the framework.

This study first proposes a deepfake literacy framework through a qualitative analysis of scientific literature. Then it explores selected aspects of the framework in a classroom pilot with international students.

The research questions are: RQ1. How accurately do students distinguish authentic from AI-generated images under brief exposure? RQ2. What aspects of cognitive, technical-analytical, and ethical competencies are expressed in their explanations and reflections? RQ3. How do students understand the ethical risks of synthetic media and imagine the verification competencies and tools that may be needed by 2036?

1.1. Theoretical background

The theoretical field of deepfake literacy is actively developing. Research on AI-generated content highlights the role of digital literacy in addressing questions of trust and authenticity (Aggarwal & Tripathi, 2025). Deepfake literacy can be understood as a construct emerging in an interdisciplinary field at the intersection of several literacies and psychological models. For the purposes of this study, the reviewed literature is organised into three complementary perspectives: functional and verification, socio-critical and ethical, and cognitive autonomy.

The functional and verification approach examines deepfakes as a potential form of disinformation. It places particular emphasis on practical skills for identifying, evaluating, and verifying synthetic media (McGowan-Kirsch & Quinlivan, 2024; Guo et al., 2025). Within this approach, different methods support the verification of visual content. One example is the SIFT method. This stands for Stop, Investigate the source, Find better coverage, and Trace claims, quotations, and media to their original context (Caulfield, 2019). These steps encourage people to investigate the source and critically evaluate information before making a judgment. SIFT supports the evaluation of sources and context; it does not independently establish whether an image was generated by AI.

The socio-critical and ethical approach connects deepfake literacy with the development of a critical perspective on deepfakes. The main focus is on understanding who benefits from creating AI-generated content and what political, economic, or social purposes it serves. Hence, deepfakes are examined in relation to power relations, ideology, and bias. Drawing on critical pedagogy, this approach connects dialogue, reflection, and action with responsible AI practices (Freire, 2000; Aydeniz, 2025). One relevant concept, discussed in research on AI-supported intercultural learning, is the "critical AI gaze". This involves treating AI-generated information with scepticism and actively seeking to verify it through other sources (Hastomo et al., 2025). It illustrates the overlap between critical reflection, verification, and ethical interpretation.

The cognitive autonomy approach examines how generative content, the use of AI tools, and related factors may influence cognitive processes, including attention, judgment, memory, and independent decision-making. The fundamental concept here is AI literacy, which concerns the ability to understand, use, and critically engage with AI tools while recognising their potential and limitations. Self-regulated learning supports users in managing the cognitive, metacognitive, and motivational demands of AI-assisted learning (Adamakis & Rachiotis, 2025). The Elaboration Likelihood Model provides an analytical framework for understanding how individuals process persuasive information. It distinguishes between the central route, which involves careful and effortful consideration of message arguments, and the peripheral route, which relies on cues other than detailed consideration of those arguments (Hou, 2025).

Together, these perspectives provide the theoretical basis for the framework: cognitive autonomy informs judgment and metacognitive awareness; the functional and verification perspective informs technical-analytical competencies; and the socio-critical and ethical perspective informs responsibility and awareness of harm.

1.2. Deepfake literacy framework

The proposed deepfake literacy framework was developed through a qualitative analysis of scientific literature, organised around the three complementary perspectives discussed in Section 1.1. The proposed framework has two tiers: a competence level and an assessment level. The competence level specifies what deepfake literacy involves, while the assessment level outlines how evidence of these competencies can be collected in educational practice. This study then explores selected applications of the framework in a classroom pilot.

The competence level encompasses cognitive, technical-analytical, and ethical competencies. The cognitive component concerns how the user encounters synthetic content, interprets it, and decides on its credibility. Analytical competencies, critical thinking, and metacognitive scepticism are central. The user remains the key actor because they make the final decision about trust, verification, or dissemination. This component includes recognising uncertainty and distinguishing a suspicious detail from sufficient evidence of manipulation.

The technical-analytical component entails a transition from initial critical assessment to systematic verification. It includes recognising possible AI artifacts, understanding image production, using reverse image search, investigating sources, and comparing content with external evidence. SIFT and lateral reading structure actions beyond the image itself (Caulfield, 2019). This component concerns both knowledge of verification strategies and the ability to carry them out, which require different forms of evidence in assessment.

The ethical component concerns responsibility when interacting with synthetic content. It includes consent, digital identity protection, privacy, copyright, reputational harm, and manipulation of public opinion. It requires attention to who creates content, whose interests it conveys, and who may be affected by dissemination. Ethical reflection connects verification with decisions about reuse, publication, and sharing. Recognising an image as synthetic does not resolve questions about representation and harm; an authentic photograph can also be used in a misleading context.

The assessment level concerns how evidence of the three competence components can be collected. Performance tasks can assess classification accuracy

and, when source investigation is required, verification actions. Scenario-based responses can reveal verification choices and ethical reasoning, while self-reports describe perceived skills and attitudes. Rubrics can be applied across tasks to evaluate reasoning, the use of evidence, recognition of uncertainty, and ethical justification. Clear procedures and assessment instruments are essential for interpreting performance (Sanchez-Acedo et al., 2025). These are assessment possibilities within the framework. The present pilot uses selected elements: image classification, written explanations, self-reported skills, and ethical and future-oriented reflections. It does not directly assess external verification, cognitive effort, or responsible sharing behaviour.

2. Materials and Methods

2.1. Sample and study design

The study was conducted at Polimoda in Florence on 13 July 2026. Fifteen international students from two Master's programmes and 13 countries participated. Ages ranged from 22 to 30 years (mean 25.7); the group included 12 women and three men. The descriptive, exploratory pilot combined visual classification with written reflections. No comparison group or pre-test/post-test intervention was included. The fashion education context makes visual interpretation relevant, but prior visual literacy and familiarity with AI were not measured.

2.2. Materials and procedure

Participants completed a structured online questionnaire containing six still images presented in a fixed sequence. The set was balanced by origin: Images 1, 3, and 4 were authentic photographs, while Images 2, 5, and 6 were AI-generated. The synthetic images were created using ChatGPT, and the authentic photographs were obtained from Freepik on 8 July 2026. All six visual stimuli are reproduced in Appendix A, Figures A1–A6, in the order used in the task. Here, authenticity refers to the origin assigned to the stimuli; it does not imply that a photograph has never undergone conventional editing.

Each image was displayed for five seconds and was then replaced by a blank page before participants answered. They classified it as human-made, AI-generated, or difficult to determine, and explained which visual features influenced their judgment. The five-second presentation established a brief viewing condition. It was an educational approximation of rapid online exposure rather than a complete simulation of social-media use. The task assessed visual recognition without observing source verification or measuring confidence, response time, or cognitive load.

Additional questions asked participants to select cognitive skills used, describe competencies currently needed to evaluate visual authenticity, and identify ethical risks. The final question invited a short scenario for managing manipulated visual content in 2036, drawing on a weak signal visible today. Its example involved widely used verification software and fact-checking education, which may have encouraged tool-centred scenarios. The sequence combined classification, written justification, metacognitive self-assessment, ethical analysis, and futures thinking. Table 1 links these tasks to the competence components and specifies the evidence each provides.

Table 1. Links between the framework and the tasks used in the pilot.

Component	Task or response	Evidence and scope
Cognitive	Image classification; written justifications; self-reported skills	Classification accuracy, stated reasons, and expressed uncertainty. Selected skills indicate self-perception, not an independent measure of cognition.
Technical-analytical	Descriptions of image features; responses about competencies needed for verification	References to possible artifacts, image production, tools, and verification strategies.
Ethical	Written reflections on ethical risks; scenarios for 2036	Articulated concerns about consent, identity, bias, harm, and responsibility. Future scenarios reveal expectations; responsible behaviour was not observed.

2.3. Data analysis and ethical considerations

Classification responses were analysed descriptively. Correct responses matched the assigned origin; incorrect and difficult-to-determine responses received no correct score. Accuracy was calculated across 90 judgments and by image, and participant scores were summarised. Written justifications were available for 73 judgments. One researcher used inductive, descriptive thematic analysis to group recurring visual cues, ethical concerns, and future-oriented ideas. Categories could overlap. No intercoder agreement procedure was applied, so frequencies and thematic findings remain exploratory. In the discussion, the inductively identified categories are interpreted in relation to the three competence components. The framework serves as an interpretive lens; no component scores or overall deepfake literacy score were calculated. Classification accuracy is reported separately from the qualitative findings.

Participation was voluntary. Before completing the questionnaire, participants were informed about the purpose of the activity and the research use of their responses and provided informed consent. No directly identifying personal data were collected. Results are reported in aggregate, and quotations are anonymised. No formal institutional ethics approval was sought for this classroom-based pilot. The image set and aggregate classification results are included in this manuscript; participant-level responses are not included, and access to them would require consideration of consent and confidentiality.

3. Results

3.1. Classification accuracy

Across 90 individual image judgments, 68 were correct, corresponding to an overall accuracy of 75.6%. The mean participant score was 4.53 correct classifications out of six, the median was five, and scores ranged from three to six. Nine students correctly identified at least five images. Recognition rates differed across the stimuli, as shown in Table 2. The three AI-generated images were correctly classified by 86.7%, 93.3%, and 86.7% of participants. One authentic image was correctly recognised by 86.7%, while the other two were correctly classified by only 53.3% and 46.7%.

Table 2. Classification accuracy by image (15 participants).

Image	Assigned origin	Correct classifications	Accuracy
1	Authentic	8/15	53.3%
2	AI-generated	13/15	86.7%
3	Authentic	7/15	46.7%
4	Authentic	13/15	86.7%
5	AI-generated	14/15	93.3%
6	AI-generated	13/15	86.7%
Total	**Balanced set**	**68/90**	**75.6%**

Note. Difficult-to-determine responses were not scored as correct.

Authentic images received 28 correct classifications out of 45 judgments (62.2%), compared with 40 out of 45 for AI-generated images (88.9%). Thus, the main difficulty was not limited to accepting synthetic images as authentic. Students also rejected authentic photographs when they appeared unusual, highly composed, or inconsistent with their expectations. Image 1 was classified as AI-generated by seven participants. For Image 3, seven selected authentic, seven selected AI-generated, and one found it difficult to decide. Four difficult-to-determine responses occurred across Images 2, 3, and 5. This option was used less frequently than incorrect classifications; confidence was not measured, so the latter cannot be described as confident errors.

3.2. Visual cues and cognitive skills

Participants' explanations focused mainly on visible features. The exploratory coding identified references to lighting, shadows, and reflections (15 mentions); background and compositional incongruity (12); anatomical and facial anomalies (11); texture and skin smoothness (eight); photographic properties such as focus and depth of field (seven); resemblance to non-photographic media (six); and intuition without an articulated cue (six). These counts refer to the 73 available justifications

and are overlapping, illustrative categories rather than an exhaustive account of the language used. Images were sometimes described as excessively smooth, "plastic," "cartoon-like," or similar to a video game.

The same visual feature could support opposite conclusions. Regarding authentic Image 1, one participant wrote, "The lighting and shading looks very real," while another questioned the balloon's reflection and the apparent light sources. Suspected anatomical anomalies were also identified in authentic photographs. Attention to detail therefore produced both useful observations and false positives. Other explanations relied on "a feeling" or "the vibe," without a procedure another person could reproduce.

The self-reported cognitive skills followed this perceptual orientation. All 15 participants selected attention to detail, seven logical analysis, six scepticism, and four critical thinking. One reflected that "for this quiz I actually had to think what details exactly look AI generated". Requesting a justification made this student's reasoning more explicit, but does not establish a learning effect. Selected skills describe participants' understanding of their process rather than independently assessed competencies.

3.3. Recognition and articulated verification strategies

None of the 15 responses about the competencies currently needed to evaluate visual authenticity explicitly named source checking, lateral reading, reverse image search, or the SIFT method. Answers instead referred to perceptual and technical fluency, including the diagnosis of lighting details, knowledge of photography, and a general awareness that images may be synthetic. Some mentioned AI-detection tools or an understanding of image production. Two participants acknowledged difficulty explaining a judgment, writing "i don't know why" and "i don't really know how to explain".

These answers indicate a gap between image-internal cues and explicitly articulated verification procedures. Students noticed that an image looked wrong, but rarely explained how external evidence could establish its origin. Because the questionnaire did not require external verification, the absence of these procedures in answers does not establish an inability to use them in other conditions.

3.4. Ethical reflection and future verification

Ethical and socio-critical reflection was broader. Eleven of the 15 responses referred to misinformation, manipulation, or the erosion of a shared sense of truth. Nine referred to privacy, consent, identity misuse, or reputational harm. Participants also discussed scams, political manipulation, incitement, racial stereotyping, false accusations, and the possibility that authentic evidence could be dismissed as AI-generated. One connected synthetic representation with stereotypes, explaining that AI-generated people may reproduce assumptions about a particular race. Another described the consequences as ranging from false advertising to risks that could change someone's life.

The 2036 scenarios extended verification responsibility beyond the individual. Recurring themes included regulation and institutional governance (five responses), verification tools and software (four), individual cognitive competencies (three), educational adaptation (two), provenance and technical traceability (two), and journalistic fact-checking (one). Categories overlapped. Participants imagined mandatory labels, platform filtering, verification applications, watermarking,

blockchain-based traceability, and dedicated newsroom verification teams. These are participants' projections rather than evaluations of the effectiveness or feasibility of such solutions.

Only three responses imagined improved individual cognitive competencies. One participant questioned whether companies would help users retain control. The scenarios located responsibility across individuals and institutions. These responses reveal expectations about future verification; they do not establish participants' willingness to develop or use personal verification practices.

4. Discussion

4.1. Competencies under brief exposure

The findings illustrate the educational value of examining classification accuracy alongside explanations and reflections, as proposed in the Deepfake Literacy Framework. RQ1 identified 75.6% accuracy, with stronger recognition of synthetic images than authentic photographs. For RQ2, explanations revealed attention to visual details and, in some cases, intuitive judgments without articulated evidence. Technical-analytical aspects appeared in references to possible AI artifacts and image production, while systematic external verification was absent from the strategies explicitly named. Ethical reflections addressed personal rights, public trust, and dissemination. These observations concern aspects expressed in the responses and do not constitute a comprehensive assessment or validation of the three competence components.

From an educational perspective, errors on authentic images are particularly relevant. Cues associated with AI generation could also reflect photographic lighting, unusual composition, or an unexpected scene. Deepfake literacy should not produce generalised distrust, because excessive suspicion may weaken confidence in legitimate visual evidence. Learners need to manage uncertainty without replacing uncritical trust with automatic disbelief. A suspicious detail should prompt investigation rather than function as a verdict, although this small image set cannot establish patterns across authentic photography generally.

The predominance of visual cues is consistent with brief viewing followed by classification. Hou's (2025) application of ELM helps frame questions about cue-based judgment, but the pilot did not measure processing routes directly. Without an extended-viewing condition, it cannot establish that brief exposure caused errors. Its relevance to attention and self-regulation concerns the educational decision about when an initial impression requires investigation.

4.2. Implications for teaching and assessment

Classroom activities could connect perceptual recognition with a second stage of verification. Students could classify an image, explain their initial decision, then investigate its source and compare impressions with external evidence. Authentic photographs that appear suspicious can be used to discuss the limits of artifact-based reasoning. Deepfakes can also serve as cases within problem-based or case-based learning, where students investigate possible manipulation and justify conclusions through procedures another person can reproduce. Guo et al. (2025) support specific visual guidance. The present findings motivate combining such guidance with source investigation, for which SIFT provides a practical structure (Caulfield, 2019), although this combination was not tested in the pilot.

Assessment should distinguish classification accuracy from the quality of reasoning. A rubric could examine whether students identify a relevant cue, recognise uncertainty, choose an appropriate verification action, and explain how evidence changes their conclusion. Ethical scenarios can assess whether students consider consent, representation, and possible harm before sharing an image. These proposed applications remain unvalidated; they distinguish intuitive answers from conclusions supported by transparent procedures.

In relation to RQ3, ethical responses identified risks involving misinformation, identity, consent, and public trust, while the future scenarios made assumptions about tools, institutions, and personal responsibility visible. Futures literacy uses imagined futures to examine assumptions in the present (Miller, 2018). The exercise can support discussion of what students expect verification systems to do and what they themselves need to learn. The future-oriented task complements the three competence components by eliciting assumptions about future verification practices and responsibility; it is not a separate competence measure. Teaching could ask what evidence a tool provides, how to handle conflicting results, and who remains responsible for decisions.

4.3. Limitations and future research

The study involved 15 students at one institution and six images presented in a fixed sequence. Findings cannot be generalised to higher education students as a whole or to video, audio, or newer generation systems. Furthermore, the pilot explored only selected aspects of the proposed framework. A more comprehensive study is needed to examine all three competence components, including directly observed verification practices and ethical decision-making. Future research should therefore use larger, more diverse samples and adopt a pre-test/post-test design, with an educational intervention between the two assessments to examine changes in students' recognition accuracy, verification strategies, and ethical reasoning.

5. Conclusions

This study develops a deepfake literacy framework from a qualitative analysis of scientific literature and explores selected aspects of it in higher education. The framework includes cognitive, technical-analytical, and ethical competencies and distinguishes the competence level from the assessment procedures used to examine them. The classroom pilot illustrates how selected aspects of this framework can be explored through image classification, written explanations, and ethical reflections. Students recognised many synthetic images but also misclassified authentic photographs. These findings support educational activities linking visual judgment, source investigation, and responsible decision-making. Further research with larger samples and observed verification tasks is needed to refine the framework's educational application and develop validated assessment instruments.

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Appendix A. Visual stimuli used in the classification task

The six stimuli are reproduced in their presentation order. Authentic photographs were obtained from Freepik on 8 July 2026; AI-generated images were created using ChatGPT. The origin labels below were not part of the classification task.

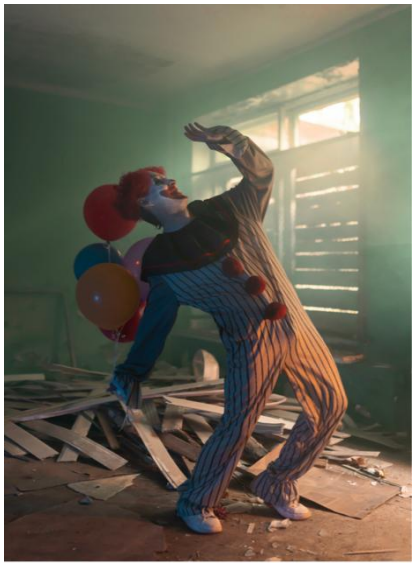


Figure A1. Image 1 used in the classification task (authentic photograph). Source: Freepik (accessed 8 July 2026).



Figure A2. Image 2 used in the classification task (AI-generated image). Source: Created using ChatGPT.

Appendix A. Visual stimuli continued



Figure A3. Image 3 used in the classification task (authentic photograph). Source: Freepik (accessed 8 July 2026).



Figure A4. Image 4 used in the classification task (authentic photograph). Source: Freepik (accessed 8 July 2026).

Appendix A. Visual stimuli continued



Figure A5. Image 5 used in the classification task (AI-generated image). Source: Created using ChatGPT.

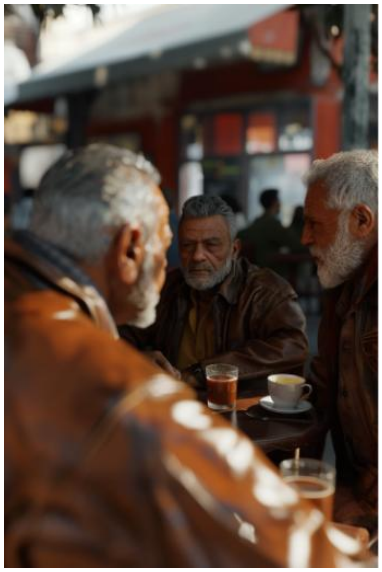


Figure A6. Image 6 used in the classification task (AI-generated image). Source: Created using ChatGPT.