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TAL2025

Teaching for Active Learning

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Content

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TAL2025 - Teaching for Active Learning

Special focus: Teaching with AI

In November 2025, SDU Centre for Teaching and Learning (SDU Universitetspædagogik) hosted its 13th Teaching for Active Learning conference. The main theme of the conference was active teaching and learning, which is the underlying principle for teaching at SDU. The aims of the annual TAL conference are to provide opportunities for teachers, developers, and others with a special interest in teaching to:

- share, demonstrate, reason, and analyze their own examples of active teaching and learning
- be inspired to develop one's own active teaching practice for students to learn actively.

The TAL conference provides an annual space for teachers and consultants to share their pedagogic discoveries, which in turn can inspire conference delegates' future practices. In addition to a variety of pedagogic discoveries, which activated students' learning and teachers' teaching, TAL2025 had a special focus on Teaching with AI.

In addition to the main theme of active teaching and active learning, this year's conference explored the topic of teaching with AI, addressing questions such as: How can we use AI critically and constructively to support learning, feedback, and supervision? How can pedagogical thinking guide AI use? And how can teaching with AI be supported through organisational structures and competence development?

José Antonio Bowen, a highly experienced academic leader, presented two insightful and tightly packed keynotes – "Teaching and Thinking with AI" and "Educating Humans to Thrive in an AI World" – covering a wide range of perspectives. Below are a few selected points.

1. Chatbots, APIs, and prompts

Although GenAI has been publicly available for only three years, it no longer makes much sense to speak of "GenAI" in the singular. There are now several major competing language models on the market, and even more so-called APIs (application programming interfaces) designed for specialised use.

AI competence now also entails being able to select tools appropriately for different purposes. And there is growing collaboration around sharing effective prompts and prompting techniques, including for teaching purposes.

José Bowen's resource page (https://weteachwithai.com/) provides valuable guidance for those wishing to navigate this rapidly evolving field.

2. GenAI as a new condition in higher education – AI literacy as a new educational mission
Another key point from Bowen was that regardless of our position on GenAI, it has quickly become an unavoidable condition of modern teaching. It is now the responsibility of teachers to help students use GenAI critically, with academic integrity and as a tool for learning.

AI literacy involves: (i) the ability to ask good questions, and (ii) the ability to recognise limitations and critically evaluate AI outputs.

Bowen described prompting as a new form of academic writing: the more precise, nuanced, and well-structured a prompt or a dialogue sequence is, the greater the chance of receiving a meaningful response. "Prompting is writing" – and, in the university context, prompting is also thinking.

He also underscored the distinction between novices and experts: (i) Novices often use AI to 'figure out what to do' but lack the ability to assess the quality of responses; (ii) Experts, on the other hand, use AI to accelerate what they already know and can critically revise, challenge, and refine its outputs.

Our educational task, then, is to cultivate experts – learners equipped to use AI responsibly and insightfully. AI literacy thus becomes a new form of educational formation, closely aligned with traditional goals of critical thinking, source criticism, and academic integrity – not something apart from disciplinary learning.

3. AI separates writing from thinking – teaching must reconnect them
A recurring theme in Bowen's presentations was that AI increasingly separates writing from thinking: text of high linguistic quality can now be generated within seconds, without the writer necessarily undergoing any meaningful cognitive process.

If teaching and assessment continue to reward only the finished product (report, essay, or assignment), we risk assessing AI's linguistic proficiency rather than the student's understanding.

Bowen emphasised the need to design assignments where the process takes centre stage. This might involve:

(i) dividing writing tasks into distinct phases (idea development, outline, first draft, revision, reflection) and requiring documentation of where and how AI has been used;

(ii) allowing students to use AI for restructuring or language editing while insisting that analytical choices, argumentation, source work, and disciplinary reasoning remain their own;

(iii) encouraging meta-reflection: Did AI help you understand the material better – or merely make your writing more polished?

As Bowen put it, the goal is not to ban the tool, but to 'reconnect thinking, writing, and AI use' in ways that make clear that what is being assessed is the thinking itself.

In his book *Teaching with AI, 2nd Edition*, Bowen provides numerous examples of how such assignments can be designed.

4. From “cheating” to academic progression – transparency in AI use

According to Bowen, the difference between “cheating” and “progression” often comes down to framing. Many activities that can now be automated (such as drafting, translation, or proofreading) were once considered signs of diligence – but in an AI context, these tasks can no longer constitute learning outcomes in themselves.

Teachers should therefore clarify which parts of an assignment may (or must) be completed with AI, and which represent the authentic academic performance.

Bowen suggested that we move from hidden to transparent AI use, where students document how they used AI and how it influenced their work.

This could include short reflections, documentation of prompts, or comparisons between AI-generated suggestions and the student’s own solutions.

In this way, AI becomes not a shortcut that bypasses learning, but a prompt for explicit discussions of disciplinary quality, ethics, and source critique.

5. AI as the new “average” – everyone becomes an AI manager

Bowen described how generative AI is rapidly becoming the new “average”: a baseline level of problem-solving, text production, and analysis that is now accessible to both students and teachers.

This means that many standard tasks – such as summaries, first drafts, and simple analyses – can be produced faster and more cheaply by AI than by humans.

Rather than competing with this new “average worker,” our challenge is to determine which aspects of academic work can be delegated to AI and where human judgement, ethics, creativity, and relationships remain essential.

A central insight was that AI constitutes a new form of labour: everyone – including students – has in effect become an “AI manager,” responsible for delegating tasks, evaluating outputs, and taking ownership of final products.

This increases the importance of viewing teaching not merely as a matter of content and methods, but also as workflow design: Which steps in an assignment can be supported by AI, and where must the student think, decide, evaluate, and take ownership?

Happy reading!

On behalf of the conference organisers

SDU Centre for Teaching and Learning

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Quantitative evaluation of the quality of research based teaching

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Context

The title of the course is "Experts in Teams Innovation". It is an advance course for final year MSc. Students. The students come from 3 different backgrounds: Robotics, Drones and Software and naturally looking to get their MSc. in respective subjects. Given that these are final year students, they have good technological background in their subject.

The course is typically attended by 100 students every year. The students are divided into team of 4 to 5 students per teams. Each team is required to have students from at least two different backgrounds, i.e. it shall be a mix between Robotics, Drones and Software students. Each team is assigned a real-world industrial challenge and the team members must apply their combined knowledge and skills to develop a solution (hence, the course title 'Experts in Teams Innovation'). Teams are required to compile their development activities (learning activities) in a 'Final report' and submit it as a compulsory requirement to pass the course. The exam format is Oral, where individual students are questioned and graded based on the Final report.

As I took the course over in 2024, I analysed the contents of the course from last years. I noticed that Final report was defined very loosely with not a precise template. The report size varied from 40-60 pages. It is worth mentioning that students believed that their grades in the exam are directly correlated to the success in solving the industrial challenge, and therefore they focused on reporting their successful completion. It was interesting to note that every team of students reported to solve these industrial challenges successfully, even when the experts from industry have been trying to solve these for several years.

Learning objectives

The overall aim of the course is for students to apply their knowledge on real world unsolved problems. In essence, they will need to create new knowledge and combine it together with their existing knowledge as the problem cannot be solved with only existing knowledge. The practice can be attributed to the Student-Content side of the Didactical triangle (Gundem, B.B. & S. Hopmann 2002). The students must investigate what has already been done and shall create a formal state of the art about what others have tried. Students are also given full access to the laboratory and the equipment they need to try novel approaches. However, the idea is not that students must succeed in solving the problem, but rather to develop understanding and gain confidence through multiple trials. Hence, the students must engage in the research activities in this context. With this background my objectives were to:

- Change the mindset of the students that they are not graded based on the successfully solving the industrial challenge, but they are graded based on what they learn using the scientific and research-based approach to solve the industrial challenge.
- I needed to formulate a 'Final Report' template for the students, which not only guide them to follow the scientific approach but also makes it possible to evaluate their scientific approach.

So fundamentally I want to develop my teaching such that it is research based and want to develop a methodology through which I can objectively evaluate (Bergsmann, E., Schultes, M-T., Winter, P., Schober, B., Spiel, C. 2015) the quality of my research based teaching.

Formulation of methodology

As described in the first section, during past years, students reported their learning activities in a loosely defined format. A very generic template was provided to the students, and the average length of their submitted reports was around 50 pages. The students focused on producing on lengthy reports where actual essence of their work was lost. It was nearly impossible to evaluate the contents of the reports scientifically and objectively.

To ensure that students follow a scientific approach, and there is an alignment between course objectives and students' learning activities (Biggs & Tang 2007), a new reporting template was needed following the format of a scientific publication. Hence, I created a 'Final report' template following standard IEEE scientific publication, which includes all the elements required for a qualified research work. These templates have already been designed and used for reporting scientific work and there is already existing detailed scoring rubrics and internationally established methodology (Girden & Kabacoff 2010) to evaluate the scientific publications. The Table 1 below shows the sections of the 'Final report' which are used as criteria to assess the quality of research based approach by the students.

Table 1: Sections of the 'Final report' template and rubrics

Report section (Criteria)	Description	Weight	Score
Description of the industrial challenge	It is clear what is the industrial challenge and why it is important to solve this industrial challenge.	10%	0-5

State of the art	Report describes the most recent and relevant research and developments related to the industrial challenge with appropriate number of references.	20%	0-5
Approach	Report clearly describes how the presented solution is different and better.	20%	0-5
Experimental prototype	The experimental prototype is clearly described and it adequate for testing the approach.	20%	0-5
Results	Reports clearly shows the completion of the experiment and provides measurable results from the experiments.	20%	0-5
Summary	The report is well summarized in the Abstract. Conclusion clearly shows the success and shortcomings of the approach and describes the future direction.	10%	0-5

The length of the 'Final report' was also limited to 6-8 pages, making it compulsory for the students to strictly follow the scientific reporting practices and further instructions were added guiding students to understand and follow the template. Each criterion is scored from 0-5 and weighted as per given percentage to generate a single overall score of the 'Final report' indicated by a single number. For further objectivity, a scale was assigned for the scores of 0-5, as shown in the Table 2 below, which was used by the evaluators to score each section of the 'Final report'.

Table 2: Scaling guide for scoring the 'Final report' sections

Score	Scale
0	Missing
1	Not missing
2	Poor
3	Good
4	Very good
5	Excellent

Therefore, the overall score of the class can be calculated as average scores of all the final reports which will be a number from 0-5 indicating the overall ranking for the research based learning by the students, reflecting on my success in research based teaching.

Data collection

The course was attended by 98 students. The students were divided into 24 groups (22 groups with 4 students and 2 groups with 5 students), and hence 24 reports were submitted by the students. The 'Final report' template together with above rubrics and the scale was first presented to the students during a feedforward session early in the semester. Students were asked to conduct their development work according to the given evaluation criteria and following the provided template for the 'Final report'. Students were encouraged to compile their learnings in the report on weekly basis and get regular feedback from me to ensure that they are meeting the expected quality. However, none of the students approached for the feedback during the semester. At the end of the semester (2 weeks before the submission deadline), I organized an individualized feedback session for each group, for which 12 groups (50%) signed and showed up to get the feedback.

After the submission deadline, an independent review procedure was organized for the evaluation and scoring of the reports. 6 external examiners were selected, which was also a requirement from the university to ensure the independent evaluation of the students. 6 examiners were selected from within the university, who were not directly involved in the teaching. All examiners were familiar with and experienced in the evaluation of scientific publications. A joint meeting was organised for all the examiners, where they were introduced with the course and briefed on the rubrics and evaluation criteria. I deliberately, did not participate in the evaluation of the reports to ensure that the scores are independent and unbiased. The Table 3 below gives the scores of 'Final report' for all 24 groups.

Table 3: Scores of 'Final report' for all 24 groups

Group #	Score	Group #	Score	Group #	Score	Group #	Score
1	3	7	4	13	4	19	4.5
2	4	8	3.7	14	3.5	20	4.7
3	4.2	9	3.5	15	3.5	21	4.6
4	4	10	3.7	16	3	22	4.7
5	4	11	4	17	3.5	23	4.4
6	3.5	12	3.5	18	3	24	4.5

Results and evaluation

As a starting point, when the new 'Final report' template was presented to the students, they were resistant to the idea that they are required to follow a scientific approach. Many of them pointed out the course description which did not mention any research related activities. I had to explain to the students that as per Danish law, all university education is required to be research based, hence it does not require to be explicitly mentioned in the course description. So after some discussion, students agreed to follow the template. However, I was positively surprized during the final feedback session, when 12 groups send me their first draft for the feedback. At least 5 of these reports could be considered a high quality scientific work. In fact, these reports could even be submitted to some scientific conference, which I recommended to these groups. This was one of the positive indicator for me to continue this approach for the future.

Later, once I received the scores on the reports from the evaluators, it was further affirming that students given the right guidance can be engaged into research based learning. The graph in Figure 1 shows the distribution of scores across the 24 'Final reports'. As it can be seen that students scored in the range of 3 (Good) to nearly 5 (Excellent). Naturally fewer students ended up in the excellent range.

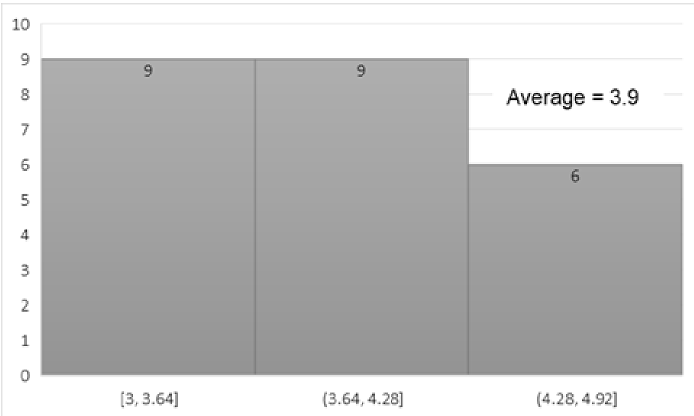

Figure 1: Distribution of scores among the groups and the overall average of the class

Further, the average of the 24 scores can be calculated from Table 3 which is 3.9 (Very good). This indicates that the methodology adopted to improve the research based teaching was a right approach. However, there remains the room for improvement and some actions are underway for the course to be held in the autumn of 2025.

Reflection

Over the course of my participation in Lecturer Training Program, I have come across several useful concepts to improve the teaching. It is always a challenge to create the right formulation of these concept when they need to be implemented for a specific course. When it comes to research based teaching/learning, I was enticed to implement it for my course. However, listening to the fellow lecturers in SDU, I found it difficult to get an objective point of view, what they regarded as the research based teaching. Being a researcher in control system technology, for me an objective and measurable KPI (Key Performance Indicator) is a way to fine tune my actions to constantly optimize the system's output.

This led me to ask a fundamental question from myself: How can I say that my teaching is research based and more importantly, how can I improve it? The answer I came with is: "I need to measure it". I realized that in fact, several other concepts and tools I learned during Lecturer Training Program, such as Rubrics, Feedback/feedforward, alignment of expectations, etc. can be combined and deployed here systematically to create a measurable output from the course, helping me to improve my teaching practices and for better implementation of the course each year.

Hence, this paper is an initial attempt to formulate a methodology to objectively measure the performance of a teacher attempting to implement research based learning. This formulation may not be generalizable for every course and other teachers may need to formulate different methodologies to obtain a measurable KPI for their respective courses, such as the specific case presented by (Viennot, L., & Rainson, S. 1999). Hence, this report shall be considered as an attempt to encourage the teachers to adopt more scientific approach towards the evaluation of their performance. Furthermore, the concept of measurable KPI may not be limited only to measure the success of research based teaching. But this concept can be extended further for teachers to improve other aspects of their teaching, such as: Feedback/feedforward, expectations alignment, supervision, etc. where appropriate KPIs and data collection methodologies can be implemented as per course structure and requirements.

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Enhancing Engagement in Pharmacology Through Flipped Learning: A Mixed Approach to Active Learning

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Introduction

Pharmacology is traditionally taught through lecture-based formats, partly due to the perceived density and complexity of the subject matter. However, this assumption may overlook the potential of active learning approaches to support understanding of complex concepts. In response to this challenge, we implemented a partial flipped learning intervention in a Master's-level pharmacology course. The purpose was not to replace traditional lectures entirely, but to explore whether flipping selected sessions could enhance engagement and deepen conceptual understanding.
The intervention was inspired by the concept of constructive alignment to ensure coherence between intended learning outcomes, teaching activities and assessment [1]. It also drew on the flipped classroom framework, in which lower-order cognitive tasks are shifted outside the classroom and class time is dedicated to active learning. Evidence from Science, Technology, Engineering and Mathematics (STEM) education suggests that active learning strategies are associated with improved student performance and reduced failure rates [2], providing additional theoretical justification for the redesign.

Objectives

The intervention was implemented within the Master's programme in Molecular Health Science at Roskilde University. The course is a 5 ECTS pharmacology module delivered to approximately 35 postgraduate students. Teaching is traditionally lecture-based, and assessment consists of a written exam including both knowledge-based and applied questions. The intended learning outcomes include understanding pharmacological mechanisms, applying concepts to clinical scenarios and developing analytical reasoning skills. The primary objective of the intervention was to promote active engagement and deeper learning among students. Specifically, the redesigned sessions aimed to enable students to acquire knowledge independently before class, to apply theoretical concepts to problem-based scenarios during class and to engage in collaborative reasoning. Data originally reported in the abstract referred to the 2024 cohort. For the present proceeding, these results have been updated to include data from the 2025 cohort.

The intervention

In 2024 and 2025, two teaching sessions were redesigned according to a flipped learning model. The selection of the two sessions to be redesigned was done at random. The intervention consisted of three phases: pre-class preparation, active in-class learning and post-class evaluation. Prior to class, students were provided with narrated PowerPoint presentations covering the theoretical content later applied during in-class activities and quizzes hosted on the learning management system. These quizzes were designed to consolidate understanding and provide immediate feedback. In 2024, 28 students completed the pre-class quiz for the first session, with 24 attending in class and an average quiz score of 7.3 out of 10. For the second session, 17 students completed the quiz, 13 attended in class, and the average score was 6.9 out of 10. These data suggest a positive engagement, although participation declined in the second session. In 2025, 28 students completed the pre-class quiz for the first section, with 27 attending in class and an average quiz score of 7.9 out of 10. For the second session, 21 students completed the quiz, 17 attended in class and the average score was 7.3 out of 10. A comparison between 2024 and 2025 shows a more stable pattern of participation in 2025. Average quiz scores were slightly higher in 2025 across both sessions. The more stable engagement in 2025 may be related to minor adjustments in communication and integration of pre-class activities into in-class work, although no causal conclusions can be drawn.

Regarding classroom times, they were reserved for team-based activities. Students worked in small groups to analyse pharmacological mechanisms, interpret data and discuss clinically relevant scenarios. The instructor’s role shifted from primary content transmitter to facilitator of discussion, guiding reasoning processes and clarifying misconceptions when necessary. The aim was to create a learning environment in which knowledge was actively mobilized rather than passively received. Following the sessions, students completed evaluation questionnaires addressing the usefulness of the pre-class materials, the quality of in-class activities and their overall preference regarding teaching format. In 2024, between 45% and 57% of students rated the format as better than traditional lectures, while a substantial proportion considered it equivalent. Pre-class materials were highly valued in both sessions (88-91% positive ratings), and in-class activities were positively evaluated by 82% of students. A majority preferred a hybrid model combining flipped and traditional teaching. In 2025, responses were more uniformly positive. Between 78% and 83% of students rated the flipped format as better than traditional lectures, all respondents found the pre-class materials useful, and 92-100% evaluated the in-class activities as effective. Reported engagement was high in both sessions (around 75-78%), and peer collaboration was viewed more positively than the previous year.

Impact on assessment

Exam performance across cohorts from 2022 to 2026 is presented in Figure 1. Prior to the introduction of flipped learning, average scores were 50.2 in 2022, 41.5 in 2023 and 49.3 in 2024. Following the introduction of flipped sessions, average scores reached 56.2 in 2025 and 55.1 in 2026.

This comparison does not allow causal inference, but the upward trend after the implementation of flipped sessions suggests a possible positive contribution of the redesigned teaching format.

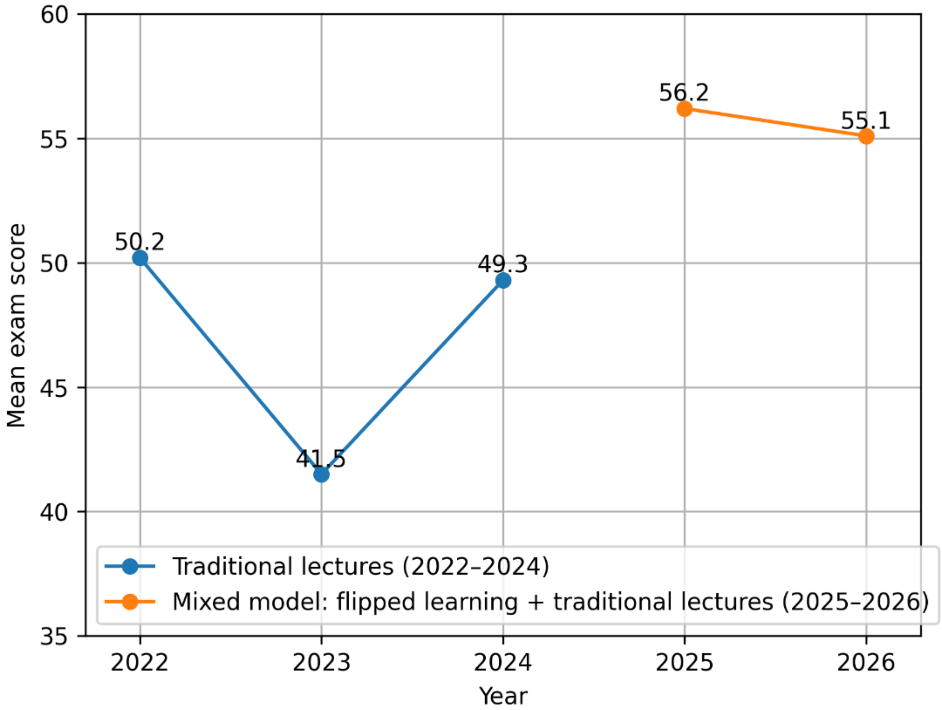

Figure 1. Average scores of pharmacology exam before and after the introduction of flipped learning. Traditional lecture-based teaching was used in 2022-2024, whereas flipped learning sessions were introduced from 2025 onwards.

Reflections

Several insights emerged from the implementation of the flipped sessions. The technological requirements were minimal, as the approach relied mainly on narrated slides and the standard learning management system. In practice, the key element was not the flipped structure itself, but the use of classroom time for student-centred activities. First, the level of student preparation influenced the quality of the in-class discussions. When most students had completed the pre-class activities, group discussions were more active and conceptually deeper. When preparation was lower, the potential of the in-class exercises was more limited. Second, students appreciated the flexibility of preparing before class, but many also expressed a preference for a combination of flipped sessions and traditional lectures. This suggests that a fully flipped course may not be necessary to improve engagement. This experience also challenged the assumption that complex content is best delivered through lectures, suggesting instead that complexity may benefit from interactive and student-centred approaches. A mixed format may represent a more practical and sustainable way to introduce active learning. Third, from the instructor's perspective, preparing the narrated presentations required a considerable initial effort. However, this investment may decrease over time, as the materials can be reused and gradually improved. This experience suggests that a partial flipped approach may be applied in other courses and disciplines, especially where educators want to introduce more active learning without completely replacing lectures. Future iterations will focus on improving student preparation before class, refining the design of formative quizzes and analysing learning outcomes more systematically across cohorts.

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Writing positive climate futures: Active learning and AI in climate fiction writing

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Introduction and context

This article is based on the presentation *"Writing Positive Climate Futures: Active Learning and AI in Climate Fiction Writing"*, presented at the Teaching for Active Learning (TAL) Conference 2025 at the University of Southern Denmark. The activity was developed and implemented within the Climate Elite Centre PACA (*Mobilising Post-Anthropocentric Climate Action: A New Root Narrative*) through a collaboration between educators and researchers at SDU.

As part of a Citizen science (CS) project, which in its broad term covers the engagement of the public in authentic scientific research (Phillips et al., 2018), second – and third-year high school students participated in the Climate Future Fiction project implemented as part of their English classes. Where CS has various levels of engagement, it can be argued that the participating students in this project functioned as both data creators and data collectors, just as they took part in the analysis of the data.

As a starting point, the students were asked to participate in a flash fiction task, which over the course of the project, was gradually developed into a fictional climate short story (Yazell & Wolf, 2023). During the flash fiction activity, the students were instructed to write spontaneously and without prior planning about a specific topic, using only longhand. They were given just three minutes to capture whatever thoughts, associations, or ideas immediately came to mind (Yazell, B., & Wolf, P, 2026). During the class lessons, the students were also asked to prompt their story into an AI story and to analyse (in groups) the anonymised stories across their class and create an overview of the patterns in the stories.

The activity is informed by research demonstrating that young people's involvement in climate action is influenced by their access to hopeful and emotionally meaningful visions of the future (Ojala et al., 2021; Kurth & Pihkala, 2022). At the same time, dominant climate narratives in journalism, fiction, documentaries, and social media remain largely dystopian (Roquebart & Debucquet, 2024), often contributing to feelings of anxiety, disengagement, and helplessness. Stories function as powerful instruments of change (Zaidi, 2017), yet the growing presence of generative artificial intelligence in creative writing introduces new questions concerning how such narratives are created, shaped, and attributed. In parallel, only limited research has explored how AI may assist young people in developing engaging, hopeful, and action-oriented visions of future life scenarios (Wolf & Yazell, 2025).

Building on this research context, the activity explored how creative writing combined with generative AI can function as an active learning approach that supports students' engagement with climate futures. This article clarifies the learning objectives that frame the activity, provides a detailed description of its design and implementation, and reflections on experiences, learning outcomes, and transferability to other educational contexts.

Learning objectives

The primary learning objective of the activity was to strengthen students' ability to imagine and express positive yet complex climate futures through creative writing, while simultaneously developing critical and reflective competencies in their use of generative AI as part of an active learning process.

More specifically, the activity aimed to enable students to:

1. Imagine and articulate positive yet complex climate futures through creative writing.
2. Engage critically and reflectively with generative AI as a co-creator in a creative learning process.
3. Identify and analyse differences between human-authored and AI-generated narratives, particularly in relation to style, plot, character development, and agency.
4. Develop emotionally engaging and action-oriented climate narratives that can inspire reflection and a willingness to act.

The objectives emphasise active learning by engaging students in writing, comparison, and analysis. At the same time, the activity supports broader educational goals related to critical AI literacy, narrative competence, and engagement with complex societal challenges.

Description of the learning activity

The activity was conducted as a case study involving 78 Danish upper secondary school students aged 16–18 from three different schools. The learning design consisted of a two-phase writing experiment that combined creative writing, active learning, and the use of generative AI.

Phase 1: Human-authored climate fiction

In the first phase, students worked individually with short flash fiction exercises. They were asked to write intuitive, short narratives about climate futures without using AI. The focus was on imagination and intuition, emotional resonance, and the construction of future life-worlds. These texts were later, under the guidance of their English language class teachers and using a structured worksheet, expanded into complete short stories, still authored exclusively by the students. This phase aimed to establish narrative ownership, creativity, and a personal voice before introducing AI into the writing process.

Phase 2: Climate fiction with generative AI

In the second phase, students were introduced to generative AI as a writing tool. They fed the original flash fiction story to AI and then used a structured worksheet to prompt AI to develop the flash fiction story into a complete short story. AI was explicitly framed as a reflective and experimental tool rather than a substitute for students' own creativity, and students were encouraged to question, adapt, and critically assess AI-generated suggestions.

Analysis and validation

Human-authored and AI-assisted texts were analysed using thematic and structural analysis. To strengthen the validity of the findings, coder triangulation and iterative coding were applied (Flick, 2009). In addition, an external validation was conducted using a separate language model (Claude 3.5 Sonnet), which was tasked with identifying distinguishing features between the two sets of texts.

The implementation of the activity highlighted distinct differences between narratives written by humans and those produced with AI support. Texts generated by AI showed recurring linguistic structures, standardised transitions, formalised dialogue, and repeated metaphorical expressions. Their plots were generally linear and foreseeable, frequently organised around simplified binary oppositions (such as human versus nature) and ending in harmonious yet reduced resolutions. By contrast, the students' own narratives demonstrated greater linguistic diversity, unpredictability, and sensitivity to context. These stories more often contained ambiguity, interruptions in narrative flow, and developments driven by action rather than solely introspective reflection. AI-generated characters were commonly archetypal, such as the isolated outsider or the contemplative observer, and were typically introduced through explicit markers of age and social role before unfolding along predictable trajectories. In comparison, human-authored characters displayed greater complexity, stronger relational anchoring, and more distinct narrative agency.

One of the most important learning outcomes became visible through the students' own assessments of the texts. They consistently described the AI-generated climate futures as dull and lacking motivational force, whereas their own narratives were experienced as emotionally engaging and more capable of encouraging action. This comparison created a key reflective moment, allowing students to articulate the limitations of AI as a creative co-author and to recognise the value of human imagination and narrative specificity.

Reflections and educational implications

The activity illustrates how generative AI can be integrated into teaching in ways that reinforce, rather than diminish, students' active role. By positioning AI as an object of comparison and critical reflection, students developed a more nuanced understanding of how AI shapes narratives, meaning making, and perceptions of agency. Climate fiction proved to be a powerful pedagogical tool that combines subject knowledge, creativity, and emotional engagement. Rather than simply learning about climate change, students actively explored possible futures, supporting deeper reflection and sustained engagement.

The activity design is transferable to a range of educational contexts, including humanities subjects (such as Danish, English, literature, and cultural studies), social studies and sustainability education, and interdisciplinary courses addressing technology, ethics, and future thinking. The model can be adapted across educational levels by adjusting narrative complexity, text length, and the degree of AI integration.

Beyond this specific context, the activity may also inspire educators and institutions seeking to work with AI in a pedagogically grounded way that foregrounds human creativity, critical reflection, and meaningful student engagement.

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Enhancing Student Engagement and Learning Outcomes in Programming Courses using Student-generated Quizzes

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Introduction
The increasing availability of generative artificial intelligence has introduced a new pedagogical challenge in programming education. In introductory programming courses, students can now produce answers, code fragments, and explanations with limited engagement in the underlying concepts. This creates a risk that participation appears satisfactory at the level of task completion while conceptual understanding remains weak. Accordingly, there is a need for teaching activities that retain student engagement while also requiring explanation, justification, and critical thinking.

This project examined the use of student-generated quizzes in a programming course. The central idea was to shift students from answering questions to constructing them. In this setting, students were asked to create weekly multiple-choice questions based on lecture content, often using short Python code snippets, and to bring these questions into a shared classroom activity. The design was intended to support active learning, peer instruction, and a flipped classroom structure (Estes, Ingram, & Liu, 2014; Mazur, 1997; Smith et al., 2009).

A central feature of the activity was that students were not only required to formulate a quiz question, but also to explain and justify it in class. This included explaining the code logic, identifying the correct answer, and discussing why the distractors were incorrect. In this way, the activity aimed to make student reasoning visible. The design also allowed students to use AI as a support tool during question generation, but the expectation was that AI should assist the learning process rather than replace it, in line with recent discussions on teaching with AI (Bowen & Watson, 2024).

The project was carried out across two course iterations. In Fall 2024, the activity focused on quiz creation and in-class discussion. In Spring 2025, a peer grading component was added to the design. This made it possible to examine not only whether students found the activity useful, but also how specific design choices influenced their experience. This paper presents the learning objectives connected to the activity, outlines how the activity was implemented, and discusses the main experiences from the two iterations, with particular attention to the role of AI and the problems associated with peer grading.

Learning objectives
The activity was connected to the learning objectives of the introductory programming course in Programming for Engineering Sustainability. At the course level, students were expected to develop a basic understanding of computational thinking and of how programming can be used to

analyse and solve engineering problems. Within this broader framework, the quiz activity was designed to support a more specific set of learning goals related to weekly lecture content.

In particular, the activity aimed to help students read and interpret short Python code snippets, identify the logic of a program, and distinguish between correct and incorrect answer options. This was important because the quiz format required students not only to recognize a correct answer, but also to construct plausible distractors. To do so, they had to think carefully about common misunderstandings and about where reasoning can go wrong in introductory programming tasks.

A second objective was to strengthen students' ability to explain their reasoning. The activity, therefore, did not end with the submission of questions. During the in-class quiz session, students whose questions were selected had to explain the code logic, justify the correct answer, and clarify why the other options were incorrect. This explanation phase was intended to make students' understanding explicit and to support peer learning through discussion, which is consistent with the principles of peer instruction described by Mazur (1997) and later examined by Smith et al. (2009).

A further objective concerned the role of AI in the learning process. Students were allowed to use generative AI while preparing their quiz questions. However, the pedagogical intention was not that AI should provide ready-made answers. Rather, students were expected to use it as a support tool while remaining responsible for the academic quality of the question, the quality of the distractors, and the correctness of the explanation. In this sense, the activity also aimed to support more critical and reflective use of AI in teaching and learning, in line with Bowen and Watson (2024).

Taken together, the learning objectives connected to the activity can be understood in three related parts. First, students should develop a stronger conceptual understanding of introductory programming content. Second, they should be able to articulate that understanding in a precise and public way. Third, they should learn to use AI in a manner that supports rather than replaces their own reasoning.

The activity was also directly aligned with the course assessment. Student-generated quizzes accounted for 20% of the final grade and were evaluated based on the quality of the question and the associated in-class explanation, with students working in groups of two or three. This meant that the learning objectives addressed through the activity, particularly code interpretation, explanation, and justification, were also part of the formal assessment structure. The remaining assessment consisted of individual assignments worth 30% and a group capstone project worth 50%, assessed through a written report and oral defense.

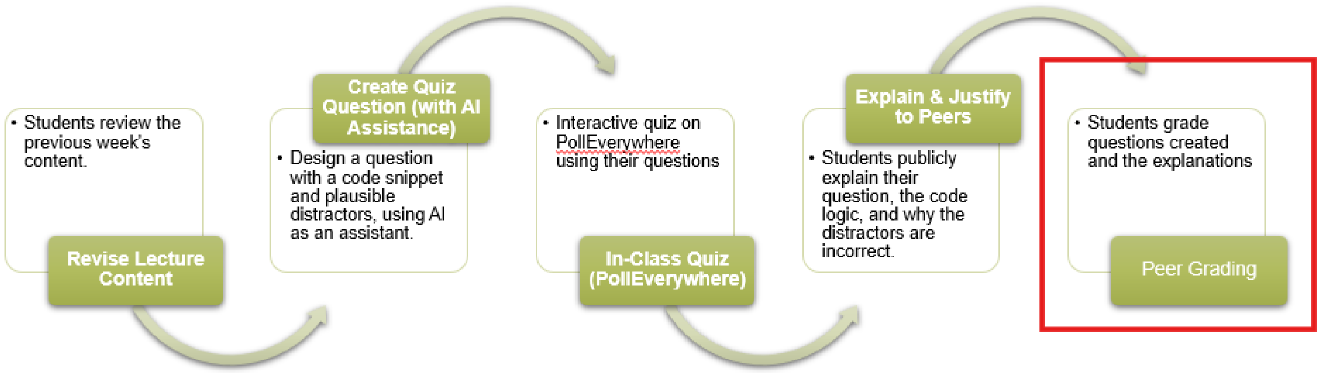

Figure 1. The weekly structure of the student-generated quiz activity, Spring 2025, includes an extra Peer Grading Component (highlighted in Red).

Implementation of the activity

The intervention was organized as a weekly student-generated quiz activity linked to the lecture content in Programming for Engineering Sustainability. Each week, students were asked to create a multiple-choice quiz question based on the previous lecture. The questions were expected to address core programming concepts and, in many cases, included short Python code snippets. This design placed students in the position of formulating questions rather than only answering them, which was intended to increase active engagement with the course material. Each group submitted two/three questions per week. The questions used for the in-class quiz were selected by the instructor. The selection process was intentionally inclusive, and most submitted questions were used unless they were factually incorrect, not related to the lecture content, or too easy to support meaningful discussion. Students were also given guidance on what constituted a good question and were shown examples in advance. Over the duration of the course, all students had an opportunity to explain questions in class as part of the activity.

The activity followed a repeated cycle. In the first step, students reviewed the previous week's lecture content and prepared a quiz question. In the second step, they could use generative AI as support while drafting the question and refining the answer options. Students were told that AI could be used to explore different aspects of the lecture content and to help generate plausible distractors and alternative formulations of the question. At the same time, they were explicitly instructed to verify the correctness of any AI-supported output by running the code and checking that the answer options were correct. Students were also given examples of acceptable AI use and were expected to follow the course AI policy, including declaring their use of AI where required. In the third step, selected questions were used in an in-class competitive quiz conducted through PollEverywhere. Finally, students whose questions were used had to explain the logic of the question to their peers. This explanation included identifying the correct answer and clarifying why the incorrect options were not valid.

This final step was particularly important in the design. The educational value of the activity did not rest only on writing a question. It also depended on the requirement that students justify the question publicly. In this way, the activity made student reasoning visible and reduced the possibility that a question could be produced without understanding the underlying concept. The explanation phase also created a direct connection between individual preparation and collective class discussion, which aligned well with the course design's peer-instruction perspective (Mazur, 1997; Smith et al., 2009).

The activity was implemented in two iterations (see Figure 1). In Fall 2024, the main structure consisted of question creation, AI-supported preparation, classroom quizzing, and explanation. In Spring 2025, the same overall structure was retained, but a peer grading component was added. The motivation was that the students who engaged with the quiz questions as participants were also well placed to evaluate the quality of the questions and the quality of the explanations. Accordingly, students were asked to assess peer submissions on both question quality and explanation quality. The peer grading used a rubric with the following criteria: Clarity (25 points), Difficulty Level (30 points), Innovativeness (15 points), and Explanation Quality (30 points), for a total of 100 points. The scores given by the students were averaged across the class. This peer grading contributed to the 20% course component assigned to the quiz activity. Students were given a rubric for the grading process, although they were not provided with specific examples illustrating the criteria.

From a pedagogical perspective, the activity drew on principles associated with flipped classroom teaching and active learning. Students engaged with the lecture material before class by preparing questions, and classroom time was then used for interaction, discussion, and clarification rather than passive review. In this sense, the activity was designed not as an isolated quiz exercise, but as a structured learning cycle intended to connect preparation, participation, and explanation.

Student Feedback and Key Findings

Student feedback from the two course iterations suggests that the activity was successful in engaging students more actively with programming content, but that its effectiveness depended strongly on how the activity was structured. Across both semesters, the most consistent positive finding was that the process of creating quiz questions helped students work more carefully with the lecture material. Students had to revisit concepts, read code more closely, and think about how to distinguish between correct and incorrect reasoning. In this sense, the value of the activity appeared to lie not only in the final quiz question but in the process of producing it.

A second finding concerns the role of AI. Many students found AI useful while preparing their questions, especially when they needed support in formulating answer options or refining question wording. At the same time, the feedback did not indicate that AI by itself led to deeper understanding. The material from both semesters instead suggests a distinction between utility and learning. AI was often helpful for completing the task, but the learning value depended more on whether students had to explain and justify the question afterwards. This point is important in relation to current discussions of teaching with AI, where the pedagogical challenge is not simply whether students use AI, but whether the activity requires them to remain intellectually responsible for the output.

The classroom explanation phase appeared to be central in this regard. When students were required to explain the code logic, identify the correct answer, and discuss why the distractors were incorrect, the activity moved beyond task completion and into shared reasoning. This part of the design made student understanding more visible and gave the teacher a clearer basis for identifying misconceptions. The plenary explanation phase likely supported learning for several related reasons. First, it created accountability, since students had to explain and defend their questions publicly rather than relying on AI-generated text without understanding it. Second, it prompted peer discussion and gave the teacher an opportunity to examine concepts in greater depth when they had only been treated more briefly during the lecture. Third, it allowed other students to hear the teacher's evaluation of the questions and explanations, which helped make explicit what counted as a strong question and what did not.

The comparison between Fall 2024 and Spring 2025 also revealed an important limitation. In Spring 2025, a peer grading component was introduced as part of the activity design. This element was intended to involve students more directly in evaluating the quality of quiz questions. However, student responses to this addition were predominantly negative. In the Spring 2025 feedback, students described the peer grading process as subjective and difficult to apply consistently, which suggests that this part of the design introduced both logistical and pedagogical problems. A likely reason for this response is that students experienced the grading process as subjective and were uncertain about how to rank submissions against some of the criteria. In particular, criteria such as difficulty level, innovativeness, and explanation quality may have allowed for different interpretations across students. As a result, the grading process appears to have introduced a sense of unfairness rather than supporting a shared understanding of quality. Rather than strengthening the activity, the peer grading component seems to have reduced its pedagogical value. The feedback suggests that students were more positive toward creating questions and discussing them than toward taking part in summative judgment of each other's work.

Informal discussions with students also suggested that peer involvement in evaluating quiz questions should not necessarily be abandoned, but rather redesigned. A more suitable alternative may be peer feedback without numerical grading, where students comment on the clarity, difficulty, and explanation of a question without assigning marks. Such an approach may preserve the reflective value of peer engagement while reducing the subjectivity and uncertainty associated with peer grading.

This contrast is one of the clearest findings of the project. The activity worked well when it emphasized preparation, explanation, and discussion. It worked less well when a formal peer grading layer was added. This suggests that the success of the intervention depended on maintaining a clear focus on learning rather than evaluation. In practical terms, the findings indicate that formative discussion around student-generated questions can support engagement and conceptual work, whereas summative peer grading may introduce tension without producing comparable educational benefit.

Taken together, the two iterations point to a consistent conclusion. Student-generated quizzes can function as a useful active-learning strategy in introductory programming, particularly when students are required to justify their reasoning in public. The use of AI can be accommodated within this design, but the pedagogical structure must ensure that students still do the conceptual work themselves. The Spring 2025 experience further indicates that not every additional design feature improves the activity. In this case, peer grading did not support the intended learning process and should be reconsidered in future implementations.

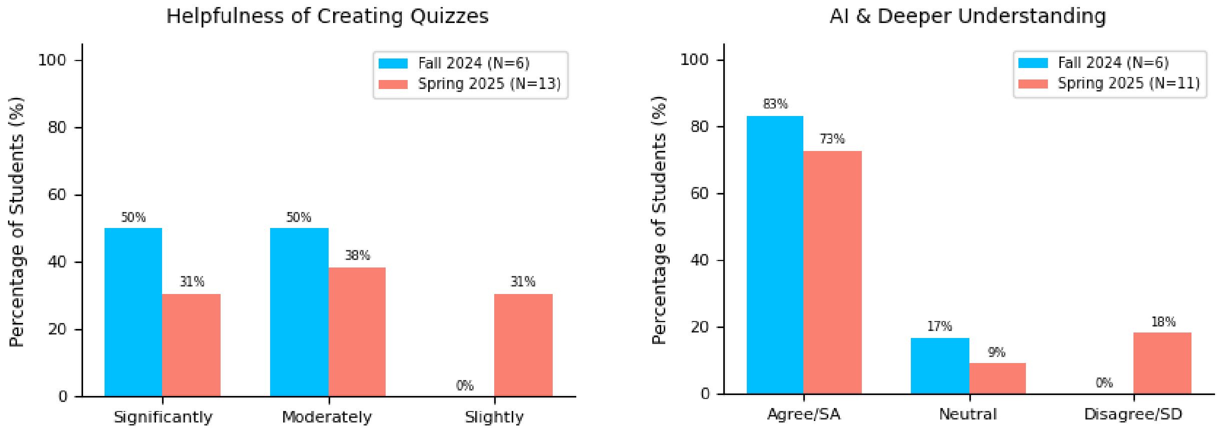

Figure 2. Comparison of Fall 2024 and Spring 2025 survey results on quiz creation and AI for deeper understanding.

Conclusion

This project indicates that student-generated quizzes can support active engagement and conceptual understanding in programming education when the activity is organized around question creation, in-class participation, and public explanation. The work draws on a flipped approach in which students revisit course content before class and on peer instruction in which understanding is made visible through discussion. In this setting, the strongest element was the requirement that students explain the code logic, justify the correct answer, and clarify the distractors.

The comparison between Fall 2024 and Spring 2025 also provides a practical lesson for future teaching with AI. AI can be useful in supporting the activity, but its value for learning is not automatic. At the same time, the Spring 2025 iteration showed that the peer grading component introduced both logistical and pedagogical difficulties and was not well received by students. Accordingly, future use of this activity should retain the student-generated quiz model and remove the summative peer grading element.

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Synthetic Horizons: Enhancing Data-Driven Education Through Simulated Environments

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Synthetic and Simulated Data for Education

Educational institutions are increasingly adopting data-driven approaches to enhance teaching and learning (Amer-Yahia, 2022; Custer et al., 2018). This has raised an array of ethical, practical, and technical challenges on how to use real-world educational data (Khine, 2024; Knox, 2023). Privacy regulations such as the General Data Protection Regulation (GDPR), as well as institutional ethics guidelines, limit the scope of using identifiable personal data for educational purposes. Additionally, data oftentimes is of critical value for most businesses, constituting part of their unique selling point, making them reluctant to share data for educational purposes even in anonymized form. In this context, realistic synthetic data, e.g. artificially generated data that mimics the statistical properties and behavioral patterns of real data, without disclosing personally identifiable information, emerged as an essential tool to provide training data for students to develop and enhance their data-driven skills and competencies (Nikolenko, 2021; Raghunathan, 2021).

Generally, synthetic data can be defined as “data that has been generated using a purpose-built mathematical model or algorithm, with the aim of solving a (set of) data science task(s)” (Jordon et al., 2022, p. 5). An additional method to provide valuable input for data-driven education is simulated data (Blejec, 2002; Halley, 1991), with agent-based modelling being a prominent example of this approach (Macal & North, 2009). The latter can be defined as allowing “one to simulate the individual actions of diverse agents, and to measure the resulting system behaviour and outcomes over time” (Crooks & Heppenstall, 2012, p. 85). In the following, we will provide four showcases from different courses and disciplines, where either synthesized or simulated data are used to provide data-driven education for students. More specifically, we will introduce possible scenarios from research methods, social media, learning analytics, and business data.

The Case of Research Methods

"Design and research methods" is a first-year course shared by three humanities' bachelor's degree programmes. The course aims to introduce students to different phases of research such as idea generation and research question formulation, choice of method, data collection and analysis. One widely used form of data collection is the research interview, and the introduction of different kinds of coding (Saldaña, 2021) or thematic analysis (Braun & Clarke, 2022), using a CAQDAS such as QualCoder or NVivo, naturally follows.

Conducting interviews is a time consuming process, as is the ensuing processing and coding of a set of interviews. Generation of synthetic interview data enables the rapid creation of teaching material which in turn allows for comparability of coding decisions among the students. Through detailed prompting, interviews were generated, on topics that the students are very familiar with (aspect of the experience of taking a specific university course), and a range of personas with different points of view were created. These were to be expressed in the different interviews along with other themes and outlooks (age, gender, interests and more). Microsoft Copilot was chosen for university policy reasons, and it took several iterations of prompting to create interviews of sufficient length and complexity. The primary aim of using synthetic data was to allow a discussion between groups of students of their coding of interview data. This is otherwise done on data created by themselves, which limits the interaction and reasoning about particular constructs one can entertain in a classroom setting. Beyond coding practice, using synthetic interviews also lends itself to methodological comparison: interviews can be generated at varying levels of structure, mirroring their possible setting in different research traditions such as ethnography or grounded theory.

The general question of possible skill loss and skill transfer arises also in this context. While transparency about the process of synthetic data generation can offer the students increased AI literacy, they might become less familiar with the intricate task of carefully preparing and carrying out a research interview. Further, the artificial construction of personas might raise a set of flawed expectations for any future coding the students do. Synthetic data do not fully replicate real interviews, and care will have to be taken to raise awareness of, and discuss, possible differences.

The Case of Social Media

Social media platforms present a rich source of data for understanding social learning, online communication, change communication, peer interaction, and informal educational discourse (Kumar et al., 2010; Rehm et al., 2025; Torphy et al., 2020). However, using authentic social media data in educational research or classroom simulations poses significant ethical and legal concerns, including user consent, data ownership, and the risk of deanonymization. Moreover, given recent developments on widely studied platforms, these types of data are getting increasingly difficult and expensive to attain. In this context, synthetic social media data provides a viable alternative. In order to generate the applicable data, in the following we will suggest a step-wise approach to collect, and analyse real world social media data, which can then subsequently be used to train models and generate synthetic data for educational purposes. First, the teacher chooses a scenario that fits the educational topic of the course (e.g. crisis communication). Next, as social media data essentially constitutes multilevel and multimodal network data (McLevey et al., 2026), the educator needs to employ social network analyses (Tabassum et al., 2018) and natural language processing (Chowdhury, 2003), in order to assess and understand not only how the communication flow and underlying processes are structured, but also what information is being shared. Finally, these insights can then be used to train a large language model (LLM) (Blank, 2023) by using zero-, but preferably few-shot prompting (Al Nazi et al., 2025). The underlying idea is to not only help the LLM to make sense of the data, but also to provide clear examples that are relevant and theoretical sound from the perspective of the course description. Once these steps have been iteratively completed, the educator can then start to prompt the LLM to create synthetic data (Long et al., 2024).

By using these steps, an LLM can be engineered to reflect the linguistic patterns, interaction dynamics, and emotional expressions observed in real conversations, without exposing any individual's identity. For example, artificial datasets from Twitter / X, BlueSky, Instagram, Facebook, etc. can be generated to mimic discussions on topics related to courses. Such datasets also allow to create realistic case studies, train students in social media analysis, and simulate communication processes with the specific goal of applying relevant theoretical frameworks. Consequently, the ability to tailor data to specific educational goals (e.g. spreading of misinformation, crisis communication, collaborative discourse) makes synthetic social media data a flexible and powerful resource for educational practice that can be adjusted and tailored to the specific preferences and interest of the students. This has been suggested as a valuable approach to provide relevant examples and support students in their learning trajectory, particularly in the context of solving problems (Atkinson et al., 2000; Chi et al., 1989).

However, there are also two notes of caution that should be considered. First, while training a LLM can assist in mimicking discussions, it requires a careful and often time-consuming qualitative verification by the teachers at the beginning. Guiding questions include: Does the provided output make intuitive sense? Is the content being generated too generic and rather replicates than synthesize existing data? Second, students are currently not used to this type of data and will need careful scaffolding, including structured reflections, and guided comparisons between real and synthetic data to support deeper understanding and critical analysis.

The Case of Learning Analytics

Learning analytics education relies on rich traces of learner activity—such as discussion posts, clickstreams, and collaboration networks—to develop students' skills in data analysis, modelling, and interpretation. However, using authentic student data raises significant ethical and legal concerns related to privacy, informed consent, and institutional governance (Drachsler & Greller, 2016). These constraints often limit instructors' ability to provide students with realistic datasets for hands-on analysis. Synthetic data provides a viable alternative by generating statistically plausible yet fully artificial datasets that retain key structural characteristics of real learning environments while protecting individual identities (Long et al., 2024).

Creating pedagogically meaningful synthetic data typically involves three steps. First, educators define a learning scenario grounded in established theories, such as self-regulated learning or collaborative knowledge construction (Scardamalia & Bereiter, 2005). Second, they specify data-generating parameters using one of three approaches: deriving distributional patterns from anonymized institutional datasets, drawing on empirical findings reported in learning analytics research (Gašević et al., 2015), or simulating from publicly available datasets such as the Open University Learning Analytics Dataset (Kuzilek et al., 2017). Third, these parameters guide generative models or large language models through few-shot prompting to produce synthetic datasets that replicate realistic learning behaviors at scale (Al Nazi et al., 2025). This approach creates substantial pedagogical opportunities. Synthetic datasets allow students to experiment with predictive modelling, early-warning systems, and ethical data governance in a risk-free environment (Lang et al., 2017). Moreover, instructors can tailor scenarios to specific learning objectives such as critically assessing the ethical implications of learning analytics and designing theory-driven analytics-based learning activities. This approach supportsproblem-based learning and encourages students to engage critically with both the technical and ethical dimensions of learning analytics (Atkinson et al., 2000).

In practice, designing synthetic datasets for learning analytics involves balancing realism, privacy, and instructional focus. Instructors may need several iterations to avoid common missteps such as overly clean patterns, unrealistic learner behaviours, or simplified relationships that mislead students about how educational data work. Students also often assume synthetic data is neutral or fully representative, creating opportunities to discuss bias, uncertainty, and model limitations. For this reason, instructors choose tasks and theoretical frameworks that not only support technical skill development but also prompt critical reflection on interpretation, ethics, and data quality.

The Case of Business Data

Large collections of data have become constitutive of contemporary business practice. Economic transactions are digitally recorded by default, production technologies are increasingly connected, and products are evolving into smart-connected systems that continuously generate telemetry data (Porter & Heppelmann, 2015). In parallel, firms are repositioning themselves within digital ecosystems rather than linear value chains (Weill & Woerner, 2015). Regulatory developments such as the EU Data Act (Kerber, 2024) further challenge established assumptions about data ownership and access by granting users rights to Internet-of-Things (IoT) -generated data and enabling data mobility towards third parties. These shifts open new arenas for business model innovation and reconfiguration of power relations in existing networks. Consequently, the ability to interpret, combine, and innovate with business data is becoming a core competence for business graduates—not only for data scientists, but for managers operating in digitally mediated environments. Generative AI tools further lower technical barriers, enabling students without advanced programming backgrounds to conduct analyses in R or Python. However, authentic business data are rarely accessible for educational purposes due to strategic and competitive constraints. The data most valuable for teaching data-driven business design are often precisely those that cannot be shared. The modern automotive industry provides a particularly illustrative context. Contemporary vehicles generate extensive telemetry, including geolocation data, component state variables, gyroscopic motion data, event data (e.g., hard braking), and infotainment usage. Traditionally, such data have been controlled by manufacturers. Under the EU Data Act, vehicle owners may gain rights to access and share these data with third parties, potentially enabling new mobility services and ecosystem configurations. Yet access to real vehicle telemetry is limited by ownership rights, privacy concerns, and sheer data volume.

To address this pedagogical gap, an agent-based vehicle data simulator was developed (https://sctm.sdu.dk/car-simulator/). The simulator generates simulated but structurally realistic datasets representing drivers with different behavioral profiles operating vehicles with varying technical characteristics across diverse route topologies. Rather than providing a single flat dataset, the simulator produces multiple interrelated tables (e.g., driver profiles, trip data, event logs, vehicle specifications). This relational structure enables students to practice core data competencies: joining tables, cleaning and transforming data, engineering features, and constructing meaningful performance indicators. Importantly, the simulator does not merely train technical skills. It is designed to support higher-order learning objectives. Students are invited to:

1. Formulate business problems grounded in mobility ecosystems.
2. Explore how different data sources can be combined to generate new value propositions.
3. Reflect on data ownership, governance, and regulatory implications.
4. Experiment with scenario variation (e.g., aggressive vs. conservative driving styles, urban vs. rural routes) and assess strategic consequences.

In this sense, the simulator functions as a pedagogical infrastructure: it creates a safe yet realistic sandbox in which students can experiment with data-driven business innovation, explore ecosystem logics, and develop competencies that bridge technical analysis and strategic imagination.

However, integrating such approaches into educational practice is not straightforward. It requires bringing together technical data work, business understanding, and reflections on governance—elements typically separated across disciplines. In strategy courses, data is often treated as an add-on rather than as constitutive (Talaoui et al., 2023). Addressing this gap therefore requires a re-prioritization of course content, which is time-consuming and demands new competencies from instructors in designing learning activities where data becomes integral to how strategic problems are defined and explored.

Conclusion

Synthetic and simulated data offer complementary approaches to support data-driven education while addressing ethical, legal, and practical constraints associated with real-world datasets for education. By enabling educators to generate these types of datasets, while preserving essential statistical, behavioral, and linguistic patterns, these approaches allow students to engage in realistic analyses, explore communication dynamics, and apply theoretical frameworks in safe and controlled learning environments. While synthesizing data, particularly via large language models, allows for scalable, privacy-preserving replication of authentic interactions, simulations, e.g. through agent-based modeling, fosters understanding of underlying processes and causal mechanisms.

Taken together, both methods can expand the possibilities for data-driven teaching and learning, enabling scenario-based exercises across diverse disciplines. By enabling educators to generate these datasets while preserving essential statistical, behavioral, and linguistic patterns, these approaches allow students to engage in realistic analyses and explore communication dynamics in safe, controlled learning environments. As demonstrated in the "Design and research methods" showcase, the use of synthetic data facilitates a fundamental shift from time-consuming "data labor" to high-level analytical reasoning. By utilizing applicable tools to generate diverse personas and interviews, instructors can bypass the weeks traditionally required for manual data collection and coding. This allows students to focus immediately on the nuances of thematic analysis and collective coding, exploring a wider range of perspectives.

Moreover, the synthesis of data, particularly via Large Language Models (LLMs), provides a scalable replication of authentic interactions, which is especially valuable given that authentic social media data is increasingly difficult and expensive to attain. However, it is important to note that personal data should ideally be only inserted into local language models, as data provided to commercial AI companies and LLMs in most cases become their property.

Taken together, it is suggested that the most valuable results will be achieved via a rigorous approach that involves selecting an educational scenario, employing natural language processing and social network analysis to understand communication flows, and finally training an LLM using few-shot prompting to ensure the synthetic output maintains methodological integrity. Furthermore, simulations, such as agent-based modeling, foster a deep understanding of underlying processes and causal mechanisms. Taken together, these methods expand the possibilities for data-driven teaching across diverse disciplines, empowering educators to tailor content to specific learning objectives and student preferences while maintaining strict theoretical, methodological, and ethical integrity.

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LLM-PAPERSTORM: COLLABORATIVE PAPER READING WITH LARGE LANGUAGE MODELS

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1 Introduction

Large language models (LLMs) can support rapid information retrieval and problem-solving [Achiam et al., 2023, Guo et al., 2025], but they also exhibit well-documented problems such as sycophancy (reinforcing user's beliefs) and hallucination (confidently producing fabricated content) [Perez et al., 2023]. When students accept LLM outputsat face value, the result is superficial learning at best [Bommasani et al., 2021, Bengio et al., 2025]. Large language models thus challenge entire educational systems and require teachers and learners to develop new competencies and literacies [Kasneci et al., 2023].

A natural reaction is to view this as a cat-and-mouse game: students try to offload work to LLMs, and teachers try to design assignments that are LLM-proof. But no assignment design can outpace LLM capabilities for long (e.g., progress on Humanity's Last Exam Phan et al. [2025] advanced from 2% to 46% in a year). The only durable response is to increase students' intrinsic motivation for learning and to reframe LLMs as tools for learning better – not as shortcuts around it. Concretely, if we make the critical evaluation of LLM-generated content the cognitively demanding task, then interacting with an LLM is no longer a shortcut around learning – it becomes the learning activity itself.

This paper presents LLM-Paperstorm, a teaching activity built around this idea. Students collaboratively use LLMs to engage with state-of-the-art research papers, but the focus of the activity is on judging the outputs: Where did the model get it right? Where did it hallucinate? Was it sycophantic? The activity was developed and tested in the course AI506: Advanced Machine Learning at the University of Southern Denmark.

More broadly, LLM-Paperstorm illustrates a pattern that may be applicable beyond paper reading: rather than trying to make assignments LLM-proof, we can embrace LLM use in the classroom – provided the activity is structured so that human judgment remains the hard part. As LLMs become more capable, the ability to critically evaluate their outputs will only grow in importance – not just for computer science students, but across all disciplines. If educational systems can make this shift, the widespread availability of LLMs becomes less of a threat to deep learning and more of an opportunity to practice a skill that was always important but is now indispensable.

2 The risk of superficial learning

When students use LLMs as a tool for assignments, there is a risk that cognitively demanding tasks are fully offloaded to the language model. This comes with the risk of superficial learning, as the cognitively demanding task effectively degrades towards merely (re-)calling the outputs of an LLM – it is as severe as a task from the highest level of Bloom's taxonomy (create) degenerating into the lowest level (remember), or falling out of the taxonomy completely.

ishful thinking could let us hope that this offloading frees up time for cognitively even more demanding tasks. But in practice, those more demanding tasks are not in place yet, and cannot be easily integrated, as fair chances have to be given to students who do not make use of such technology.

Instead of engaging in a cat-and-mouse game of LLM-proofing assignments, teachers can invert the problem: make the critical evaluation of LLM outputs the cognitively demanding task. If judging what a language model produces requires understanding the underlying material, then the learning is preserved – and students additionally gain the ability to responsibly interact with AI technology, a competence that will be essential in their prospective careers.

3 Learning objectives

The key insight connecting these objectives is that validating LLM outputs (objective 2) is itself a cognitively demanding task that requires genuine engagement with the source material (objective 3). In other words, the learning objectives are achieved through LLM use. That is because the activity demands critical judgment rather than passive consumption of AI-generated content. Responsible interaction with AI technology (objective 1) then emerges naturally from this process, as students experience first-hand where LLMs succeed and where they fail.

1. **Responsibly interact** with modern AI technology (specifically, large language models).
2. **Validate the outputs** of large language models in the context of paper reading.
3. Engage with **course-relevant material** from a pool of state-of-the-art research papers to spark curiosity.

The first two objectives address the broader challenge of AI literacy and critical thinking, while the third objective ensures that the activity is grounded in the course curriculum. Note that the activity is not designed to teach students how to use LLMs, but rather to develop their ability to critically evaluate what LLMs produce and when to trust them.

4 The LLM-Paperstorm activity

LLM-Paperstorm is a structured teaching activity in which students are guided to use large language models to summarize and explain the main takeaways from state-of-the-art research papers. The activity proceeds in five phases.

Phase 1: Preparation
As preparation, the teacher puts up a pool of research papers related to the course's topic. Students may also contribute their own suggestions. The papers should be recent and relevant, so that students are exposed to state-of-the-art research while working on the activity.

Phase 2: Modeling
At the beginning of the session, the teacher models the approach that the students are expected to adopt. This modeling is interactive: the teacher demonstrates how to upload a paper to an LLM, how to prompt it for a summary, and – crucially – how to check the validity of the LLM-generated output by looking manually into the paper. The teacher explicitly asks the students what they would need to do to verify the LLM's claims, establishing the norm that validation is the central task.

Phase 3: Group work
The modeling phase is followed by group work. Students form groups, and each group selects one paper from the pool. Students then engage in a dialogue about the chosen paper with a language model of their choice. They ask the language model to summarize the paper, and engage in a back-and-forth dialogue with the goal of understanding the main contributions of the paper. The main purpose of this exercise is to validate the LLM-generated outputs by looking into the paper itself.

Phase 4: Synthesis
One group after the other presents their findings in plenum, reporting where the model has failed, where it has done a good job at summarizing the paper and answering questions about it, and what the key insights from the paper are. The emphasis during presentations is on judging the language model outputs: did the LLM get this right? Did it hallucinate? Was it sycophantic?

Phase 5: Reflection
In the final phase, the class engages in a meta-discussion to reflect on the process and the pedagogic outcomes, guided by the question whether students would recommend this teaching pattern to their peers.

5 Experiences
The LLM-Paperstorm activity was carried out in the course AI506: Advanced Machine Learning with 28 students in the AI Bachelor's program at the University of Southern Denmark.

Observations during the activity
Students were positively impressed by the assistance supplied by LLMs and how it can accelerate paper reading. At the same time, they became aware of potential pitfalls of using AI technology, in particular the excessive degree of sycophancy exhibited by many LLMs. Students began to dissect the pros and cons of different AI tools – for instance, noting that NotebookLM stays close to its sources, while Gemini benefits from a long context window.

One particularly instructive moment occurred when a group discovered that the language model was confidently summarizing a completely different paper than the one they had uploaded. The LLM had apparently latched onto the topic and title keywords and produced a plausible-sounding but entirely fabricated summary based on a different, presumably more well-known paper in the same area. This anecdote became a powerful teaching moment during the synthesis phase: it vividly demonstrated to the entire class why validation against the actual source is indispensable, and why plausible-sounding output should not be mistaken for correct output.

The synthesis phase produced an excellent overview of the different papers. However, students also noted that they "get a lot of insights of my own paper, but not so much about the others." This suggests that a longer synthesis phase could be beneficial, giving more time for cross-group discussion and for students to engage deeply with papers they did not work on directly.

Student feedback

Overall, students enjoyed the activity and found it a valuable addition to the course. In the reflection phase, students provided the following key pieces of feedback:

- Some students wished for a longer synthesis phase to allow for deeper cross-group discussion.
- Others noted that this is how they do group work anyways – indicating that LLM-assisted paper reading is already becoming part of student practice, whether or not it is formally integrated into the curriculum. This reinforces the importance of providing a structured framework for it.

When asked whether they would recommend LLM-Paperstorm to other courses, the students answered yes – but with the suggestion that courses outside AI/CS would benefit from a brief introduction to prompting or a longer modeling phase, since students in other disciplines may not yet be familiar with interacting with LLMs.

Takeaway

LLM-Paperstorm is a controlled activity that enables teachers and students to openly discuss the risks and opportunities of modern AI technology. It shifts the focus from using language models to judging language model outputs. The activity is relatively lightweight to set up – the teacher only needs to prepare a pool of papers and be willing to model the process – and it can be adapted to various disciplines.

6 Conclusion and recommendations

This paper presented LLM-Paperstorm, a teaching activity designed to mitigate the risk of superficial learning in the era of large language models. By centering the activity on validating and critically judging LLM outputs, students develop AI literacy and critical thinking skills while engaging with course-relevant research papers.

Based on the experiences from carrying out this activity, I offer the following recommendations for teachers interested in adopting LLM-Paperstorm.

Invest in the modeling phase. The modeling phase sets the tone for the entire activity. It is crucial that the teacher demonstrates both the capabilities and limitations of LLMs, and establishes the expectation that students must validate what the LLM produces. A well-executed modeling phase primes students to approach the group work with a critical mindset rather than passively accepting what the language model generates. Without this framing, students may default to treating the LLM as an authoritative source, which is precisely the pattern the activity aims to counteract.

Allow sufficient time for synthesis. Students benefit greatly from hearing about the other groups' papers, but the cross-group discussion requires adequate time. In our first iteration, students noted that they gained deep insights into their own paper but not so much about the others. Consider allocating a longer synthesis phase, or even splitting the activity across two sessions – one for the group work and one dedicated to presentations and discussion.

Adapt for non-technical audiences. Students in the AI Bachelor's program were already familiar with interacting with LLMs, which allowed the activity to proceed smoothly with a relatively brief modeling phase. When transferring LLM-Paperstorm to courses outside of AI or computer science, a brief introduction to prompting and interacting with LLMs may be needed before students can productively engage with the activity. The modeling phase can absorb this by being extended accordingly.

The activity template, including detailed instructions, is publicly available at https://lgalke.github.io/llm-paperstorm and can be freely adapted for use in other courses and disciplines.

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Samarbejdslæring mellem studerende – udfordringer og løsninger

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Formål, baggrund og data

Vi er i gang med et projekt, hvor formålet er at afdække humanistiske studerendes egne erfaringer med samarbejde med medstuderende og at udvikle forslag til, hvordan vi på universitetet kan fremme de studerendes samarbejdslæring.

Baggrunden for projektet er, at aftagere af humanistiske kandidater ofte taler om, at et af de allervigtigste krav til kandidaterne er store samarbejdsevner, og at samarbejde i høj grad skal udgøre en vigtig konkurrencefordel for Danmark. Aftagerne oplever ofte, at kandidaternes samarbejdskompetencer ikke er gode nok, og opfordrer til, at vi på universitetet gør endnu mere ud af at udvikle de studerendes samarbejdsevner gennem obligatoriske studiegrupper, gruppeprojekter mv.

Vi har gennemført en spørgeskemaundersøgelse blandt humanistiske bachelor- og kandidatstuderende med 123 respondenter og mere end 500 uddybende kommentarer. Efterfølgende har vi des desuden gennemført 10 opfølgende kvalitative interviews blandt humanistiske bachelor- og kandidatstuderende.

Teoretisk grundlag

Det er ikke kun aftagerne, der fremhæver værdien af samarbejde. Det har også et stærkt grundlag i forskningslitteraturen. Vil vi nævne tre teoretiske inspirationskilder til vores arbejde: Etienne Wengers teori om læringsfællesskaber, Michael Wests teori om teamsamarbejde samt Peter Senges begreb om teamlæring fra hans teori om den lærende organisation.

Etienne Wengers teori om *læringsfællesskaber* (Wenger 1998) beskriver, hvordan læring opstår gennem aktiv deltagelse i sociale fællesskaber, hvor mennesker deler en fælles interesse eller praksis. Ifølge Wenger er læring ikke primært et individuelt, kognitivt anliggende, men en social proces, hvor viden og identitet udvikles i samspil med andre. Et læringsfællesskab består af tre centrale elementer: et fælles domæne**,** der definerer det fælles interessefelt og giver retning; et fællesskab, hvor medlemmerne engagerer sig i fælles aktiviteter, deler erfaringer og bygger relationer; og en praksis**,** som består af de fælles ressourcer, værktøjer, sprog og rutiner, der udvikles over tid. Gennem deltagelse i sådanne fællesskaber tilegner medlemmerne sig både viden og en følelse af tilhørsforhold – de lærer "at blive nogen" i et socialt og professionelt fællesskab. Wengers teori er særligt relevant i organisationer, hvor samarbejde, videndeling og kollektiv refleksion er afgørende for udvikling og forandring, fx på universiteter.

Michael Wests teori om teamsamarbejde (West 2012) tager udgangspunkt i, at effektivt teamwork i organisationer afhænger af både klare fælles mål**,** støttende sociale processer og psykologisk tryghed**.** Ifølge West er et team mere end blot en gruppe mennesker, der arbejder sammen – det er en social enhed, der deler et fælles formål, koordinerer deres indsats og er gensidigt ansvarlige for resultaterne. Han fremhæver, at gode teams har klare og fælles mål**,** veldefinerede roller**,** åben kommunikation samt en refleksiv praksis, hvor medlemmerne løbende vurderer og forbedrer deres samarbejde. Et centralt element i Wests teori er begrebet *team reflexivity* – evnen til at reflektere over mål, strategier og arbejdsprocesser og tilpasse sig for at forbedre effektiviteten. Derudover understreger han betydningen af støttende ledelse og en positiv teamkultur, der fremmer læring, innovation og trivsel. Wests tilgang er således både psykologisk og organisatorisk og er derfor også velegnet til at forstå, hvordan man kan arbejde med teamwork i så komplekse arbejdsmiljøer som universitetet er.

Peter Senges teori om *teamlæring* er en central del af hans begreb om den lærende organisation, som han præsenterer i *The Fifth Discipline* (Senge 1990). Ifølge Senge er teamlæring en af de fem discipliner, der gør det muligt for organisationer at udvikle sig kontinuerligt og tilpasse sig forandringer. Teamlæring handler om, at grupper af mennesker udvikler evnen til at tænke og handle sammen på måder, der overstiger summen af deres individuelle bidrag. Det kræver, at teamet skaber fælles forståelse og fælles vision, samt at medlemmerne deltager i dialog snarere end debat – hvor formålet ikke er at vinde en diskussion, men at udforske og udvikle nye perspektiver i fællesskab. Senge understreger også betydningen af at suspendere egne antagelser for at kunne lære af hinanden, og at teams arbejder med systemtænkning**,** så de forstår de dynamikker og mønstre, der påvirker deres fælles resultater. Teamlæring bliver dermed et redskab til organisatorisk læring og innovation, fordi den kollektive refleksion og handling styrker både teamets præstation og organisationens samlede evne til at lære og kan derfor udgøre en væsentlig inspirationskilde til at udvikle samarbejdslæring på universiteter.

Præferencer for samarbejde

Vores undersøgelse viser, at omkring to tredjedele af de adspurgte studerende foretrækker at arbejde alene, mens en tredjedel foretrækker samarbejde i studiegrupper. De studerende, der foretrækker individuelt arbejde, begrunder det især med et ønske om selvbestemmelse over det faglige indhold, frustration over forskellig arbejdsmoral og ambitioner samt oplevelsen af, at koordinering og hensyntagen til andre gør arbejdsprocessen mere tidskrævende. Flere respondenter udtrykker desuden, at individuelt arbejde giver større fleksibilitet og kontrol over egen tid, selvom mange samtidig anerkender, at gruppearbejde kan føre til læring og faglig udvikling.

Eksempler på udtalelser fra respondenter, der foretrækker at arbejde alene:
"Man skal ikke forholde sig til gruppemedlemmer, som ikke besidder samme arbejdsmoral som en selv."
"Når man er alene, så behøver man ikke at skulle tage hensyn til andre, og hvad de synes. Det kan tage lang tid at tage, f.eks. beslutninger, når man er i gruppe. Udover det så skal man altid være mindful over andre. Man bruger mere tid på at tage hensyn, end man gør på at lave arbejdet."
"Jeg foretrækker at arbejde alene, fordi så har jeg mere selvbestemmelse over min tid. Men jeg vil dog sige, at jeg på hele kandidaten har arbejdet i gruppe. Jeg har lært så meget. Jeg er rigtig glad for at være i den studiegruppe. Men hvis min studiegruppe ikke spørger, spørger jeg ikke, om vi skal arbejde i gruppe. Det er svært med tiden."

De studerende, der foretrækker at arbejde i grupper, fremhæver derimod samarbejdets læringsmæssige og sociale kvaliteter. De oplever, at samarbejde giver mulighed for faglig sparring, perspektivudvidelse og øget motivation. Mange peger på, at de lærer mere ved at høre andres overvejelser og meninger, og at samarbejde kan styrke både faglig forståelse og engagement. Dog understreges det, at kvaliteten af samarbejdet afhænger af, at gruppemedlemmerne er lige engagerede og ansvarlige.

Eksempler på udtalelser fra respondenter, der foretrækker at arbejde sammen med andre:
"Det er dejligt at kunne reflektere over idéer og tanker, og det er dejligt at kunne støtte sig op ad andre, når man selv er i tvivl."
"Jeg kan bedst lide at arbejde i grupper, så jeg kan sparre med nogen, dog er min motivation til at indgå i gruppearbejde afhængig af, om mine medstuderende er lige så engageret i et godt samarbejde og resultat, som jeg er."
"Jeg lærer ofte mere af at høre andres overvejelser, meninger og viden. Når jeg arbejder alene, er læringsprocessen mindre, når man som på mit studie primært har skriftlige frie eller bundne hjemmeopgaver. Derudover har gruppearbejde en kæmpestor positiv virkning på min motivation for at gøre mig umage".

Kendetegn ved den gode studiegruppe

Både tilhængere og modstandere af gruppearbejde i vores undersøgelse er dog bemærkelsesværdigt enige om, hvad der kendetegner et velfungerende samarbejde. Den gode studiegruppe er præget af åben og ærlig kommunikation, hvor der er plads til nysgerrighed, tvivl og kritik. Forventningsafstemning fremhæves som afgørende; det vurderes som en fordel, når gruppen fra begyndelsen drøfter mål, ambitionsniveau, arbejdsform og deadlines. Lige deltagelse og ansvar anses som centralt for at sikre engagement og tillid, ligesom gensidig respekt, rummelighed og forståelse for individuelle forskelle vurderes som forudsætninger for et konstruktivt samarbejdsmiljø. Endelig tillægges socialt fællesskab og tryghed stor betydning – en god studiegruppe beskrives som et rum, hvor man kan være ærlig, sårbar og samtidig opleve faglig stimulering og støtte.

Samtidig peger flere i vores undersøgelse på, at negative oplevelser kan opstå, når forskelle i værdier, ambitionsniveau eller venskabsrelationer skaber konflikter. Særligt nævnes sammenligning og socialt pres som kilder til mistrivsel og stress.

Digitale samarbejdsformer

Digitale værktøjer spiller ifølge vores undersøgelse en markant rolle i de studerendes samarbejde. Kun 2 % angiver, at de ikke anvender digitale platforme. Mest udbredt er delingsværktøjer som Google Docs, sociale medier (især Facebook) og onlinemødesystemer som Zoom og Teams. Størstedelen af de studerende kombinerer fysiske og digitale mødeformer, og 64 % oplever, at digitale platforme generelt bidrager til et mere effektivt samarbejde. Samtidig vurderer en mindre gruppe, at de digitale medier ikke har væsentlig betydning for samarbejdets kvalitet.

Sammenligning mellem studie- og arbejdssamarbejde

Et gennemgående tema i både spørgeskema og interviews er, at de studerende ikke anser samarbejde på universitetet som direkte sammenligneligt med samarbejde på en arbejdsplads. De oplever, at samarbejde i arbejdslivet indebærer større ansvar, tydeligere konsekvenser og en mere professionel ramme. Flere studerende beskriver, at det er lettere at håndtere konflikter i arbejdssammenhænge, fordi relationerne dér er mere distancerede, mens tætte personlige relationer i studiegrupper kan gøre konflikter mere følelsesladede og svære at adressere. Samtidig viser data, at hele 95 % af de studerende vurderer, at de har de nødvendige samarbejdskompetencer til at indgå i faglige samarbejder efter endt uddannelse – en vurdering, der dog langtfra deles af arbejdsgiverne.

Udtalelser om sammenligninger mellem universitetet og en arbejdsplads: *"På arbejdet er det tydeligt, at man har et ansvar, og det bliver taget alvorligt."* *"Hm, ja der havde man nok taget den i lidt bedre tid, der havde jo nok været nogle andre konsekvenser, nu sidder jeg jo ikke med dem hver dag, men det ville skabe en dårlig kultur hver gang, man mødte ind og et dårligt billede ud af til, hvis man ikke får det fikset."*

Samlet vurdering

Samlet peger vores undersøgelse på et komplekst forhold mellem samarbejdets potentialer og udfordringer i studiekonteksten. De studerende anerkender samarbejdets betydning for læring, motivation og trivsel, men oplever samtidig praktiske, relationelle og organisatoriske barrierer. Resultaterne indikerer et behov for, at universitetet i højere grad understøtter udviklingen af samarbejdskompetencer, herunder forventningsafstemning, konflikthåndtering og refleksion over samarbejdsprocesser, som led i de studerendes faglige dannelse og forberedelse til arbejdsmarkedet. Teorierne af Wenger, West og Senge giver tilsammen et solidt teoretisk grundlag for at forstå, hvordan samarbejdskompetencer kan udvikles i en universitetskontekst.

Etienne Wenger**'s** teori om *Communities of Practice* (1998) fremhæver, at læring sker gennem deltagelse i sociale praksisfællesskaber, hvor viden og identitet formes i interaktion med andre. Set i forhold til de studerendes samarbejde indebærer det, at samarbejdskompetencer udvikles bedst, når de studerende indgår i meningsfulde fællesskaber, hvor de deler ansvar, forhandler forståelser og opbygger fælles praksis. Universitetet kan således understøtte samarbejdslæring ved at skabe rammer, hvor studiegrupper og projektarbejde ikke blot bliver organisatoriske former, men reelle læringsfællesskaber, der værdsætter refleksion, dialog og fælles vidensudvikling.

Michael West**'s** forskning i *teamarbejde* (2012) bidrager med indsigt i, hvilke betingelser der fremmer effektivt samarbejde. Ifølge West kræver teamlæring klare fælles mål, psykologisk tryghed, gensidig respekt og en kultur, hvor refleksion og feedback er naturlige dele af samarbejdet. Hans teori understreger dermed, at samarbejdskompetencer ikke alene handler om sociale evner, men om at udvikle strukturer og processer, der gør teams i stand til at lære sammen. På universitetet kan dette omsættes til didaktiske tiltag som faciliterede studiegrupper, forventningsafstemning og refleksive samtaler om samarbejdsprocesser.

Peter Senge's teori om *teamlæring* (1990) tilføjer et organisatorisk og systemisk perspektiv. Han ser teamlæring som en disciplin, hvor grupper lærer at tænke og handle i fællesskab gennem dialog og fælles refleksion. For Senge er samarbejde et middel til at udvikle kollektiv intelligens og skabe lærende organisationer. Overført til universitetet betyder det, at udviklingen af de studerendes samarbejdskompetencer kræver, at læringsmiljøet understøtter eksperimenteren, fælles målsætning og åbenhed for feedback.

Sammen bidrager de tre teoretikere til en helhedsforståelse: Wenger forklarer, hvordan læring i fællesskab former identitet og faglighed; West viser, hvordan teams kan fungere effektivt gennem tryghed, fælles mål og refleksiv praksis; og Senge betoner den kollektive læringsproces som forudsætning for udvikling og innovation. Tilsammen peger de på, at universitetet må arbejde strategisk og pædagogisk med at skabe læringsmiljøer, hvor samarbejde ikke blot er et middel, men et mål i sig selv – og hvor de studerende lærer *at samarbejde ved at samarbejde*.

Perspektivering og forslag til udvikling af samarbejdskompetencer

Både vores undersøgelse og de nævnte teoretikere peger på et behov for, at universitetet i højere grad understøtter de studerendes udvikling af samarbejdskompetencer som en integreret del af den akademiske dannelse. Hvis universitetet skal imødekomme aftagernes stigende krav til kandidaters evne til at indgå i professionelle samarbejdsrelationer – og samtidig adressere de studerendes oplevelse af, at samarbejde i studiekontekst adskiller sig væsentligt fra samarbejde på arbejdsmarkedet – bør samarbejde i højere grad gøres til en obligatorisk og bedømmelig del af uddannelsesforløbene.

Et muligt tiltag er at indføre *obligatoriske gruppeeksamener og vurdering af samarbejdsevner* som et eksplicit læringsmål. De studerende prioriterer i høj grad det, som universitetet vægter og bedømmer, og en formel vurdering af samarbejdskompetencer vil derfor kunne signalere, at samarbejde anses som et centralt akademisk og professionelt kompetenceområde.

Hvis samarbejdsevner skal bedømmes, må de imidlertid også *undervises og trænes systematisk.* Dette indebærer, at universitetet aktivt bør facilitere de studerendes samarbejder og tilbyde undervisning i teambuilding, kommunikation og konflikthåndtering. En sådan indsats vil ikke alene styrke de studerendes læringsudbytte, men også understøtte deres evne til at håndtere samarbejdssituationer professionelt og reflekteret.

Som et yderligere initiativ kunne universitetet indføre *årlige gruppeudviklingssamtaler (GRUS)* for studerende. Disse samtaler kan fungere som et forum for refleksion over samarbejdsprocesser, forventningsafstemning og løbende udvikling af gruppedynamikker. En sådan struktureret opfølgning vil signalere, at samarbejde ikke blot betragtes som et praktisk redskab, men som et centralt element i akademisk læring og professionsforberedelse.

Samlet set peger resultaterne på, at en mere systematisk og forpligtende tilgang til samarbejdslæring vil kunne bidrage til at bygge bro mellem studiernes læringskontekst og arbejdsmarkedets samarbejdskrav – og dermed styrke universitetets rolle som ramme for både faglig og social dannelse.

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GenAI & the human touch. Improved classroom management with a little help from GenAI idea generation

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Når AI bliver en del af projektledelse - Erfaringer med didaktisk integration af generativ AI i projektledelsesundervisning

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Introduktion
Generativ kunstig intelligens har på kort tid ændret forudsætningerne for mange videns- og professionsuddannelser.[1] AI-sprogmodeller og -systemer kan formulere tekst, strukturere komplekse problemstillinger og generere forslag til analyser og løsninger. Dermed udfordrer teknologien både de etablerede læringsformer og eksamenspraksisser på flere videregående- og ungdomsuddannelser.[2]

I takt med at teknologien bliver mere tilgængelig, står undervisere over for et centralt spørgsmål: *Hvordan kan AI integreres i undervisningen på en måde, der understøtter læring frem for at underminere den?* Samtidig peger den bredere AI-udvikling på, at organisationer i stigende grad stilles over for et strategisk valg mellem proaktiv og systematisk integration af AI og en mere afventende eller reaktiv tilgang. Konsekvensen kan være et voksende kapacitets- og udviklingsgab, hvor aktører, der tidligt opbygger kompetencer, arbejdsgange og organisatorisk modenhed, opnår et varigt forspring. Meget kan ske inden 2030.[3] En sådan problemstilling gør det relevant at undersøge, hvordan AI i en uddannelseskontekst kan indgå som en fagligt og didaktisk meningsfuld del af undervisning, projektarbejde og eksamen.

Denne artikel præsenterer erfaringer fra et undervisningsforløb i faget *Projektledelse 1* på uddannelsen *Medieproduktion og Ledelse (MPL)* ved *Danmarks Medie- og Journalisthøjskole (DMJX)*. I forløbet blev AI integreret systematisk i undervisning, projektarbejde og eksamen. Artiklen redegør for de læringsmål, der var knyttet til læringsaktiviteten, beskriver det didaktiske design, og diskuterer de erfaringer, der er gjort i praksis.

Læringsmål
Integrationen af AI i *Projektledelse 1* tog udgangspunkt i en ambition om at styrke de studerendes

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[1] O. Teutloff, J. Einsiedler og F.S. Møller (2024). *Store sprogmodeller og det danske arbejdsmarked.* Københavns Universitet og Danmarks Statistik. https://www.dst.dk/Site/Dst/Udgivelser/nyt/GetAnalyse.aspx?cid=53013
[2] Danmarks Evalueringsinstitut (2026). *Elevers brug af AI i gymnasiet. https://eva.dk/udgivelser/2026/feb/elevers-brug-af-ai-i-gymnasiet.* ISBN 9788771828719
[3] E. Mollick (2026). "AI will reshape work – if we let it" [Video: 05:08]. Implement OPEX 2026: Reinventing operations for the AI era. Implement Consulting Group.
https://studios.implementconsultinggroup.com/ethan-mollick-ai-will-reshape

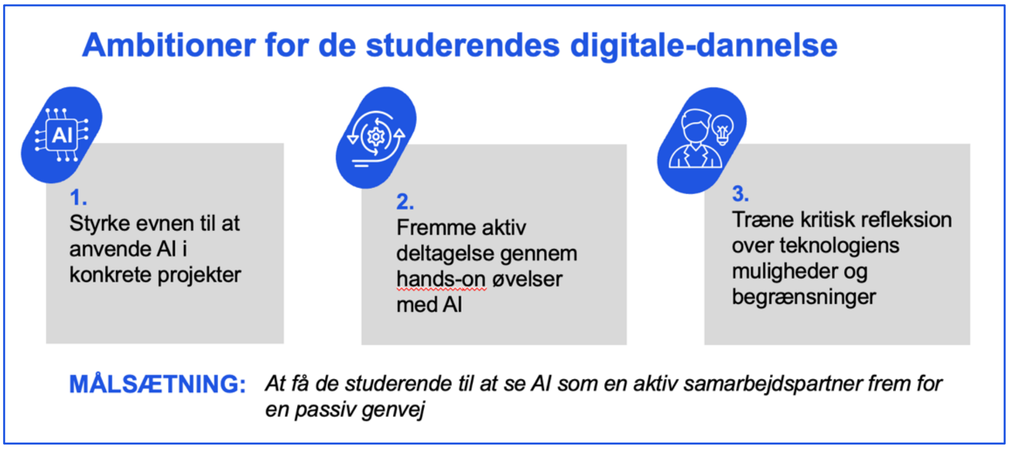
digitale dannelse og deres evne til at arbejde refleksivt med nye teknologier i projektbaserede arbejdsprocesser.

Tre læringsmål var centrale for læringsaktiviteten (Figur 1):
For det første skulle de studerende opnå erfaring med at anvende AI i konkrete projektprocesser. Projektledelse indebærer typisk arbejde med analyse, idéudvikling, planlægning og koordinering. AI kan i denne sammenhæng fungere som et redskab til research, brainstorming, rapportering, estimeringer og opsamlinger.[4]

For det andet var målet at understøtte aktiv læring og deltagelse gennem eksperimenterende arbejde med AI. I stedet for at diskutere teknologien på et abstrakt niveau blev AI integreret direkte i øvelser og projektarbejde. På den måde blev teknologien en del af de studerendes arbejdsproces frem for et isoleret tema i undervisningen.

For det tredje skulle undervisningen styrke de studerendes kritiske refleksion over teknologiens muligheder og begrænsninger. Generative AI-systemer kan producere overbevisende svar hurtigt, men output er ikke nødvendigvis korrekt. Derfor er det centralt, at de studerende udvikler kompetencer til at validere og kritisk vurdere AI-genereret materiale, imens de også udvikler stærke kompetencer indenfor kritisk tænkning og refleksion.

Inspireret af Ethan Mollicks arbejde med generativ AI blev AI introduceret ud fra fire grundprincipper: 1. invitere AI ind i arbejdsprocessen, 2. behandle systemet som en samarbejdspartner, 3. fastholde mennesket som kontrolinstans og 4. samtidig antage, at teknologien fortsat vil udvikle sig markant.[5] Målet var således ikke blot at lære de studerende at anvende AI-værktøjer, men at udvikle en refleksiv praksis, hvor AI indgår som et redskab til at lede projekter.



Figur 1. *Oversigt over de læringsmål, der knytter sig til integrationen af AI i Projektledelse 1.*

[4] Project Management Institute (2025). "Talking to the Machine – Prompt Engineering Essentials for Project Professionals." https://www.pmi.org/learning/thought-leadership/prompt-engineering

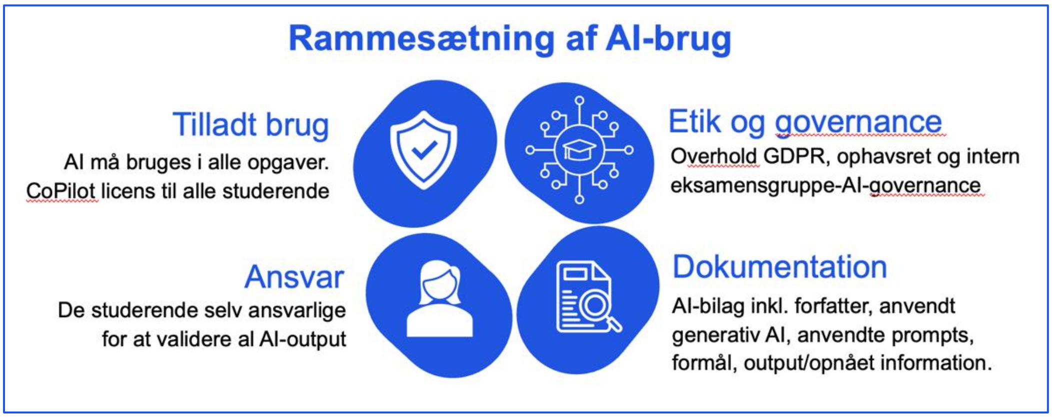
[5] E. Mollick (2024). *Co-intelligence: Living and Working with AI*. New York: Portfolio/Penguin.

Rammesætning af læringsaktiviteter
For at integrere AI på en måde, der både understøtter læring og sikrer akademisk ansvarlighed, blev der etableret en tydelig didaktisk ramme for brugen af AI i undervisningen af faget *Projektledelse 1* (Figur 2).

Udgangspunktet var, at AI i princippet måtte anvendes i alle opgaver, men at brugen skulle være transparant og systematisk dokumenteret. De studerende blev derudover gjort ansvarlige for selv at validere alt AI-genereret tekst og billeder og for at redegøre for, hvordan teknologien havde været anvendt konkret i deres opgaver.[6]

Som en del af denne rammesætning skulle alle projekter indeholde et AI-bilag, hvor de studerende dokumenterede deres brug af AI. Bilaget indeholdt blandt andet prompts, formålet med anvendelsen af AI, genereret output samt refleksioner over kvalitet og anvendelighed.

Derudover skulle alle studerende som led i de obligatoriske gruppekontrakter forholde sig til, hvordan AI måtte anvendes i samarbejdet, og hvordan ansvaret for validering af AI-genereret output skulle sikres i forbindelse med eksamensprojektet. På den måde blev AI-brugen ikke alene gjort til et individuelt anliggende, men også til et fælles spørgsmål om ansvar, transparens og arbejdsdeling i gruppen. De studerende blev dermed ansvarlige for selv at etablere og efterleve en intern AI-governance i samarbejdet med deres medstuderende, som en integreret del af projektarbejdet.



***Figur 2.** Didaktisk rammesætning af AI-brug i projektarbejde og opgaveskrivning.*

Læringsaktiviteterne blev understøttet af en række konkrete undervisningselementer, hvoraf en LLM-workshop udgjorde et centralt didaktisk greb. Workshoppen havde til formål at styrke de

[6] E. Mollick og L. Mollick (2023). "Why All Our Classes Suddenly Became AI Classes: Strategies for Teaching and Learning in a ChatGPT World." Harvard Business Impact: https://hbsp.harvard.edu/inspiring-minds/why-all-our-classes-suddenly-became-ai-classes

studerendes praktiske AI-kompetencer ved at træne deres anvendelse af AI-baserede værktøjer.[7] Derudover skulle den udbygge deres viden om prompt engineering og centrale IT-begreber knyttet til AI. Som led i denne proces blev KORIS-modellen introduceret som et redskab til at strukturere og kvalificere prompts gennem elementerne klarhed, oplysning af kontekst, resultatformat, instruktion og specificitet.

Derudover arbejdede de studerende med en AI-refleksionsmodel, der havde til formål at skabe balance mellem teknologisk anvendelse og kritisk tænkning samt refleksion. Modellen illustrerer, hvordan både AI-frygt og ukritisk AI-brug kan skabe ubalance i læringsprocessen, mens målet er at udvikle en balanceret ekspertrolle, hvor AI anvendes aktivt, men hvor den studerende fortsat fastholder dømmekraft og ansvar.[8]

I vejledningssituationen blev der desuden arbejdet med SAIL-modellen (Student AI Individualized Learning), hvor AI-vejledning differentieres efter de studerendes motivation og AI-kompetencer. Modellen bygger på principper fra situationsbestemt ledelse og anvendes til at tilpasse vejledningsformen til den enkelte studerendes behov.[9]

Erfaringer fra undervisningsforløbet

Erfaringerne fra forløbet peger på flere væsentlige udviklinger i de studerendes arbejde med AI. For det første oplevede mange studerende, at AI kunne fungere som en form for ekstra projektmedarbejder, der bidrog med idéudvikling, strukturering, sproglig bearbejdning og alternative perspektiver i projektarbejdet. Denne oplevelse understøtter ambitionen om at få de studerende til at forstå AI som en aktiv samarbejdspartner snarere end en passiv genvej. Samtidig blev det tydeligt, at en sådan anvendelse forudsætter udvikling af praktiske AI-kompetencer, herunder især evnen til at formulere og forfine prompts, så teknologien faktisk bidrager meningsfuldt til arbejdsprocessen.

For det andet bidrog integrationen af AI til øget engagement i undervisningen. De praktiske øvelser gjorde det muligt for de studerende hurtigt at afprøve idéer og se konkrete resultater af deres arbejde, hvilket understøttede en mere eksperimenterende tilgang til læringsprocessen. Samtidig blev undervisningen brugt til løbende at undersøge teknologiens begrænsninger og etiske dilemmaer, hvilket styrkede de studerendes kritiske tænkning og analytiske vurderingsevne. Dette gjaldt blandt andet diskussioner om brugen af AI som sparringspartner i personalesager og ledelsesmæssige problemstillinger, hvor de studerende erfarede, at balancen mellem dømmekraft, erfaring og ansvar i sidste ende må bero på menneskelig vurdering frem for maskinel respons.

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[7] Teknologisk Institut (2024). *AI-kompetencer i medie- og kommunikationsbranchen*. Aarhus: Pressens Uddannelsesfond.
[8] A. Stecher og C. Juncker (2025). ”Vejledning med Kunstig Intelligens.” *TAL2024: Proceedings from the Conference Teaching for Active Learning*. SDU Centre for Teaching and Learning, s. 12-27.
[9] Stecher og Juncker (2025), s. 15-16.

For det tredje viste forløbet, at tydelig rammesætning er en afgørende forudsætning for en fagligt meningsfuld integration af AI. Uden klare krav til dokumentation, validering og ansvar risikerer AI-brugen at skabe usikkerhed om både arbejdsprocesser og bedømmelsesgrundlag. Kravet om AI-bilag og eksplicitte retningslinjer for anvendelsen af AI bidrog derfor ikke alene til transparens, men syntes også at mindske de studerendes oplevelse af, at brugen af teknologien var ensbetydende med snyd. I stedet blev AI i højere grad positioneret som et legitimt og refleksivt arbejdsredskab inden for tydeligt definerede faglige og etiske rammer.

Endelig førte integrationen af AI også til en ændring af eksamensformen i *Projektledelse 1*. Tidligere bestod eksamen af en ren skriftlig gruppeopgave. I takt med at AI blev en integreret del af undervisningsforløbet, opstod der behov for at sikre, at bedømmelsen fortsat kunne vurdere de studerendes individuelle kompetencer og akademiske niveau.
Derfor blev eksamen ændret til en kombination af skriftlig opgave og individuel mundtlig eksamination. Den skriftlige del dokumenterer projektets analyse og løsning, mens den mundtlige del giver mulighed for at vurdere den enkelte studerendes refleksioner over metodevalg, projektprocesser og brugen af AI.

Perspektivering
Arbejdet med AI i undervisningen kan også forstås som en organisatorisk udviklingsproces. Pedersen og Ritter (2025) beskriver, hvordan organisationer typisk bevæger sig gennem flere faser i arbejdet med kunstig intelligens, fra individuel nysgerrighed og eksperimenteren til kollektiv integration og gradvis institutionalisering.[10]

En tilsvarende udvikling kan retrospektivt iagttages i forbindelse med DMJX og MPL's integrering af AI. Først opstod en fase præget af individuelle eksperimenter blandt undervisere. Herefter fulgte en fase, hvor underviser-teamet udviklede fælles principper for brugen af AI, begyndte at integrere teknologien i undervisningen, og samtidig justerede studieordningen.

På længere sigt er ambitionen, at generative AI-systemer bliver en ”normal” del af undervisningspraksis, vejledning og projektarbejde, understøttet af tværfaglige forløb, fælles AI-principper og et underviser-team, der deler viden og udvikler AI-kompetencer som en integreret del af fagligheden. I denne udvikling ses de studerende desuden ikke blot som brugere af teknologien, men som medskabere af fremtidens bæredygtige AI-medieprojekter.

Konklusion
Erfaringerne fra *Projektledelse 1* viser, at AI kan integreres meningsfuldt i projektledelsesundervisning, hvis teknologien indgår i et tydeligt didaktisk design.

[10] M. Pedersen og T. Ritter (2025). *Gunstig intelligens – sådan skaber din organisation værdi med kunstig intelligens.* Frederiksberg: Samfundslitteratur.

Ved at kombinere praktisk anvendelse, kritisk refleksion og gennemsigtig dokumentation kan AI fungere som et redskab, der både styrker de studerendes læringsprocesser og udvikler deres kompetencer til at arbejde med teknologi i professionelle sammenhænge.
Samtidig viser erfaringerne, at integration af AI ikke kun påvirker undervisningsaktiviteter, men også kræver justeringer i eksamensformer og studieordning. Integreringen af AI forstås derfor ikke som et afgrænset projekt, men som en løbende udvikling, hvor processer kontinuerligt må kvalificeres, så teknologien gradvist bliver en del af den operationelle praksis.[11]

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[11] E. Mollick (2026). "The nexus where everything is going to happen is in operations." [Video: 08:26]. Implement OPEX 2026: Reinventing operations for the AI era. Implement Consulting Group. https://studios.implementconsultinggroup.com/ethan-mollick-the-nexus-where

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