

Ten recommendations for the use of generative artificial intelligence in epidemiology teaching: Results from an expert workshop

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Research Article

Keywords: Generative artificial intelligence, teaching, epidemiology, instructor recommendations, large language models, epidemiology education

Posted Date: September 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10974790/v1>

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Abstract

Generative artificial intelligence (GenAI) is rapidly reshaping higher education and research. For epidemiology teaching, this creates a dual challenge: students must learn how to use GenAI critically and effectively, while continuing to develop their reasoning, quantitative, and critical appraisal skills that underpin epidemiological competence. Without thoughtful integration, GenAI may contribute to deskilling among instructors and “never-skilling” among students, while raising important questions around transparency, data protection, ownership, human oversight, and accountability.

Building on two years of activities within the joint working group “Teaching in Epidemiology” of three German scientific societies, a three-day expert co-creation workshop was convened in March 2026. Epidemiologists, students, and GenAI experts developed 10 evidence-informed recommendations for epidemiology instructors, which were subsequently refined using feedback from additional students and instructors.

Our recommendations for instructors are organized into three domains: governance and good practice, competencies and assessment, and feedback and evidence. They address the need for clear institutional policies, transparent disclosure and human verification of GenAI use, continuing educator development, integration of GenAI literacy into epidemiology curricula, preservation of core epidemiological and scientific competencies, and appropriate assessment strategies. They also emphasize regular student feedback and the need to generate and share evidence on this emerging topic.

The recommendations provide practical guidance, including concrete examples and experiences from fellow instructors, to support responsible GenAI integration in epidemiology teaching. While developed in a European context, many of the underlying principles are broadly applicable and can serve as a useful starting point for instructors worldwide.

Introduction

Generative artificial intelligence (GenAI), a type of artificial intelligence which generates outputs such as text and images based on patterns and probabilities found in broad training data [1, 2], has become part of everyday life, including in higher education and research [3, 4]. While GenAI has widesweeping consequences on education, different disciplines have different requirements, risks, and opportunities surrounding GenAI use.

In epidemiology, students must master core competencies such as quantitative reasoning, bias assessment, and critical appraisal. Many of these skills can now be supported, augmented, and/or partially automated by GenAI systems, with the potential to enhance learning but also to inadvertently undermine these competencies if used inappropriately.

As described in Anderson and Krathwohl’s revised Bloom’s Taxonomy, teaching aims to guide students in climbing up the ladder of knowledge levels (factual, conceptual, procedural, and metacognitive) and through the cognitive processes of learning, moving from remembering to understanding, applying, analyzing, evaluating, and finally to creating [5, 6]. While GenAI offers clear opportunities to support teaching and learning, it also introduces sizable risks. A key concern is that students may rely on GenAI too early in the learning process, preventing them from progressing up the steps of the learning ladder, thereby limiting their understanding of key concepts and the development of core epidemiological skills—a phenomenon referred to as never-skilling [7]. Specifically, GenAI may tempt students to rely on artificial intelligence (AI)-generated outputs before developing a sufficient understanding of the material themselves [8]. It may also promote metacognitive offloading, where students outsource elements of self-monitoring and self-regulation during learning, leading to metacognitive laziness and missed opportunities for developing the cognitive skills that underpin learning [9, 10]. Similar concerns apply to instructors, as uncritical reliance on GenAI may contribute to deskilling [7] when core epidemiological and pedagogical tasks are increasingly outsourced to these tools.

AI-generated answers can create an illusion of competence by producing polished texts, even when these include hallucinated references or biased outputs [11, 12]. Overreliance on GenAI may reinforce poor scholarly practices, including uncritical acceptance of plausible-sounding text, citation of unverified sources, and use of analytic outputs without independent validation [11, 13]. These risks underscore the current importance of explicitly training students to critically appraise GenAI outputs, treat them as non-authoritative, and verify all generated content, thus ensuring the future analytic and critical integrity of the epidemiology workforce.

Simultaneously, GenAI provides valuable opportunities for teaching and learning, particularly in epidemiology. While instructors can benefit from additional input to make their teaching more interactive and cohesive, students can use GenAI to help explain and understand complex methodological concepts. Moreover, as GenAI becomes increasingly integrated into epidemiological research and practice. The ability to use these tools critically and appropriately will become an important professional competency. To help ensure that students will be able to keep up in the epidemiology workforce in an AI-driven world, instructors should teach students skills for maximizing responsible and effective GenAI use. To this end, both instructors and students must master how to use GenAI effectively, responsibly, and sustainably, including being able to judge when its use is appropriate and critically assess and verify its outputs.

Although guidance on GenAI in higher education is growing (emphasizing concepts such as the need for human oversight and accountability, privacy protection, fairness, and transparency) [14], discipline-sensitive recommendations tailored specifically to epidemiology teaching are

lacking. Guidance is needed not only on how GenAI can support learning within epidemiology, but also on how its use should be governed.

We therefore developed ten recommendations aimed at instructors who teach epidemiology, either within dedicated epidemiology degree programs or through courses and modules embedded in other health-related programs. The recommendations are organized into three domains: governance and good practice, competencies and assessment, and feedback and evidence. Given the rapidly evolving technology, we focused on overarching, durable principles for GenAI use in epidemiology education and the broader institutional context rather than tool-specific or research-use recommendations. Together, the recommendations are intended to help instructors to address the dual-challenge of encouraging deliberate, transparent, and responsible use of GenAI while preserving key epidemiological skills.

Methods

The joint Working Group “Teaching in Epidemiology” of the German Society for Epidemiology (DGEpi), the German Association for Medical Informatics, Biometry and Epidemiology (GMDS), and the German Society for Social Medicine and Prevention (DGSMP) addressed the role of GenAI in epidemiology teaching during its November 2025 annual teaching epidemiology workshop in Halle, Germany. An expert in artificial intelligence in teaching and learning, who is also an epidemiologist by training (co-author ML), was invited to give a keynote presentation and we had a dedicated world café session. The workshop identified a pressing need for tailored, field-specific guidance and concrete suggestions for the responsible implementation of GenAI in epidemiology teaching.

In response, the working group convened a three-day expert workshop in March 2026 in Münster, Germany to develop consensus-based recommendations for the responsible use of GenAI in epidemiology education within the European context.

Nine experts with complementary expertise and a range of perspectives relevant to epidemiology education participated in the Münster workshop. Eight were based at German institutions and one at a Norwegian institution. The group was composed of experienced epidemiology instructors and researchers, specialists in GenAI in education, MSc and PhD program coordinators and board members, curriculum developers, instructor trainers, and PhD students, with many of the experts belonging to more than one of these categories.

Content development followed an iterative, collaborative process. First, the group identified four thematic areas based on outputs from the November 2025 annual teaching epidemiology workshop: (1) policies and regulation; (2) teaching content; (3) assessment and feedback; and (4) balancing upskilling (with new GenAI literacy skills) with the risk of deskilling in GenAI-supported education.

Participants were then divided into writing groups of three to five people with alternating group compositions and developed rough drafts of recommendations. We decided to restrict the scope to GenAI use in epidemiology education, encompassing the many dimensions of teaching and learning within its broader institutional context. Therefore, specific suggestions for how researchers should use GenAI and endorsements of specific tools were considered out of scope. Results were presented and discussed among the entire group. On the final day, all draft recommendations were critically reviewed, consolidated, prioritized, and refined into ten final recommendations. The consensus building process was moderated by the working group speakers and based on the following key considerations: relevance to epidemiology teaching and training, practical value, inclusion of examples, and clarity.

Following the workshop, the recommendations were further developed collaboratively by all participants, together with three additional contributors (NW, KSO, LH), who brought complementary perspectives from epidemiology education and research in Germany, Norway, and Austria. The elaborations, examples, and epidemiology-specific use cases drew on published literature as well as practice-based materials from the participants’ own institutions, including resources published on institutional or departmental websites and examples documented in the supplementary materials.

The coauthors further refined the recommendations into a pre-final draft, which was then circulated for feedback to the broader membership of the Working Group “Teaching in Epidemiology,” information specialists, and to students in epidemiology, medicine and related fields at the Bachelor’s, Master’s, and Doctoral levels. The recommendations were further revised based on this feedback. During the writing and revision process, we incorporated several recommendations proposed by Weissgerber et al. (2025) for the coordination and management of large, multi-author, non-empirical manuscripts [15].

Given the rapid evolution of GenAI-related resources and guidance, all referenced online materials are cited using their original links and accompanied by archived copies to ensure continued access should the original links become unavailable. To support ongoing maintenance of the recommendations, we established a GitHub repository where links to cited resources can be updated as new versions become available: <https://github.com/WorkingGroup-TeachingEpidemiology/AI-Recommendations>.

GenAI was used for specific tasks including the formulation of recommendations based on comprehensive notes as well as for language editing, reference harmonization, and testing the example prompts presented in the paper. GenAI was also used to create an initial draft of Fig. 1. All outputs were verified and revised by the authors. A complete list of when we used GenAI and the specific prompts and models we used will be

Results

The workshop process resulted in ten consensus-based recommendations for the use of GenAI in epidemiology education. These are summarised in Fig. 1 and are each presented in detail in the sections that follow.

Recommendation 1: Establish, follow, and communicate clear GenAI use policies

In order to use GenAI responsibly, instructors need to understand and adhere to existing legal and institutional regulations, adapt these to epidemiology teaching, and communicate them to students and other instructors.

First and foremost, instructors and students are responsible for ensuring that their GenAI use follows relevant legal regulations (e.g., European Union (EU) AI Act and General Data Protection Regulations (GDPR), copyright laws), since these regulations are the overarching authority on GenAI use [1, 2]. Since regulations exist at many levels, including international, national, local, and institutional, instructors’ awareness of which regulations apply is essential [14, 16, 17]. When deciding whether GenAI should be used for a specific task or which tools to use, it is important for the instructors and students to consider the types of data being shared (e.g., anonymized vs. non-anonymized personal data, content generated by others, simulated data) and where the GenAI tools are hosted (e.g., cloud-based tools or local tools) [1, 18, 19]. Importantly, data sharing is not limited to direct uploads; for example, when coding, sensitive data may also be exposed when GenAI plugins—such as Copilot integrated into Visual Studio Code—are used to assist with coding.

When using GenAI, instructors and students must also adhere to institutional regulations, including checking what tools are allowed or disallowed by the institution. As an example, UiT The Arctic University of Norway has developed a legislation-compliant *Guideline for classification of sensitive data* [20, 21], describing acceptable use and security measures for each category of data (open, internal, confidential, strictly confidential) [17]. The guideline is not GenAI specific, but provides a framework for managing all data within the institution and thus covers how data must be handled by staff and students in relation to GenAI tools. If no institutional regulations exist, we encourage instructors to take action to facilitate their development at an institutional level.

Every course must have a unified GenAI use policy on when and how students can use GenAI in the course to minimize instructor-specific differences and ensure expectations are clear for students (see example in **Box 1**). For example, instructors can use an AI Assessment Scale such as the one developed by Perkins et al. [22] to define categories of GenAI use, such as "AI-assisted research" or "AI-generated content," and provide clear guidelines on what level of GenAI use is allowed for learning, coursework, and examinations. Furthermore, instructors should rely on institutional-level guidance to handle suspected student misuse of GenAI, or, if necessary, advocate for the establishment of such guidelines. In this context, lessons learned from existing plagiarism-related policies and the use of deterrence strategies, such as monitoring student activity during exams, may prove particularly useful.

It is the responsibility of the instructor to clearly communicate relevant regulations on whether and how GenAI tools can be used in a specific course. These regulations should be available to students in a written and easily accessible format. Instructors should lead by example by demonstrating responsible GenAI use themselves. Furthermore, instructors and institutions should provide students with resources and support to help them understand the policies of GenAI use. Importantly, any external/guest instructors, supervisors, or reviewers should be made aware of institutional/course policies about GenAI use to ensure conformity and consistency for students. Examples of institutional GenAI guidelines are provided in **Appendix 1**.

Box 1. Suggested elements of a clear GenAI use policy to govern epidemiology courses.

The policy should include clear examples for all elements listed below:

- Describe permitted uses: e.g., for language editing, coding support
- Describe prohibited uses: e.g., generating full assignments, exam answers
- Detail GenAI use disclosure requirements: what, where, and level of detail (**see Recommendation #2**)
- Explain who is accountable: student takes responsibility for final output (**see Recommendation #3**)
- Outline assessment rules: how GenAI-assisted work is graded (and any differences to non-AI assisted work) (**see Recommendation #8**)
- Refer to data protection regulations: what can and cannot be entered into GenAI tools or be used in the presence of GenAI plugins
- Be upfront about possible consequences of non-compliance with policies: warning system, possible grading penalties if caught, etc.

Recommendation 2: Disclose GenAI use transparently

Epidemiologists are trained to transparently report the methods used to generate their findings, and similar transparency should apply to GenAI use in education. Instructors should lead by example and disclose their own use of GenAI in teaching materials, including, for example, AI-generated multimedia, GenAI-assisted content creation, and synthetic data used in classroom exercises. Explicitly stating “no GenAI use” when applicable can distinguish non-use from missing disclosure. By modeling transparent practices, instructors can foster a culture in which students feel comfortable disclosing their own GenAI use and critically reflecting on its role in learning and knowledge production.

Importantly, disclosure statements should not only indicate whether GenAI was used, but also *how* it was used, as GenAI use can range from minor editing for language and flow of a solid first draft to prompting to fill a blank page. Frameworks like the AI in Research (AIR) [23] or the Generative AI Delegation Taxonomy (GAIDeT) [24] were created to support researchers and institutions in transparently describing, reflecting, and explaining their use of GenAI responsibly across the research process. Guided by such frameworks, instructors can create a unified, comprehensive disclosure structure (e.g., a checklist of possible GenAI uses - see **Recommendation #1**) to ensure that all relevant uses of GenAI are covered. This structure should ideally be tailored to fit the context/setting in question and provide clear examples of how students can use GenAI while remaining aligned with course policies.

Instructors should also teach students early on that they themselves—and not chatbots—are responsible for the final contents of their work (see also **Recommendation #3**). Therefore, we recommend including an accountability statement as part of the disclosure, e.g., “I have reviewed the final product and take full responsibility for its contents” (see example in **Box 2**). Even if the GenAI policy governing a course is fully restrictive for students (i.e., no GenAI use permitted by students), students should practice disclosing that no GenAI tools were used in the generation of their work. We provide a list of sample disclosure statements e.g., by The Arctic University of Norway (UiT) in **Appendix 2**. Furthermore, we point readers to an interactive online tool developed by GAIDeT for researchers that helps generate a genAI use declaration in a standardized, accessible format [25].

For supervised thesis projects or team-based project work, we additionally recommend creating a *planned* GenAI use statement already at the thesis proposal stage (see an example in **Appendix 2.5**). This way, students and their supervisors can discuss and agree upon possible GenAI tool use in accordance with applicable GenAI use policies *before* the work commences. Once completed, an actual use declaration should be included in the thesis (see **Appendix 2.6**).

Beyond transparency, disclosure also supports fair assessment. Because GenAI availability may influence how students approach assignments, instructors should establish clear expectations for its use and design assessments that remain aligned with the competencies they aim to evaluate. However, disclosure alone cannot ensure fairness; it should be complemented by assessment designs and grading criteria that remain robust to both disclosed and undisclosed GenAI use (see **Recommendation #8**).

When it comes to the level of detail necessary in GenAI use disclosures, pragmatically, we advise instructors to be careful what they ask for. While asking students to submit chat logs or prompting histories may seem beneficial, these can quickly become excessively long and time-consuming to review. We instead recommend easy-to-use templates that allow for flexibility (see example in **Box 2**). Furthermore, as a pedagogical exercise, instructors may consider asking students to explicitly reflect on their use of GenAI (e.g., “When and how was it useful in preparing this assignment, and when was it not?”). These reflections may also provide instructors with insights that can inform future course design and be shared with subsequent cohorts (see also **Recommendation #9**).

Box 2. Example GenAI Use Disclosure Statement: Master's Thesis

In spring 2023, the Berlin School of Public Health developed and adopted the 'BSPH Statement on the Use of AI and AI-Assisted Technologies', which includes a template for a 'Declaration on the Use of Artificial Intelligence (AI) and AI-Assisted Technologies'. This declaration must be included with all graded assessments, including the Master's thesis.

The statement and declaration template, which has since been updated, can be found in the *Information Leaflet Master's Thesis* for the Master of Science in Public Health (MScPH) program [26]. The guidance specifies that GenAI tools may be used during the writing process of Master's theses, including "to improve grammar, spelling, language, and overall clarity, coherence and readability", following a decision of the MScPH Examination Board [26].

The declaration template requires students to disclose whether GenAI tools were used during thesis preparation and, if so, to specify:

- the name(s) of the tool(s) or service(s) used;
- whether the tools were used to draft text, including the relevant thesis sections;
- whether the tools were used for language editing or improving clarity and grammar;
- and any additional tasks for which the tools were used, including how they contributed to the work.

The template concludes with the following statement: "After using these tools/services, I/we reviewed and edited the content as needed and I/we take full responsibility for the final submitted work" and requires a signature [26].

All students are required to submit this declaration when handing in their thesis or any other assessment, including those who did not use GenAI tools. [26].

Recommendation 3: Verify and take responsibility for GenAI-assisted work

Instructors need to ensure and take responsibility for the accuracy and validity of their GenAI outputs and obligate students to do so as well.

As instructors and students increasingly utilize GenAI tools to assist with teaching and epidemiological tasks such as course concept and content generation, literature reviews, data analysis, and report writing, they need to verify the accuracy and validity of AI-generated content [14, 27]. For instance, instructors must take responsibility for checking AI-generated work, and teach students to do the same. Furthermore, instructors and students should be aware of automation bias, the human tendency to over-trust and defer to automated systems, such as GenAI, accepting their outputs and overlooking contradictory cues, leading to errors [28].

Students should also be taught to critically evaluate GenAI-generated content (see **Recommendation #5**). This includes verifying the accuracy and validity of references (see example in **Box 3**), as recent work has documented substantial rates of fabricated citations in biomedical research in 2023 to 2026 [12]. They should also practice verifying that the output fulfills its intended purpose and that conclusions follow logically from the content. To achieve this, students should use quality-assurance methods [16, 29] (see Table 1). These methods represent established approaches used in information verification, scholarly review, and translation validation that can also be applied to the evaluation of GenAI-generated content. Additionally, when GenAI generates content in a field or specialty beyond the expertise of the student, instructor, or thesis supervisor, consultation with a domain expert can help ensure the accuracy and validity of the generated output. By implementing these verification strategies, instructors can support students in maintaining academic integrity and accountability when using GenAI tools.

Table 1

Suggested quality-assurance methods applicable to the verification of GenAI-generated content. Methods compiled and adapted from [16, 29]. Further examples in **Appendix 3**.

Method	Description or example in the context of GenAI
Source triangulation	Locate the same scientific claim in multiple independent scholarly sources such as journal articles, textbooks, and official statistics, and subsequently record the supporting citations.
Back-translation	When GenAI is used to translate a text into another language, translate the output back into the original language using a different tool or model and check whether the meanings remain consistent.
Peer or tutor critique	Present GenAI-generated content to a classmate or tutor and ask them to identify inconsistencies or factual errors that may have been overlooked.
Keyword cross-verification	Paste unfamiliar names, data figures, or citations into a search engine or library database to verify whether they exist and whether the information is accurate.
Glossary consistency checks	Cross-check discipline-specific terminology against authoritative glossaries, textbooks, or bilingual glossaries to ensure correct and consistent usage.

Box 3. Checking for hallucinated references

To help instructors verify students' work, instructors in an epidemiology course could, for example, inform students that reference lists may be checked for fabricated or implausible citations and encourage students to conduct similar checks themselves. To facilitate this process, instructors should consider requiring students to include persistent Digital Object Identifier (DOI) links in their references, making it easier to verify and spot-check the validity of the students' cited sources. Instructors could further require students to submit a supplemental file including the first page of each referenced article as evidence that they have accessed the original source, thereby confirming its existence.

Recommendation 4: Stay up to date on the responsible use of GenAI in epidemiology teaching through training

Instructors should have sufficient, up to date knowledge and skills in GenAI use. We recommend that instructors involved in epidemiology teaching receive regular training from pedagogical trainers who have experience with GenAI in education and develop both general GenAI competencies and GenAI-specific didactic skills. Training should go beyond basic familiarity with popular tools and cover two levels: Basic GenAI literacy for all instructors (how GenAI works, practical prompting skills, its limitations, legal and ethical obligations in educational settings) and advanced competencies (pedagogically meaningful integration of GenAI into teaching and assessment, epidemiology-specific methodological training). In the European context, this is also a compliance issue. Article 4 of the EU AI Act requires organizations that provide or use AI systems to ensure sufficient AI literacy among their staff, taking into account their knowledge, training, and the context in which the AI is used [30]. The existence of the EU AI Act and its provisions should be incorporated into the AI training.

Training should be pedagogically grounded and discipline-specific. UNESCO's GenAI Competency Framework for Teachers defines 15 competencies across five dimensions—human-centred mindset, ethics of GenAI, GenAI foundations and applications, GenAI pedagogy, and GenAI for professional learning—and serves as a guide for teacher training and professional development [31]. In epidemiology, instructor development should cover practical uses of GenAI, including literature search, code generation and debugging, interpretation of statistical outputs, and preparation of teaching materials. It should also help instructors develop the judgement needed to decide when GenAI use is pedagogically inappropriate because it may weaken methodological understanding or professional reasoning. Training should therefore address how to design learning activities that integrate GenAI appropriately and how to evaluate student GenAI use critically.

Because GenAI tools and their regulatory context evolve quickly, institutions should treat instructor upskilling in AI literacy as an ongoing responsibility rather than a one-time activity (see example in **Box 4**). Institutions should offer local training, allocate time for instructors to participate, establish attendance as an expectation for internal instructors, and ensure guest lecturers are informed about institutional GenAI policies. Where institutional training is not yet available, instructors should take active responsibility for developing their own competence by seeking relevant external courses, guidance, and peer-learning opportunities rather than waiting for institutional provision (see example courses in **Appendix 4**). Guest lecturers should be briefed on the relevant GenAI use policies and be expected to align their teaching practices with them.

We recommend training be organized in two stages: the first stage should cover general GenAI competencies for all instructors, ideally taught by pedagogists with AI expertise. The second stage should be more epidemiology-specific, and may be particularly effective at the departmental level, where small groups of epidemiology instructors can exchange concrete teaching examples, test tools in relation to shared course needs, and learn from one another through structured peer support and mentoring. Ideally, attendance should be recognized as part of continued professional development.

Box 4. Examples of institutional initiatives supporting GenAI in teaching

The ZLD – Centre for Innovative Teaching and Learning at UMIT TIROL [32] supports teaching staff, program and examination committees, and the doctoral committee in all matters related to teaching, learning, and educational quality. The professional development program enables instructors to continuously develop their teaching competencies, explore innovative teaching approaches, and exchange ideas and experiences on effective teaching practices with colleagues. As part of the program, several initiatives using GenAI in teaching have been implemented.

- In depth courses: e.g., Hype or Impact? Understanding, Trusting, and Using AI Responsibly; Recent topics in eLearning: AI Literary
- AI cafe: monthly ongoing informal exchange of instructors on experiences of using AI in teaching across disciplines
- Teaching Lunch: Monthly lunch series with internal and external speakers covering recent developments in didactics, including use of GenAI (e.g., 'chatbots in teaching - chances and risks'), with slides and recordings available for instructors after the events

Recommendation 5: Support students in developing necessary GenAI literacy for epidemiology

It is vital to provide students with a foundational understanding of GenAI and its use and limitations. Ideally, introductory training should be offered by the parent institution (e.g., the university, research institute) at the beginning of a program (e.g., Bachelor's, Master's, PhD), for example as part of an introductory day provided by the program coordinator. Foundational training should include all relevant aspects of the parent institution's GenAI policy (see **Recommendation #1**), including data protection issues to prevent breaching applicable laws. Furthermore, the training should focus on the parent institution's rules on declaring GenAI use (see **Recommendation #2**), verification and accountability (see

Recommendation #3), and ethical aspects, e.g., sustainability and data ownership, to promote responsible use. The training should include a comprehensive overview of commonly available GenAI tools and their recommended use cases, clearly indicating whether the use of each tool is permitted or prohibited by the parent institution.

Additionally, institutions need to ensure that all students have equal access to the GenAI tools used in the respective courses or modules. To ensure that instructors and students are on the same page, instructors should be aware of any training provided to students by the study program and/or parent institution. Notably, the implementation of compulsory modules may require curriculum-level modifications and, in some cases, program reaccreditation. Elective modules may provide an interim solution to ensure speedy implementation of training before curriculum modifications are approved. Regardless of how GenAI training is implemented, it needs to be updated regularly to accommodate the rapid developments in GenAI.

Subsequently, students should be upskilled in GenAI competencies through deliberate and thoughtful integration into epidemiology curricula as part of a workforce-relevant, digital “future skill set” [33]. Students increasingly need to know how to use GenAI responsibly for tasks such as refining literature search strings, supporting science communication, preparing reports for non-specialist audiences, or assisting with coding. At the same time, students should always critically reflect on their GenAI use, which can be guided by instructors through the inclusion of GenAI reflection questions in their courses and exercises (see **Appendix 5**).

Curricula should include hands-on tutorials in prompt engineering (prompt formulation, iteration, and documentation). Solid skills in prompt engineering are essential, as well-designed prompts obtain the most accurate and effective output from a GenAI model. Further, a high prompt engineering competence enhances students’ knowledge acquisition and knowledge application when using GenAI [34]. On the other hand, low quality prompts (e.g., applying human-to-human conversational structure, asking questions instead of giving explicit instructions) result in low quality outputs. In addition, students must learn that biased prompts can produce biased outputs, and that GenAI responses reflect the strengths and weaknesses of the underlying training data [13, 14, 35]. Without this knowledge, there is a risk that students may conflate linguistic fluency with evidential validity. In epidemiology, these issues can be linked explicitly to familiar concepts such as selection bias, publication bias, external validity, and representativeness.

Given the importance of prompt engineering skills, several prompting strategies (see example in **Box 5**), guides, and frameworks have been developed by experts from different areas, including information science, machine learning, and GenAI developers. For example, the CLEAR framework (**C**oncise, **L**ogical, **E**xplicit, **A**daptive and **R**eflective) was designed to optimize interactions with GenAI with students in mind [36]. In educational settings, such frameworks support students in developing systematic prompting habits that enhance both the quality and consistency of GenAI-assisted work. Further, leading GenAI companies have created their own distinct guides and best practices for their respective models [37–39].

GenAI should also be taught as a support tool for coding and code-related tasks, after students have acquired the necessary foundations. Such tools are already standard in the workflows of many jobs, and students should learn how to use GenAI to generate code suggestions, debug syntax issues, explain code segments, and support code review. At the same time, students must be taught about potential risks of such tools, and whether GenAI plugins can be used in a coding interface given required protection levels of loaded datasets (see **Recommendation #1**). It is important that students learn to critically review GenAI-generated output and verify whether the suggested code or code modifications produce the intended results. Further, teaching students proper and transparent documentation of where and how GenAI contributed to scripts or analytic workflows (see **Recommendation #2**) is essential. Instructors also need to address issues of code ownership, consent, and accountability when feeding existing code written by someone else into GenAI.

Finally, epidemiology education should prepare students for the serious risks that GenAI poses to the production of scientific knowledge, including the manipulation of data, metadata, images, and existing research. This requires teaching principles of research integrity, evidence traceability, and transparency as core competencies.

Note

Across all uses of GenAI, students must understand that analytic decisions remain their responsibility and must be transparently documented and reported (see also Recommendation #3).

Box 5. Guiding epidemiology students in more thoughtful prompting

Different prompt engineering methods have been developed to solve common issues (e.g., generating hallucinated responses, difficulties in solving math problems or completing reasoning tasks) arising when using GenAI in specific use cases [40, 41]. Therefore, it is important for students to know which prompt engineering method to apply in which context to have GenAI generate the best possible response. Three common methods and their suggested usage applications are:

Input-Output Prompting (IOP)

The most basic/default form of prompting where GenAI is given a task (*input*) to which it will generate a mostly unspecific response (*output*). Two common varieties can be categorized under this method: *Zero-shot prompting* and *Few-shot prompting*.

During *zero-shot prompting* [42], no examples are provided within the prompt. It is best applied for broad problems where not much data is available.

Example prompt: *Explain confounding in a cohort study of physical activity and breast cancer risk to a first-year epidemiology student. Include one simple example and one sentence on why adjustment may matter.*

During *few-shot prompting* [43], a few examples are provided within the prompt. It is best applied for complex tasks where a lot of data is available.

Example prompt: *Classify each variable as exposure, outcome, confounder, mediator, or collider: Example 1, age in smoking → myocardial infarction = confounder; Example 2, blood pressure in salt intake → stroke = mediator. Now classify BMI in physical activity → diabetes, socioeconomic status in education → hypertension, and hospital admission in infection → mortality.*

Chain-of-Thought Prompting (CoT) [44]

A series of prompts is given to the GenAI model with the goal of solving a complex task in a step-by-step approach until a final output is generated. Recommended applications include multi-step math word problems (arithmetic reasoning), common sense reasoning, and symbolic reasoning.

Example prompt: *A study finds a crude risk ratio of 2.0 and an age-adjusted risk ratio of 1.2 for alcohol use and cancer. Reason through the epidemiological interpretation step by step, then give a short final conclusion.*

Chain-of-Verification Prompting (CoVe) [45]

Developed using CoT as a base. Given an initial draft response, verification questions are constructed and given to GenAI. Answering these questions, GenAI will correct and refine the initial response. This method was developed with the specific goal of reducing hallucinated responses. However, the approach does not lead to a complete elimination of hallucinations (especially for reasoning tasks). Therefore, students and instructors alike are still required to validate responses.

Example prompt: *First draft an interpretation of the results from this cohort study (Reference). Then create three verification questions about bias, confounding, and temporality, answer them, and revise the interpretation accordingly.*

Additional prompt engineering methods that interested instructors may want to explore further include: **Self-Consistency Prompting (SC)** [46], **Tree-of-Thought Prompting (ToT)** [47], **Expert Prompting (EP)** [48], **Generated Knowledge Prompting (GKP)** [49], **Automatic Prompt Engineering (APE)** [50], and **Re-Reading (Re2)** [51, 52].

Example prompts for all of these prompting methods can be found in **Appendix 6**.

Recommendation 6: Prevent never-skilling and deskilling of epidemiological and scientific competencies

Epidemiology teaching should ensure that students acquire essential epidemiological and scientific competencies without developing over-reliance on automated tools.

Students should first develop and demonstrate their lower-level cognitive processes in the epidemiology domain, before moving to developing their own problem-solving approaches, reasoning pathways, and ideas. Failing to achieve these teaching aims may lead to students failing to reach higher-order knowledge and cognitive processing skills (so-called 'never-skilling'). This in turn may result in a less-skilled epidemiology workforce over time. In addition to never-skilling, the risk and speed of deskilling, i.e., losing skills which have previously been obtained, is an increasing concern which affects not only students but also instructors who increasingly rely on GenAI for assistance [7]. These risks are of particular concern in epidemiology, where methodological rigor depends on being able to justify each analytical and conceptual step independently, and where study results inform public health decision makers.

Instructors should ensure that students are competent in core epidemiological concepts, particularly those anchored in the catalog of learning objectives [53], without reliance on GenAI. These include, for example, effect measure calculation, bias, study design principles, data quality assessment, causal reasoning, methodological judgment, and scientific reasoning. The pedagogical goal is that any later use of GenAI is grounded in students' own understanding and serves to support reflection, transfer, and verification rather than substituting for intrinsic cognitive processes. This may require revisiting and refining learning objectives to specify which competencies students must demonstrate without GenAI support. Courses should include explicit phases or assignments without GenAI use, especially during early skill acquisition (see examples in **Box 6**).

Box 6. Illustrative examples of essential epidemiological skills to hone prior to reliance on GenAI tools

- Calculate effect measures by hand, explain its interpretation in their own words, and show their reasoning
- Manually inspect, clean, and analyze epidemiological datasets so students become familiar with common problems such as missing data, coding inconsistencies, and implausible values as part of learning basic coding necessary for data analysis
- Understand biases, how they arise, and how to detect, avoid, and deal with them
- Critically appraise a scientific publication using a conventional checklist (e.g., JBI Critical Appraisal Checklists) [54]

A similar approach should be taken to teach epidemiology-adjacent skills. For example, to preserve scientific writing skills, students should produce the first draft of written work themselves, while GenAI may later be used for feedback, revision, or polishing. Students also need foundational knowledge and operational fluency in at least one statistical software environment to understand the basic concepts of programming. The ability to critically appraise evidence in a landscape increasingly shaped by GenAI should also be fostered. Instructors should adapt appraisal exercises so that students learn to assess integrity concerns that may be amplified by synthetic content generation, e.g., by learning to identify paper mills, predatory journals, manipulated figures, and questionable author affiliations. This ensures that students retain independent methodological judgment and can evaluate scientific evidence critically even where AI-generated or AI-assisted content may be involved.

Note

These safeguards are also relevant for instructors. Instructors should reflect on their own use of GenAI to ensure that core teaching, feedback, and methodological judgment skills remain actively maintained and are not gradually delegated to automated tools.

Recommendation 7: Integrate GenAI meaningfully as a teaching and learning tool, complementing traditional epidemiology training

Due to its potential to increase efficiency and creativity, instructors should consider the responsible integration of GenAI as a complementary teaching and learning tool in epidemiology education.

For instructors, GenAI can be used to support pedagogical development of course content portrayal and delivery. For example, it can help to turn a frontal lecture into an interactive session which promotes student thinking. It can also support the review and revision of the course syllabus and teaching materials, the evaluation and comparison of didactic methods, and the adaptation of content to specific target groups, disciplinary backgrounds, or levels of prior knowledge and experience. This may include rephrasing explanations, clarifying complex concepts, or generating alternative examples to address different learning needs. Furthermore, GenAI can assist with drafting case studies, generating practice questions, creating quizzes and exam questions, and preparing discussion prompts for seminars and journal clubs. [27, 55, 56]. It may also support the provision of formative feedback and reflective prompts for students, provided its use complies with the EU AI Act [1] and relevant institutional policies. However, such uses should remain subject to instructors' disciplinary and pedagogical judgment, with instructors remaining accountable for the accuracy and quality of the content taught, as well as for assessment and student guidance.

For students, GenAI's role should not be to replace active student reasoning, but to support concept acquisition, reflection, practice, and selected professional tasks in ways that are transparent, critical, and pedagogically purposeful (see **Recommendation #6**). GenAI can be particularly valuable when used in ways that preserve and promote active learning (see **Box 7**).

Box 7. Study mode as a learning tool

Students may use GenAI in a guided "study/learning" or "AI tutor" mode [27] in which the tool helps them work through the steps of solving a problem rather than providing direct answers. It may also support self-assessment, generate quiz questions, produce podcast-style summaries of lecture content, simulate journal club discussions of published manuscripts, or help break down difficult concepts into smaller reasoning steps. Used in this way, GenAI can function as a structured study and reflection aid for scaffolded learning rather than a substitute for understanding. This type of AI assistant is provided by commercial GenAI tools, but is also becoming increasingly available as part of university-owned GDPR-compliant GenAI solutions (e.g., ChatUIT from UiT The Arctic University of Norway [20]).

Recommendation 8: Adapt student assessment for the GenAI era and avoid overreliance on automated grading or GenAI-detection tools

Assessments in epidemiology need to be redesigned for the era of GenAI, because written take-home assignments and other unsupervised formats are increasingly difficult to use as measures of student learning. We therefore recommend reconsidering assessment formats, question types, and scoring, and, where feasible, supplementing non-controlled assessments with controlled components (such as oral examinations, presentations, or other supervised tasks, depending on staff resources and group size) that carry meaningful weight in the final grade (see

example in **Box 8**). Especially students who study in a second language should get the opportunity to practice oral examinations and presentations within the course to reduce performance anxiety and support students who are less confident in spontaneous oral communication. In addition, clear grading criteria, including clear statements on permitted or prohibited GenAI use during assessments and the consequences of misconduct (see **Appendix 7 & 8**), will be helpful for both students and instructors.

We recommend particular caution when instructors use GenAI to support feedback or grading, as these are high-stakes assessment processes requiring validity, reliability, and transparency. GenAI outputs may be inconsistent or misaligned with intended learning outcomes, raising risks for fairness, accountability, and compliance with institutional and regulatory requirements (e.g., EU AI Act obligations [1]). Such use must be limited, transparently declared, critically reviewed by the instructor, and allowed only where it is consistent with institutional rules and data-protection requirements. This caution is reinforced by the EU AI Act [1], which classifies AI systems intended for assessment of students' learning, as well as AI systems intended to monitor and detect prohibited student behavior during tests, as high-risk use cases in education [1].

Finally, we do not recommend relying on GenAI-detection tools to review student work. Evidence indicates that these tools remain methodologically weak, may compromise privacy, and can produce false positives as well as variable performance across learner groups and writing contexts, raising concerns about fairness in assessment [57]. Recent research highlighted inconsistent accuracy, high false-positive rates, and bias against non-native writers across GenAI-detection approaches [57]. At Vanderbilt University, for example, these shortcomings in GenAI-detection tools have led to updated guidance stating that traditional plagiarism checkers are not reliable sources of GenAI-detection, that publicly available GenAI-detection tools may create privacy concerns, and that detector scores should not be used on their own in misconduct processes [58]. Instead of relying on GenAI-detection tools, at present, we recommend clear GenAI-use policies, disclosure requirements, process-based assessment, oral follow-up, and expert human judgement.

Box 8. Assessment formats that are more resilient to GenAI

No assessment format should be considered fully “GenAI-proof”. Instead, instructors should design assessments that make student reasoning, methodological understanding, and individual contribution visible. In epidemiology, this means assessing whether students can explain study design choices, justify analytical decisions, interpret results, discuss uncertainty, and critically appraise work for potential biases.

Useful formats include oral examinations, closed-book written exams in controlled environments, open-book exams without access to GenAI tools, presentations followed by in-depth questioning, annotated code walkthroughs, and short oral follow-ups to written assignments. These formats should be practiced during the course through exercises and formative feedback, so that assessment remains closely aligned with the intended learning objectives.

Importantly, the preferable format of examination is dependent on both the size of the student group and on the mode (online versus in presence) of examination. For small student groups (e.g., up to 15–20 students) and in-person examinations, oral examinations could prevent the use of GenAI. However, oral examinations are not feasible (time and staff effort) for large groups of students; in an online setting, oral examinations would also not necessarily prevent students from using GenAI. For large groups of students in an online setting, closed book written exams using tools such as The Safe Exam Browser (SEB) [59], which temporarily turns any computer into a restricted workstation, may help restrict students’ attempts to open other applications, searching the web, or using unauthorized resources while taking a tests, could be an option.

Recommendation 9: Solicit iterative student feedback

GenAI continues to develop rapidly and its integration into teaching epidemiology is likely to require ongoing adjustment. Instructors must be prepared to continuously question, reevaluate, and improve their teaching concepts related to GenAI. Direct student feedback (see **Box 9**) on GenAI use in a course or module is essential for this process and should be collected on:

- (1) Instructors’ use of GenAI, e.g., general integration of GenAI in the course or module, clarity of course-specific GenAI usage and disclosure directives, specific usage during knowledge transmission, inclusion in exercises or group work.
- (2) Students’ use of GenAI, e.g., specific use cases where students were required or allowed to use GenAI (exercises, group work, essays).

Student feedback should inform reflection and serve as a basis for further improvement. For example, students may identify tools or teaching methods that have become outdated as GenAI evolves. Overall, feedback should be solicited in a way that captures both successful and unsuccessful approaches to GenAI integration while also allowing students to give detailed suggestions for future improvements.

Therefore, we recommend updating existing course evaluation surveys and in-class feedback to integrate questions related to GenAI and its use. In cases where universities apply an automated system independent from the instructor, instructors should actively request the inclusion of GenAI-related items from the responsible authorities. To limit the burden on students and protect response rates, feedback should be kept short. Brief mid-course surveys can be applied in addition to end-of-semester evaluations. Instructors may directly ask students to reflect on their GenAI use in specific exercises, generating immediate exercise-level feedback (see **Recommendation #2**).

Box 9. Items instructors can add to their end-of-semester or course evaluation

Feedback on instructors' use of GenAI

(1) *The guidance I received on when and how to use GenAI in this course was clear and sufficient:* Assessed via 5-point Likert scale (strongly disagree to strongly agree)

(2) *The GenAI tools used in this course are up-to-date and apply the latest versions of the models:* Assessed via 5-point Likert scale (strongly disagree to strongly agree)

(3) *The GenAI-created material helped visualize core epidemiological concepts (e.g., prevalence vs. incidence; types of bias; confounding) and made them easier to understand:* Assessed via 5-point Likert scale (strongly disagree to strongly agree)

(4) *Please name one element of the GenAI-generated course materials that supported your understanding of the content and one that made it more difficult. Which specific aspects could be improved?:* Free-text response

Feedback on students' use of GenAI

(1) *The GenAI-integrated exercises supported my learning of epidemiological methods:* Assessed via 5-point Likert scale (strongly disagree to strongly agree)

(2) *The GenAI tools used in this course were easy to use:* Assessed via 5-point Likert scale (strongly disagree to strongly agree)

(3) *The GenAI-integrated coding exercises helped me improve my skills in statistical programming:* Assessed via 5-point Likert scale (strongly disagree to strongly agree)

(4) *Please describe one aspect of GenAI use in exercises or group work in this course that worked well and one aspect that could be improved:* Free-text response

Recommendation 10: Contribute to the evidence base for GenAI in epidemiology teaching and share effective practices across institutions

The use of GenAI in epidemiology teaching should be evaluated rigorously rather than merely piloted informally. Such evaluation should examine whether GenAI improves learning outcomes, enhances methodological understanding, reduces or increases workload, influences equity, and affects assessment quality and academic integrity, while also identifying any unintended consequences of its use.

Such a scholarly, research-based approach aligns with the principles of Scholarship of Teaching and Learning (SoTL) [60] that highlights the intertwined role of academics who both teach and conduct research. Contemporary interpretations of SoTL also emphasize communities of practice, reflection on the instructor's own biases and assumptions, faculty support programs, and differentiated institutional support strategies for faculty [61]. In the context of GenAI, we recommend SoTL-inspired practices at the individual, institutional, and trans-institutional levels, such as through teaching-focused working groups.

One key challenge is the rapid pace of change in GenAI tools. By the time a rigorous scientific evaluation of GenAI in epidemiology teaching is completed, the tools under investigation may already have evolved substantially or been replaced. Addressing this requires a shift from slow, one-off evaluations tied to specific tools towards continuous and adaptive evaluation approaches. In practice, this means that evaluation should focus on more stable pedagogical constructs such as learning objectives, cognitive processes like clinical reasoning and data interpretation, instructional strategies such as formative feedback and simulation-based learning, and broader use case types including case generation, assessment support, and tutoring.

Grounding evaluation in stable educational and methodological constructs will help ensure that findings remain relevant as GenAI technologies evolve. It will also improve the transferability of findings across tools, versions, and vendors. Epidemiology instructors can strengthen this evidence base by researching strategies to improve GenAI literacy. They can also engage students as partners in the development, implementation, and evaluation of GenAI teaching practices. Incorporating students' perspectives can help promote more effective and equitable approaches.

Sharing what works, what fails, and what remains uncertain is as important as conducting formal evaluations. Effective and ineffective approaches should be shared alongside evaluation findings, model policies, teaching materials, and assessment designs. Questions about assessment, disclosure, academic integrity, data protection, workload, equity, and methodological learning should also be discussed. Relevant forums include departmental meetings, program boards, faculty education committees, pedagogical development centers, national teaching networks, conferences, webinars, and open-access publications (see **Box 10**). Such collective efforts allow the field to develop cumulatively rather than through isolated experimentation. This document exemplifies such an approach by bringing together collective expertise to support field-level learning rather than proposing a locally-confined solution.

UiT's *New assessment forms* project [62] is a practical example of contemporary within-university sharing and collaboration. The project brings together staff and students across UiT to explore new assessment forms in response to challenges such as GenAI, academic integrity, learning quality, and overreliance on traditional exams. Its use of pilots, evaluations, project notes, presentations, and open conferences shows how local

experimentation can become institutional learning rather than isolated innovation. This kind of sharing can be encouraged by academic incentive structures, such as in Norwegian higher education [63]. The national guidelines and UiT's criteria for educational competence emphasize collegial development, documentation of teaching practice, systematic improvement, and dissemination of knowledge-based teaching. Sharing GenAI-related teaching experiences is therefore not only useful for the field; it is also aligned with principles of SoTL and formal expectations for academic development, merit, and educational quality work in Norwegian universities [64].

Sharing GenAI-related teaching experiences is therefore important not because GenAI adoption is an end in itself, but because collective evaluation can help determine when, where, and how these tools may contribute to meaningful learning. Such collaborative approaches will allow our field to respond critically and adaptively as the technology continues to evolve.

Box 10. How knowledge exchange can work in practice

A regional epidemiology teaching network organizes a half-day pre-conference session where instructors from three universities each present a 15-minute case study on a specific GenAI integration in their methods or data analysis courses. Each presentation follows a common structure: the teaching objective, the GenAI use, the evaluation approach, and the main finding. Slides and materials are collected and shared via an open repository afterwards. Two instructors who piloted GenAI-assisted R coding exercises report a similar pattern: students produce cleaner initial code but are less able to explain their analytical choices when asked. This shared observation prompts a discussion about redesigning the exercises to include a required "explain your code" step. The session format is repeated the following year with updated cases, creating a recurring venue for cumulative learning across the network.

From recommendations to practice: considerations for implementation

Epidemiology teaching currently faces a dual challenge of maintaining epidemiological skills and building GenAI competencies. Successfully implementing GenAI in epidemiology teaching requires coordinated changes at multiple levels and among different players. Instructors have a central role in shaping how GenAI is integrated into teaching and learning, but cannot navigate this transition alone. Institutions need to provide guidance, resources, and opportunities for collaboration so that effective practices can be developed collectively across departments and programs. Importantly, GenAI represents more than another step in educational automation: unlike tools that execute predefined tasks, generative systems can create and transform information, requiring instructors and institutions to reconsider learning objectives, assessment approaches, and how they support students in critically engaging with knowledge.

Previous technological shifts in education have been accompanied by similar challenges. The widespread availability of the internet, for example, changed the instructor's role from primarily transmitting knowledge to helping students find, evaluate, and appropriately use information while maintaining academic standards. GenAI represents a further evolution, but with important differences: rather than simply expanding access to information or automating searches, these systems can generate fluent text, code, statistical analyses, and scientific arguments that resemble expert work. Combined with their rapid development, this creates new challenges for teaching and assessment.

Maintaining focus on educational goals during times of rapid change

As GenAI rapidly transforms education, uncertainty and disruption are inevitable. Educators should remain focused on the central goal of integrating GenAI in ways that strengthen, rather than weaken, core epidemiological competencies. This will likely require alignment of learning objectives, teaching formats, and assessment methods to ensure that students develop strong foundations in epidemiological methods and scientific reasoning, as well as GenAI literacy.

Rather than focusing solely on technical proficiency, modern epidemiology teaching should reinforce principles of transparent, reproducible, and responsible research by helping students understand when and how GenAI is appropriate, how to critically evaluate its outputs, and how to document its use. While alignment with broader international principles on transparency, academic integrity, responsible use, and data protection is desirable, instructors must also keep setting-specific factors in mind, as legal frameworks, institutional resources, and assessment cultures differ widely across countries and universities.

From institutional guidance to capacity building to classroom practice

Beyond curriculum design, clear and consistent institutional guidance on the use of GenAI is essential. Instructors need their institutions, departments, and study programs to establish standards for data protection, academic integrity, and transparent reporting, while providing practical guidance on acceptable use and responses to misuse.

Institutional policies should encourage responsible experimentation with GenAI rather than discourage engagement with these tools altogether. Such policies should emphasize transparency, accountability, and opportunities for reflection on the implications, limitations, and risks of GenAI use, alongside assessment approaches that prioritize reasoning over polished final products. Importantly, these principles are not unique to GenAI; they reflect longstanding commitments to research quality, academic integrity, and responsible scientific practice.

Institutional support during this transition requires more than policies and infrastructure; it requires investment in people. Instructors need space to try GenAI, reflect on its benefits and limitations, and adapt their teaching as the technology evolves. At the same time, students need structured guidance to develop responsible and critical approaches to using GenAI. Existing competency frameworks, such as the EU DigComp 3.0 framework, provide a useful basis for this [65], and may help instructors make the case for institutional investment in GenAI literacy.

Sharpening the role of teaching: renewed value of active learning in the GenAI era

GenAI is also changing how students engage with teaching itself. When lectures are perceived as primarily delivering information that can be readily summarized or generated by GenAI, students may be less inclined to attend or engage with them. Face-to-face teaching therefore needs to offer clear added value by providing opportunities for interaction, discussion, collaborative learning, and application of epidemiological concepts to real-world problems.

This shift is particularly relevant for epidemiology as a methods-driven discipline. Many core epidemiological topics require structured reasoning, discussion of assumptions, and application to realistic scenarios rather than passive information transfer. Skills such as critical appraisal will become even more important, as students increasingly need to evaluate rather than simply produce information. Peer review of manuscripts, study protocols, or GenAI-generated outputs can help develop these skills [66], consistent with broader work on evaluative judgement emphasizing students' ability to assess quality beyond formal peer review settings [67]. As routine tasks become increasingly supported by GenAI, teaching can place greater emphasis on interactive problem solving, interpretation, and communication of findings.

Preparing future epidemiologists for GenAI in practice

GenAI should be a tool that supports rather than replaces instructors and learners. GenAI models are constrained by their training data, may generate plausible but incorrect information, and cannot reliably capture emerging evidence in real time. Therefore, as GenAI becomes increasingly embedded in research and public health practice, the ability to use and assess these tools appropriately will become an important competency for future epidemiologists. Training programs should thus focus not only on how to use GenAI, but also on when to question, verify, and challenge its outputs, ensuring that methodological rigor and epidemiological thinking remain central.

Addressing equity in GenAI-supported education

Ensuring that GenAI does not widen existing educational inequalities requires attention to both access and inclusion. Instructors should keep in mind that access to high-quality GenAI tools is not equally distributed across students, institutions, or countries, potentially creating unfair advantages [14, 68]. Even when universities provide self-hosted models within protected data environments, inequities may persist if some students have access to more capable commercial models than others. Effective applicability of GenAI tools also differs for students with different educational backgrounds and learning needs. Instructors should be aware of these inequities and, when possible, prevent existing educational inequities from being reinforced, whether intentionally or not; however, we acknowledge that this may be difficult to implement in practice.

Scope, limitations, and future directions

This set of ten recommendations were developed by a team of epidemiology instructors, doctoral students, and GenAI experts with interest or experience in GenAI-enabled epidemiology education. As such, they reflect the authors' consensus across a range of perspectives, refined in iterative rounds using additional contributor feedback, but may not represent the broader epidemiology teaching community. Furthermore, the recommendations primarily draw on experiences from Germany, Norway, and Austria; educational contexts in other settings may face different challenges and opportunities.

Beyond the contextual scope, it is important to recognize that these recommendations reflect the current state of GenAI technology. While specific applications and practical considerations will continue to evolve, we expect the underlying educational principles to remain relevant.

Overall, our recommendations for instructors aim to support thoughtful integration of GenAI into epidemiology teaching. Rather than prescribing fixed rules or recommending specific models, we offer a starting point for instructors navigating rapidly changing technologies, educational practices, and institutional policies. The central goal remains to ensure that GenAI is used as a complementary tool, while preserving the methodological rigor, critical thinking, and scientific judgement that underpin epidemiological practice.

Endorsement

This consensus recommendation has been endorsed by the German Association for Medical Informatics, Biometry and Epidemiology (GMDS). The endorsement was approved by the GMDS Executive Board (Präsidium) on August 12, 2026. At the time of submission, we have submitted a request for endorsement and are awaiting a final decision from the DGEpi Executive Board.

Statements & Declarations

Funding

The joint Working Group “Teaching in Epidemiology” received partial funding for the 2025 annual teaching conference, where these recommendations were conceived. The German Society for Epidemiology (DGEpi) supported conference-related costs, and the German Association for Medical Informatics, Biometry and Epidemiology (GMDS) supported guest speaker travel. Furthermore, ML received travel support from the European University Alliance for Global Health (EUGLOH) for travel from UiT The Arctic University of Norway to Germany for the 2026 workshop (ref. 40245816). EUGLOH had no role in the study design, data collection, analysis, interpretation, writing of the manuscript, or decision to submit the article for publication.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Contributions

AB, NG, and JLR organized the in-person workshop events that provided the basis for these recommendations. AB and NG applied for funding for the events. AB, NG, OB, VKJ, RK, HM, RP, KSO, NW, ML, LH, and JLR were involved in drafting and critically revising the recommendations. AB, NG, OB, VKJ, HM, RP, NW, LH, and JLR synthesized feedback and revised the recommendations further after input from the larger working group. JLR provided project supervision. AB, NG, and JLR are speakers of the Joint Working Group “Teaching in Epidemiology”.

Furthermore, the following individuals provided constructive and substantive feedback on an earlier draft of these recommendations (listed alphabetically). Collectively, they represent a diverse group of members of the Joint Working Group on Teaching in Epidemiology, instructors and educational researchers, information specialists, and students of epidemiology, medicine, public health, and related disciplines at the Bachelor's, Master's, and Doctoral levels. Several individuals contributed in more than one of these capacities.

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One additional individual provided anonymous feedback.

We are also grateful to Octavia Rowe (QUEST Center for Responsible Research, Berlin Institute of Health at Charité – Universitätsmedizin Berlin, Germany) for support in synthesizing the contributor feedback.

References

1. Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act) [Internet]. 2024. Available from: <https://eur-lex.europa.eu/eli/reg/2024/1689/oj>
2. Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation) [Internet]. 2016. Available from: <https://eur-lex.europa.eu/eli/reg/2016/679>
3. Gruenhagen JH, Sinclair PM, Carroll J-A, Baker PRA, Wilson A, Demant D. The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. *Computers and Education: Artificial Intelligence* [Internet]. 2024;7:100273. Available from: <https://doi.org/10.1016/j.caeai.2024.100273>
4. Stöhr C, Ou AW, Malmström H. Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study. *Computers and Education: Artificial Intelligence* [Internet]. 2024;7:100259. Available from: <http://doi.org/10.1016/j.caeai.2024.100259>
5. Bloom BS, Engelhart MD, Furst EJ, Hill WH, Krathwohl DR. Taxonomy of educational objectives: The classification of educational goals. Handbook 1: Cognitive domain. New York: Longman; 1956.
6. Krathwohl DR. A revision of bloom's taxonomy: An overview. *Theory Pract* [Internet]. 2002;41:212–8. Available from: http://doi.org/10.1207/s15430421tip4104_2
7. Ke Y, Jin L, Ong JCL, Thirunavukarasu AJ, Car J, Cheung CY, et al. AI-induced never-skilling in medical education. *Nat Med* [Internet]. 2026;32:1997–2006. Available from: <http://doi.org/10.1038/s41591-026-04438-y>
8. Bastani H, Bastani O, Sungu A, Ge H, Kabakçı Ö, Mariman R. Generative AI without guardrails can harm learning: Evidence from high school mathematics. *Proc Natl Acad Sci U S A* [Internet]. 2025;122:e2422633122. Available from: <https://doi.org/10.1073/pnas.2422633122>
9. Fan Y, Tang L, Le H, Shen K, Tan S, Zhao Y, et al. Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *Br J Educ Technol* [Internet]. 2025;56:489–530. Available from: <http://doi.org/10.1111/bjet.13544>
10. Dizon JIWT, Mendoza NB, Gasevic D, Ganotice FA Jr. Assessing AI-driven metacognitive offloading: Initial development and validation of the metacognitive laziness scale. *ECNU Review of Education* [Internet]. 2026;9. Available from: <http://doi.org/10.1177/20965311261450994>
11. Zhao Z, Wang Y, Stuart T, De Vaan M, Ginsparg P, Yin Y. LLM hallucinations in the wild: Large-scale evidence from non-existent citations [Internet]. *arXiv [cs.DL]*. 2026. Available from: <http://doi.org/10.48550/arXiv.2605.07723>
12. Topaz M, Roguin N, Gupta P, Zhang Z, Peltonen L-M. Fabricated citations: an audit across 2.5 million biomedical papers. *Lancet* [Internet]. 2026;407:1779–81. Available from: [http://doi.org/10.1016/S0140-6736\(26\)00603-3](http://doi.org/10.1016/S0140-6736(26)00603-3)
13. Furfaro D, Celi LA, Schwartzstein RM. Artificial intelligence in medical education: A long way to go. *Chest* [Internet]. 2024;165:771–4. Available from: <http://doi.org/10.1016/j.chest.2023.11.028>
14. Miao F, Holmes W. Guidance for generative AI in education and research [Internet]. UNESCO; 2023. Available from: <http://doi.org/10.54675/ewzm9535>
15. Weissgerber TL, Drude N, Rahal R-M, Kohrs FE. Ten simple rules for leading a many-author non-empirical paper. *PLoS Comput Biol* [Internet]. 2025;21:e1013283. Available from: <http://doi.org/10.1371/journal.pcbi.1013283>
16. European Commission. Living guidelines on the responsible use of generative AI in research [Internet]. 3rd ed. Brussels: European Commission; 2026. Available from: https://research-and-innovation.ec.europa.eu/document/download/2b6cf7e5-36ac-41cb-aab5-0d32050143dc_en. Archived at: https://web.archive.org/web/20260511225431/https://research-and-innovation.ec.europa.eu/document/download/2b6cf7e5-36ac-41cb-aab5-0d32050143dc_en?filename=ec_rtd_ai-guidelines.pdf (archived 2026/05/11)
17. University of Oslo. How to classify data and information [Internet]. University of Oslo. 2020 [cited 2026 Jul 16]. Available from: <https://www.uio.no/english/services/it/security/isis/data-classes.html>. Archived at:

- <https://web.archive.org/web/20260218115815/https://www.uio.no/english/services/it/security/isis/data-classes.html> (archived 2026/02/18)
18. Federal Office for Information Security. Generative AI Models - Opportunities and Risks for Industry and Authorities [Internet]. Federal Office for Information Security; 2025. Available from: https://www.bsi.bund.de/SharedDocs/Downloads/EN/BSI/KI/Generative_AI_Models.pdf?__blob=publicationFile&v=6. Archived at: https://web.archive.org/web/20251027184259/https://www.bsi.bund.de/SharedDocs/Downloads/EN/BSI/KI/Generative_AI_Models.pdf?__blob=publicationFile&v=6 (archived 2025/10/27)
 19. University of Münster CIT. Terms of Use for the “UniGPT” Service [Internet]. University of Münster. 2025 [cited 2026 Jul 10]. Available from: <https://www.uni-muenster.de/IT/en/services/arbeitsplatz/unigpt/agb.html>. Archived at: <https://web.archive.org/web/20251206160117/https://www.uni-muenster.de/IT/en/services/arbeitsplatz/unigpt/agb.html> (archived 2025/12/06)
 20. UiT The Arctic University of Norway. Information about the use of artificial intelligence [Internet]. UiT The Arctic University of Norway. [cited 2026 Jul 10]. Available from: <https://en.uit.no/om/kunstigintelligens>. Archived at: <https://web.archive.org/web/20260316175055/https://en.uit.no/om/kunstigintelligens> (archived 2026/03/16)
 21. UiT The Arctic University of Norway. Retningslinje for klassifisering av informasjon [Internet]. UiT The Arctic University of Norway. 2019 [cited 2026 Aug 5]. Available from: <https://en.uit.no/Content/741990/cache=1629791505000/Retningslinjer+for+klassifisering+-+vedtatt+5-4-19.pdf>. Archived at: <https://web.archive.org/web/20260805094309/https://en.uit.no/Content/741990/cache=1629791505000/Retningslinjer+for+klassifisering+-+vedtatt+5-4-19.pdf> (archived 2026/08/05)
 22. Perkins M, Jasper R, Furze L. Reimagining the Artificial Intelligence Assessment Scale: A refined framework for educational assessment. J Univ Teach Learn Pract [Internet]. 2025;22. Available from: <https://doi.org/10.53761/rrm4y757>
 23. Young J. AIR: AI in Research - A framework for transparent and responsible AI use mapped to the research process [Internet]. figshare. 2026 [cited 2026 Jul 20]. Available from: <http://doi.org/10.6084/m9.figshare.31268020>
 24. Suchikova Y, Tsybuliak N, Teixeira da Silva JA, Nazarovets S. GAIDeT (Generative AI Delegation Taxonomy): A taxonomy for humans to delegate tasks to generative artificial intelligence in scientific research and publishing. Account Res [Internet]. 2026;33:2544331. Available from: <https://doi.org/10.1080/08989621.2025.2544331>
 25. GAIDeT Declaration Generator [Internet]. [cited 2026 Jul 15]. Available from: <https://panbibliotekar.github.io/gaidet-declaration>. Archived at: <https://web.archive.org/web/20260713201534/https://panbibliotekar.github.io/gaidet-declaration/index.html> (archived 2026/07/13)
 26. Berlin School of Public Health. Master of Science in Public Health (MScPh) - Information Leaflet Master's Thesis [Internet]. 2025 [cited 2026 Aug 5]. Available from: https://campusnet.charite.de/studiengaenge/msc_public_health/downloads. Archived at: https://web.archive.org/web/20260805094502/https://campusnet.charite.de/studiengaenge/msc_public_health/downloads (archived 2026/08/05)
 27. Kasneci E, Sessler K, Küchemann S, Bannert M, Dementieva D, Fischer F, et al. ChatGPT for good? On opportunities and challenges of large language models for education. Learn Individ Differ [Internet]. 2023;103:102274. Available from: <http://doi.org/10.1016/j.lindif.2023.102274>
 28. Romeo G, Conti D. Exploring automation bias in human–AI collaboration: a review and implications for explainable AI. AI Soc [Internet]. 2026;41:259–78. Available from: <http://doi.org/10.1007/s00146-025-02422-7>
 29. Rhodes C. Working with AI and spotting AI-generated text [Internet]. House of Commons Library. 2026 [cited 2026 Jul 15]. Available from: <https://commonslibrary.parliament.uk/research-briefings/cbp-10823/>. Archived at: <https://web.archive.org/web/20260518175930/https://commonslibrary.parliament.uk/research-briefings/cbp-10823/> (archived 2026/05/18)
 30. European Commission. AI Literacy - Questions & Answers [Internet]. European Commission. 2025 [cited 2026 Jul 20]. Available from: <https://digital-strategy.ec.europa.eu/en/faqs/ai-literacy-questions-answers>. Archived at: <https://web.archive.org/web/20260716080130/https://digital-strategy.ec.europa.eu/en/faqs/ai-literacy-questions-answers> (archived 2026/07/16)
 31. Miao F, Cukurova M. AI competency framework for teachers [Internet]. UNESCO; 2024. Available from: <http://doi.org/10.54675/zjte2084>
 32. ZLD - Zentrum für Innovative Lehre und Didaktik. ZLD - Zentrum für Innovative Lehre und Didaktik [Internet]. UMIT TIROL - Private University For Health Sciences and Health Technology. 2025 [cited 2026 Aug 5]. Available from: https://www.umat-tirol.at/page.cfm?vpath=meta/servicecenter/hochschuldidaktik-umit-tirol&switchLocale=de_AT. Archived at: https://web.archive.org/web/20260805094823/https://www.umat-tirol.at/page.cfm?vpath=meta%2Fservicecenter%2Fhochschuldidaktik-umit-tirol&switchLocale=de_AT (archived 2026/08/05)
 33. Rampelt F, Matthes W, Hannken-Illjes K, Sandmeier A, Gehrs V, Horstmann N, et al. Future Skills 2030. An Updated Framework for Future Skills [Internet]. Stifterverband; 2026. Available from: <https://zenodo.org/doi/10.5281/zenodo.18723265>
 34. Gibreel O, Karataş K, Arpacı I. Prompt engineering competence, knowledge management, and technology fit as drivers of educational sustainability through generative AI. Sci Rep [Internet]. 2026;16. Available from: <http://doi.org/10.1038/s41598-026-46335-x>

35. Panteli D, Adib K, Buttigieg S, Goiana-da-Silva F, Ladewig K, Azzopardi-Muscat N, et al. Artificial intelligence in public health: promises, challenges, and an agenda for policy makers and public health institutions. *Lancet Public Health* [Internet]. 2025;10:e428–32. Available from: [https://doi.org/10.1016/S2468-2667\(25\)00036-2](https://doi.org/10.1016/S2468-2667(25)00036-2)
36. Lo LS. The CLEAR path: A framework for enhancing information literacy through prompt engineering. *J Acad Libr.* [Internet]. 2023;49:102720. Available from: <https://doi.org/10.1016/j.acalib.2023.102720>
37. Prompt design strategies [Internet]. Google AI for Developers. [cited 2026 Jul 23]. Available from: <https://ai.google.dev/gemini-api/docs/prompting-strategies>. Archived at: <https://web.archive.org/web/20260720111900/https://ai.google.dev/gemini-api/docs/prompting-strategies> (archived 2026/07/20)
38. Prompting best practices [Internet]. Claude Platform Docs. [cited 2026 Jul 23]. Available from: <https://platform.claude.com/docs/en/build-with-claude/prompt-engineering/claude-prompting-best-practices>. Archived at: <https://web.archive.org/web/20260716090806/https://platform.claude.com/docs/en/build-with-claude/prompt-engineering/claude-prompting-best-practices> (archived 2026/07/16)
39. Best practices for prompt engineering with the OpenAI API [Internet]. OpenAI Help Center. [cited 2026 Jun 17]. Available from: <https://help.openai.com/en/articles/6654000-best-practices-for-prompt-engineering-with-the-openai-api>. Archived at: <https://web.archive.org/web/20260531220610/https://help.openai.com/en/articles/6654000-best-practices-for-prompt-engineering-with-the-openai-api> (archived 2026/05/31)
40. Walter Y. Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education. *Int J Educ Technol High Educ* [Internet]. 2024;21. Available from: <https://doi.org/10.1186/s41239-024-00448-3>
41. TU Dublin Libraries. Introduction to Generative AI: Types of prompting [Internet]. TU Dublin Libraries. 2025 [cited 2026 Aug 5]. Available from: https://tudublin.libguides.com/GenAI/prompting_types. Archived at: https://web.archive.org/web/20260805095328/https://tudublin.libguides.com/GenAI/prompting_types (archived 2026/08/05)
42. Kojima T, Gu SS, Reid M, Matsuo Y, Iwasawa Y. Large Language Models are Zero-Shot Reasoners [Internet]. *arXiv [cs.CL]*. 2022. Available from: <http://doi.org/10.48550/arXiv.2205.11916>
43. Brown TB, Mann B, Ryder N, Subbiah M, Kaplan J, Dhariwal P, et al. Language Models are Few-Shot Learners [Internet]. *arXiv [cs.CL]*. 2020. Available from: <http://doi.org/10.48550/arXiv.2005.14165>
44. Wei J, Wang X, Schuurmans D, Bosma M, Ichter B, Xia F, et al. Chain-of-thought prompting elicits reasoning in large language models [Internet]. *arXiv [cs.CL]*. 2022. Available from: <https://doi.org/10.48550/arXiv.2201.11903>
45. Dhuliawala S, Komeili M, Xu J, Raileanu R, Li X, Celikyilmaz A, et al. Chain-of-verification reduces hallucination in large language models. *Findings of the Association for Computational Linguistics ACL 2024* [Internet]. Stroudsburg, PA, USA: Association for Computational Linguistics; 2024. p. 3563–78. Available from: <https://doi.org/10.18653/v1/2024.findings-acl.212>
46. Wang X, Wei J, Schuurmans D, Le Q, Chi E, Narang S, et al. Self-consistency improves chain of thought reasoning in language models [Internet]. *arXiv [cs.CL]*. 2022. Available from: <https://doi.org/10.48550/arXiv.2203.11171>
47. Yao S, Yu D, Zhao J, Shafran I, Griffiths TL, Cao Y, et al. Tree of thoughts: Deliberate problem solving with large language models [Internet]. *arXiv [cs.CL]*. 2023. Available from: <https://doi.org/10.48550/arXiv.2305.10601>
48. Xu B, Yang A, Lin J, Wang Q, Zhou C, Zhang Y, et al. ExpertPrompting: Instructing large language models to be distinguished experts [Internet]. *arXiv [cs.CL]*. 2023. Available from: <https://doi.org/10.48550/arXiv.2305.14688>
49. Liu J, Liu A, Lu X, Welleck S, West P, Le Bras R, et al. Generated knowledge prompting for commonsense reasoning [Internet]. *arXiv [cs.CL]*. 2021. Available from: <http://doi.org/10.48550/arXiv.2110.08387>
50. Zhou Y, Muresanu AI, Han Z, Paster K, Pitis S, Chan H, et al. Large language models are human-level prompt engineers [Internet]. *arXiv [cs.LG]*. 2022. Available from: <https://doi.org/10.48550/arXiv.2211.01910>
51. Xu X, Tao C, Shen T, Xu C, Xu H, Long G, et al. Re-reading improves reasoning in Large Language Models [Internet]. *arXiv [cs.CL]*. 2023. Available from: <https://doi.org/10.48550/arXiv.2309.06275>
52. Eliot L. Using The Re-Read Prompting Technique Is Doubly Rewarding For Prompt Engineering [Internet]. *Forbes*. 2024 [cited 2026 Jun 20]. Available from: <https://www.forbes.com/sites/lanceeliot/2024/07/06/using-the-re-read-prompting-technique-is-doubly-rewarding-for-prompt-engineering>. Archived at: <https://web.archive.org/web/20260619054113/https://www.forbes.com/sites/lanceeliot/2024/07/06/using-the-re-read-prompting-technique-is-doubly-rewarding-for-prompt-engineering> (archived 2026/06/19)
53. Working Group Teaching in Epidemiology, GMDS, DGEpi. Catalogue of Learning Objectives Epidemiology - Basics of Epidemiology [Internet]. 2019 [cited 2026 Jun 17]. Available from: https://www.dgepi.de/assets/CatalogueLearningObjectives_Epidemiology.pdf. Archived at: https://web.archive.org/web/20260306015923/https://www.dgepi.de/assets/CatalogueLearningObjectives_Epidemiology.pdf (archived 2026/03/06)
54. JBI. Critical Appraisal Tools [Internet]. JBI Global. [cited 2026 Jun 20]. Available from: <https://jbi.global/critical-appraisal-tools>. Archived at: <https://web.archive.org/web/20260607234814/https://jbi.global/critical-appraisal-tools> (archived 2026/06/17)

55. Kiyak YS, Emekli E. ChatGPT prompts for generating multiple-choice questions in medical education and evidence on their validity: a literature review. *Postgrad Med J* [Internet]. 2024;100:858–65. Available from: <http://doi.org/10.1093/postmj/qgae065>
56. Moundridou M, Matzakos N, Doukakis S. Generative AI tools as educators' assistants: Designing and implementing inquiry-based lesson plans. *Computers and Education: Artificial Intelligence* [Internet]. 2024;7:100277. Available from: <http://doi.org/10.1016/j.caeai.2024.100277>
57. Hadra M, Cambridge K, Mesbah M. Evaluating the accuracy and reliability of AI content detectors in academic contexts. *Int J Educ Integr* [Internet]. 2026;22. Available from: <http://doi.org/10.1007/s40979-026-00213-1>
58. Vanderbilt University. Academic Integrity and Generative AI [Internet]. Vanderbilt University. 2023 [cited 2026 Jul 23]. Available from: <https://www.vanderbilt.edu/generative-ai/academic-integrity>. Archived at: <https://web.archive.org/web/20260711235857/https://www.vanderbilt.edu/generative-ai/academic-integrity/> (archived 2026/07/11)
59. ETH Zurich, IT Services. Safe Exam Browser [Internet]. Safe Exam Browser. [cited 2026 Jul 10]. Available from: https://safeexambrowser.org/news_en.html. Archived at: https://web.archive.org/web/20260709233331/https://safeexambrowser.org/news_en.html (archived 2026/07/09)
60. Boyer. Scholarship reconsidered: Priorities of the professoriate [Internet]. Princeton, NJ: Princeton University Press; 1990 [cited 2026 Jun 17]. Available from: <https://eric.ed.gov/?id=ED326149>
61. Major C, Cruz L, Braxton JM. Fostering a culture of scholarship of teaching and learning in higher education: A look at emerging research. *New Dir Teach Learn* [Internet]. 2024;2024:7–10. Available from: <http://doi.org/10.1002/tl.20583>
62. UiT The Arctic University of Norway. Nye vurderingsformer [Internet]. UiT The Arctic University of Norway. [cited 2026 Jul 9]. Available from: <https://uit.no/project/nvf>. Archived at: <https://web.archive.org/web/20251218043035/https://uit.no/project/nvf> (archived 2025/12/18)
63. Universities Norway. Nasjonale veiledende retningslinjer for UH-pedagogisk basiskompetanse [Internet]. Universities Norway. 2025 [cited 2026 Jun 17]. Available from: <https://www.uhr.no/temasider/karrierepolitikk-og-merittering/nasjonale-veiledende-retningslinjer-for-uh-pedagogisk-basiskompetanse>. Archived at: <https://web.archive.org/web/20251210105812/https://www.uhr.no/temasider/karrierepolitikk-og-merittering/nasjonale-veiledende-retningslinjer-for-uh-pedagogisk-basiskompetanse> (archived 2025/12/10)
64. UiT The Arctic University of Norway. Sentrale regelverk - Utfyllende bestemmelser for ansettelser og opprykk i undervisnings- og forskningsstillinger og ansettelser i rekrutteringsstillinger ved UiT [Internet]. UiT The Arctic University of Norway. 2025 [cited 2026 Jun 17]. Available from: <https://uit.no/ansatte/regelverk/sentraleregler/bestemmelseransatte>. Archived at: <https://web.archive.org/web/20260313135430/https://uit.no/ansatte/regelverk/sentraleregler/bestemmelseransatte> (archived 2026/03/13)
65. Cosgrove J, Cachia R. DigComp 3.0: European digital competence framework, fifths edition [Internet]. Publications Office of the European Union; 2025. Available from: <https://doi.org/10.2760/0001149>
66. Rohmann JL, Wülk N, Rubarth K, Grillmaier H, Abdikarim I, Lopes Simões M, et al. Effectiveness of the researcher-led "Peerspectives" peer review training course on review quality, knowledge, and skills among doctoral students in the biomedical sciences: a pre-post study. *Res Integr Peer Rev* [Internet]. 2026;11. Available from: <http://doi.org/10.1186/s41073-026-00220-3>
67. Tai J, Ajjawi R, Boud D, Dawson P, Panadero E. Developing evaluative judgement: enabling students to make decisions about the quality of work. *High Educ (Dordr)* [Internet]. 2018;76:467–81. Available from: <http://doi.org/10.1007/s10734-017-0220-3>
68. Jamal Eddine R, Gide E, Al-Sabbagh A. Systematised evidence mapping of generative artificial intelligence (GenAI) and digital divide phenomena in higher education. *Discov Comput* [Internet]. 2026;29. Available from: <http://doi.org/10.1007/s10791-026-10044-w>

Figures

Ten recommendations for the use of GenAI in epidemiology teaching

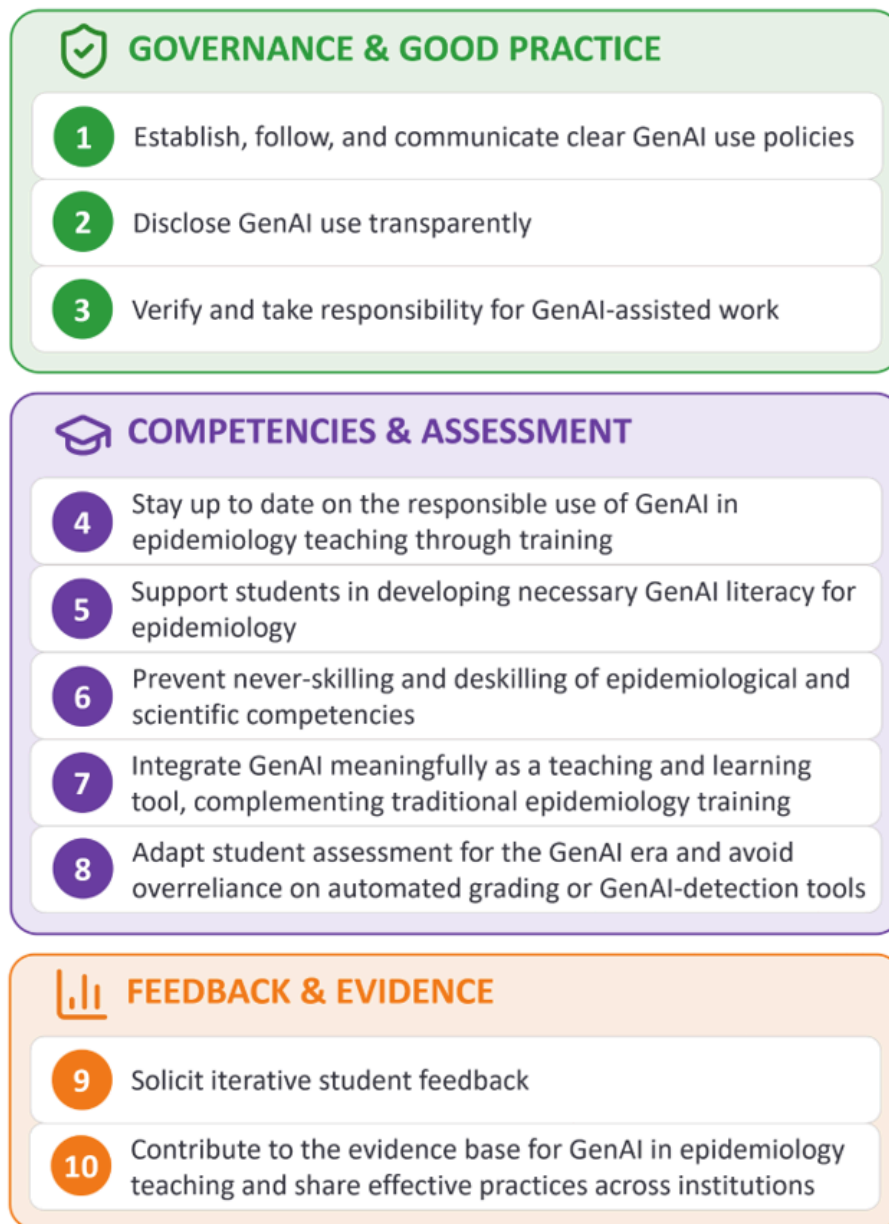


Figure 1

Ten recommendations for the use of generative AI (GenAI) in epidemiology teaching, split into three thematic groups: governance and good practice, competencies and assessment, and feedback and evidence

Ten recommendations for the use of GenAI in epidemiology teaching



Figure 1

Ten recommendations for the use of generative AI (GenAI) in epidemiology teaching, split into three thematic groups: governance and good practice, competencies and assessment, and feedback and evidence

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