

AI Generated Images for Education and Work Life: On Bias and Guardrails

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Abstract: The rapid multimodal development of Generative AI (GenAI) tools has opened up possibilities for content creation in many fields. This paper presents a study that had a focus on image generation for educational contexts and professional development in a course on artificial intelligence for education and work life. In an assignment, participants used different GenAI tools for image generation. Moreover, course participants analysed and discussed their AI generated images in essays. In the wide variety of GenAI tools two different image generation software were suggested, one from a big established IT company and the other from a small independent software developer. Both these tools were chosen because they are free to use without any licence fees, and that there are not any complex login procedures before using them. This was seen as important criteria for a group of course participants with relatively low pre-knowledge of GenAI and image generation. On the other hand, course participants with earlier experience of were allowed to use other and more advanced tools. Images could be generated individually or in groups, but the final analysis essays had to be written individually without any AI assistance. Four portraits should be generated with each tool of two world-wide well-known persons, one locally known person and a portrait of the course participant that wrote the essay. 61 essays were thematically analysed with the use of open coding and axial coding. Results were divided into the categories of Age, Gender and Ethnicity, Language, Guardrails, and Training data, with Training data as the central or axial category. Findings show that the results to a certain degree are depending on prompting and the language, but that the found bias is depending on the training data.

Keywords: Image generation, Biased data, Artificial intelligence, GenAI, AIED

1. Introduction

Humans have created sophisticated images since way back, with Palaeolithic cave art by Cro-Magnon artists 40 000 years ago (Gray, 2010). In the year of 1826 or 1827, the exact date is not verified, the French inventor Nicéphore Niépce preserved the first photo copy from a camera obscura and a new technique for generating images was created (Mcquire et al., 2024). During the following 150 years until the introduction of the first prototype for a digital camera in 1975 to 1976, an estimated 15 billion of images were created. This could be compared to the 15 billion images that were AI generated during the first year after the first accessible AI image generator was released in September 2022. (Attie, 2023; Tensetti and Rangsjö, 2024)

With this new possibility to generate more or less photorealistic images with user-friendly online tools, it is tempting to replace traditional image generation in many professional fields. As brought up in Göring et al. (2023), the use of image generating tools has rapidly increased in popularity, despite the facts that they may be of low quality, look artificial, and be less appealing when compared to real images. There are yet no objective quality models for AI-generated images, and that research studies indicate that there are huge variations in quality between different AI image generators (Göring et al., 2023; Lu et al., 2023).

There are several reasons to believe that the image quality has improved during 2023 to 2025, with Midjourney and DALL-E as two promising tools in iterative development (Adetayo, 2024). The study by Berg et al. (2024), concluded that the integration of AI generated images could add value to active and student-centred learning with creation of portraits of historical persons. This study had a focus on AI supported image generation for educational contexts and the creation of portraits of existing persons. The study was conducted in a course on artificial intelligence for education and work life where course participants generated images, analysed the images and wrote essays about their results and reflections. The majority of the course participants are working as teachers in different educational contexts, but there were also course participants that are university students or working in private companies.

At the same time as Generative AI (GenAI) has opened up new and rich possibilities for image generation in educational contexts, research studies have reported on a low AI literacy among educators. Another motivation for this study is the discussion on bias in the AI models and how that affects AI generated images. The aim of the study is to explore the potential of using AI generated images to illustrate existing persons in educational content. Two research questions were formulated to guide this exploration:

RQ1: In what ways could the use of AI-generated images contribute to richer and more multimodal teaching and learning content?

RQ2: What are the main challenges to consider when involving AI generating images in teaching and learning activities?

2. Extended Background

Synthetic data have been produced and used for more than 60 years, but developments in machine learning and GenAI have hugely increased the use (Resnik et al., 2025). Another change during the last years is the spread of AI generated images to many new contexts such as tourism (Zhu et al., 2024), art, and education (Shen et al., 2025). In some contexts, this has added creativity and value, but there are also research studies reporting on how AI generated images reinforces existing stereotypes (van Kolfschooten & Pilottin, 2024; Zhu et al., 2024).

2.1 AI Models and Training Data

In the training of AI models, it is important to enhance the diversity and representativeness of the used training data (Sharma et al., 2025). However, when this is done by web scraping that involves all kind of biased image presentations, this will also be reflected when the AI model is used for image generation. The ethical problem to address is that while synthetic GenAI data can be used to correct for biases in datasets, they can at the same time perpetuate and amplify biases in the training data. If the AI models that are used to generate synthetic data are not thoroughly evaluated and tested, the ongoing biases can lead to discrimination and inequity (Resnik & Hosseini, 2024). In contexts such as health care this is an identified problem that biased models could have serious consequences (El Emam et al., 2020; Mehrabi et al., 2021).

2.2 AI Models and Guardrails

Except for propagating societal stereotypes uncensored AI models sometimes also generates, among other offending things, strongly discriminatory language and racist argumentation. The mitigating solution is called guardrails, using the metaphor of physical guardrails we use when we cross a bridge or when we are descending steep stairs, for filtering inappropriate AI-generated output. Since AI models are vast, multi-dimensional entities using billions of parameters the implementation of guardrails in GenAI tools is more complex than constructing guardrails in traditional real-world settings (McDermid et al., 2024). As highlighted in the previous section, AI generated content reflects the bias and misalignment in the used training data. The early AI bots without any filtering frequently produced harmful and discriminating content. Today, guardrail mechanisms are no longer an optional feature, but a mandatory must (Akheel, 2025).

During the last years, an entire ecosystem of different guardrails mechanisms for constraining inappropriate LLM behaviour has emerged. Except for mere content gating guardrails can also include: 1) Real-time content moderation, where sophisticated classifiers detect and transform or remove problematic content before it reaches the end-user, 2) Privacy-preserving strategies, involving features for anonymization to prevent inadvertent disclosure of sensitive information, 3) Bias mitigation, to minimize the risk of perpetuating harmful societal stereotypes or discriminatory language in GenAI output, and 4) Value alignment, ensuring that the output harmonising with organisational and community norms. Guardrail features that have to be balanced between a guardrail that aggressively censors all risky terms, and a guardrail that allows legitimate queries, do not disturb the end-user's workflow, for a AI tool that generates useful output (Akheel, 2025).

3. Method and Materials

The overall research approach was pedagogical action research involving the idea of a concrete and systematic approach "that enables teachers to investigate their own teaching and their student's learning" (Nolen & Putten, 2007, p. 401). Pedagogical action research also comprises the dual roles where an author also has had the role of a teacher (Norton, 2009). In the research context described below, the author has had the roles of being a teacher, a facilitator, a content developer and the course developer. These multiple roles bring in the ethical issue of having a more subjective opinion toward the investigated assignment, compared to a researcher and author without any other involvement in the educational context. The quotes in 4. Findings and discussions have been translated from Swedish to English by the author. Finally, course participants have been kept as anonymous as possible.

3.1 Research Context

The course was designed and developed to be given as a nation-wide 7,5 ECTS standalone distance course. A course that should be open for all persons with general entry requirements for higher education, but with pre-service teachers and persons working in educational as a main target group. The 97 course participants that have submitted a solution to the assignment have a wide geographical nation-wide spread around Sweden and

also with some participants from Norway. Moreover, the average age of the course participants has been higher than in a standard university course and somewhere around 40 years. In the two first course iterations the majority of participants have been working in different educational contexts, and many of them are working on a full-time basis. In the moment of writing the third iteration is given as a summer course, and with a more heterogeneous group of participants and with a slightly lower average age.

Since it is a course that is given at a department of education, it ought to have a focus on pedagogical and didactical aspects of AIED. However, to better understand some of the general aspects of AIED, the course also comprises technical, administrative and ethical aspects of AI. The course is divided into the four main sections:

1. Introduction and tool testing
2. AI in Education
3. Multimodal AI
4. Discussion webinars as knowledge cafés

To introduce and support the course sections above the course was outlined to involve a mix of teacher led synchronous activities, online workshops, online and onsite group discussions, and asynchronous self-studies. These activities were built around six mandatory assignments created to assess the learning objectives that are listed below:

The overall aim of the course is to present, discuss and apply fundamental tools and theories in the field of AIED. After a completed course the participant should be able to:

- Understand and explain the history and development of AI and AIED
- Analyse and discuss the main opportunities and challenges of AIED
- Evaluate and discuss different tools for detection of AI generated texts
- Explore and apply different GenAI modalities such as text, images, sound and music
- Compare, discuss and reflect over how GenAI could affect and enhance teaching and learning activities and assessment in various educational contexts

A course that was built around the overarching idea of combining practical and theoretical aspects of AI for a deeper understanding of AIED that should be useful, not only during, but also after the course. (Mozelius, 2025)

3.2 Data Collection

There is today, a wide variety of GenAI tools for image generation. The two different image generation software used in this study were, one from a big established IT company and the other from a small independent software developer. Two tools that were chosen, and because they are free to use without any licence fees, and that there are no complex login procedures before participants with low IT-skills could start using them. This was seen as important criteria for a group of course participants without any training in computer science with relatively low pre-knowledge of GenAI and digital image generation. Participants with earlier experience of image generation were allowed to use other and more advanced AI-tools.

Course participants did, individually or in groups, generate 4 images in each of the chosen image generating tools. To solve the assignment these 8 images should later be described, analysed and reflected upon. Finally, to complete the assignment course participants had to write individual essays about their image generation process, their results, and their reflections. In two course iterations a total of 97 essays were submitted and analysed as described in the section here below. Course participants were allowed to generate and analyse more images, but the 4 mandatory images that had to be a part of every submission were:

- Two images of Greta Thunberg
- Two images of Boris Johnson
- Two images of the course participant
- Two images of the university Vice-chancellor / Rektor

Course participants were allowed to choose their tools for image generation, but the two given and cost-free suggestions were:

- Perchance Image Generator
- CoPilot / DALL-E

3.3 Data Analysis

The submitted essays have been analysed according to the Grounded theory analysis process of data being 1) fractured and labelled, and 2) conceptualised around a central category (Moghaddam, 2006). In the first analysis phase, also known as Open coding, data were split into units of meaning that later were aggregated to categories as described in Khandkar (2009). The second analysis phase, also known as Axial coding, was guided by the Grounded theory concept of "coding that treats a category as an axis around which the analyst delineates relationships and specifies the dimensions of the category" (Bryant & Charmaz, 2007, p. 603). In the Axial coding process the preliminary categories from the Open coding phase, were reassembled into more abstract conceptual categories around the central axis category of "Training data". Larger Grounded theory studies often comprise a third phase that could be referred to as Confirmatory coding (Cleveland-Innes and Campbell, 2012), or as Selective coding (Walker and Myrick, 2006). This third phase where the identified categories in the second phase should be revised put in context is future work, and not a part of this study.

4. Findings and Discussions

After four text-based assignments many course participants found it both enjoyable and frustrating. Enjoyable since image generation is fascinating and creative, but frustrating since the images often did not meet the participants expectations. All the 4 image themes involved several types of surprising results. The analysis and discussion below were based on 97 submissions from 2 course iterations.

4.1 Two Images of Greta Thunberg

In the submissions from the first course cohort both DALL-E and Perchance Image Generator generated images of Greta. However, it is very hard to associate Image 1 below with a portrait of Greta Thunberg.



It is definitely easier to recognise Greta in Image 2 but as one of the course participants wrote in his submission: "She looks like 10 years old". Another course participant prompted Perchance IG to make Greta a bit older, but the result was not particularly good. This illustrates the first category 'Age' that also was appearing in the generation of the 3 other images, but most obvious here since Greta is younger than the other persons. There were also other pictures in the submissions where she looked younger than in Image 2. The probable explanation is that training data for the tools were scraped from the web and contains images that were captured some years ago. In the second course cohort DALL-E refused to create any images of Greta and almost all course participants were meet by the standard response: "I cannot create images of contemporary political candidates or elected officials, including Greta Thunberg. Let me know if i can help you with something else!". However, one course participant in the second course cohort succeeded, with smart and iterative prompting, to create a portrait of Greta in DALL-E with much better resemblance than Image 1.

4.2 Two Images of Boris Johnson




An obvious difference between DALL-E and Perchance IG is that DALL-E has much more of inbuilt guardrails. The results differ, but already in the first course cohort a course participant did, instead of an image get the response: "I can't directly show you a photo, but you can find many images of Boris Johnson on Getty Images. Here are some links where you can browse through a large collection of his photos". However, the results differ and one course participant in the same course cohort generated the portrait shown in Image 4 below. When she asked DALL-E to make the hair thinner, it got instead thicker and the resemblance with the real Boris in Image 6 is poor.

		
Image 4. Boris Johnson in DALL-E	Image 5. Boris in Perchance IG	Image 6. The Official Portrait 2019

The image generated by Perchance IG is definitely more look-alike than the one created in DALL-E. On the other hand, Perchance IG did sometimes make caricatures of Boris and other persons. Moreover, the lack of guardrails in Perchance IG sometimes generates images of a sexual or pornographic nature. Something that also can be explained by the axial category Training data, when the web was scraped for as much data as possible, some images were gathered from fashion and porn sites as well.

4.3 Two Images of the Course Participant

According to the Pedagogical action research principle of keeping informants as anonymous as possible no images of course participants were inserted in the paper. Probably that would not have been a big issue, since very few course participants could recognise themselves in the generated images. However, this could instead be illustrated by two images of the author generated in DALL-E before the first course iteration in 2024.

		
Image 7. The author in DALL-E with simple prompting	Image 8. In DALL-E with complex prompting	

There is nothing offending in the pictures, but on the other hand nothing is right either, and none of the images can break the rule of an anonymous conference submission. In the complex prompting details such as that the author works as a senior lecturer and researcher at a university were added. The different prompts lead to the category of language, where the role of prompt engineering is a factor. Other findings for this category are the differences between prompting in English and prompting in other languages. The choice of language does not make a big difference in DALL-E, but definitely in Perchance IG, and some other tools used in the course. Male course participants were mainly surprised and disappointed over the poor resemblance in the images. Female course participants have more comments on that they "Look like movie stars", with the long neck and with the 'plastic' look that can be found in Image 1. There are also comments on sexism in the generated images, and lack of sense in the image generators regarding what was selected for the category of Gender and Ethnicity.

4.4 Two images of the university Vice-chancellor / Rektor

Finally, the images of the university's seemed on beforehand to be the least complicated task, since he is an official person that easily can be found on the Internet. However, and once again the dependency on training data and that most persons are not close to the numbers of images that have been published on Greta Thunberg and Boris Johnson. Regarding guardrails they seem to have been strengthened during 2025 in DALL-E and also in ChatGPT. An example of a response to a course participant was: "I am sorry, but I can't generate an image of the

Vice-chancellor since it goes against our content policy. If you like I could instead create a generic image of a Vice-chancellor or an academic leader".

		
<p>Image 10. Generic image in ChatGPT</p>	<p>Image 11. Generic image in DALL-E</p>	<p>Image 12. Generated with Perchance</p>

Where none of the images could be used in any educational context, or neither in any other context. Regarding the category of Gender, one course participants generated a series of generic Vice-chancellors where 5 out of 6 images depicted a male Vice-chancellor. Some submissions report that the image generators recommended links to web pages where images of the Vice-chancellor could be found. However, this was not a default answers and maybe something that was depending on the prompt that was entered. In a summarisation of all the 97 submissions there are many reports on surprising variations that confirm the fact that GenAI tools work stochastically and not algorithmically.

4.5 Data Analysis

After a two-step Grounded theory analysis process findings have been divided into the categories of Age, Gender and Ethnicity, Language, Guardrails, and Training data. Since all the other categories are depending on Training data, this was the obvious choice for the central or axial category. How the other found categories depicted in Figure 1 are aggregated and related to the central category of Training data is described here below, category by category.

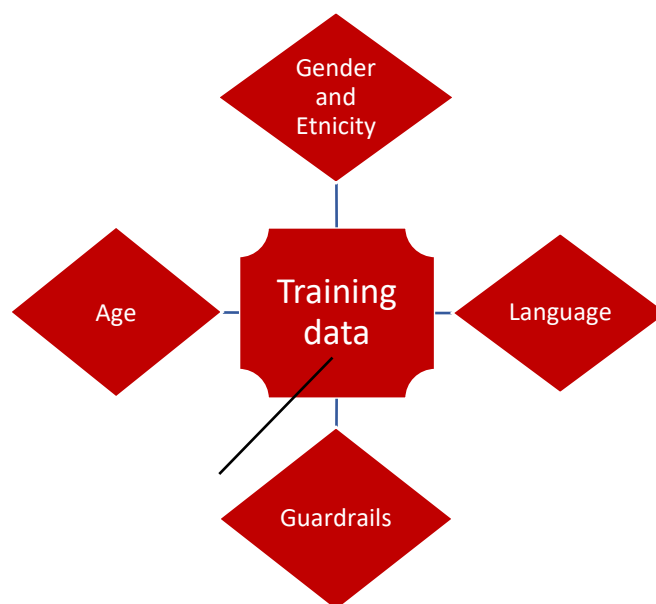





Figure 1: Found categories and their relation to the axial category of 'Training data'

Category 1: Age

There are many comments on Age in the submissions and that both the well-known official persons and the self-portraits of the course participants often look younger and sometimes inexplicably younger. This got even more extreme when course participants used the 'Painted Anime Filter' that was the default setting in Perchance IG during the first course iteration. As an example, Image 14 is a self-portrait prompted by a woman in her forties.

		
<p>Image 13. A young Greta</p>	<p>Image 14. A young course participant</p>	<p>Image 15. A young Boris</p>

This can partly be explained by the fact that training data consist of images from the past, and that the results are depending on the training data. However, as some course participants brought up in their submissions, there seems to be instructions for choosing a younger depiction, than the opposite. A solution that seems to work in the new version of DALL-E is to prompt the year of when the image should from, and that DALL-E now can link to existing images to base the generation on.

Category 2: Gender and Ethnicity

As mentioned earlier, five out of six Vice-Chancellors were depicted as men, when the prompting only consisted of Vice-Chancellor. This might represent the gender distribution in the training data, which is hard to check since the transparency is not there. The reports on sexism and ethnical bias seem also to be strongly related to the training data. When the web unconditionally was scraped for training data, this gave a US-centred focus with several types of bias. In areas such as medicine this is a serious problem where the biased impact of ethnicity and sex disturbs the prediction models (Ravindranath et al., 2025). As found in the cross-sectional study by (Gisselbaek et al., 2025) images generated by ChatGPT DALL-E and Midjourney repeats existing stereotypes regarding ethnicity, sex, and age.

Category 3: Language

This category consists of the two sub-categories 'Natural language' and 'Prompting language'. Regarding the first, the output from the AI-tools depended on which language that was used in the conversations. Especially for Perchance IG, there was a significant difference between course participant using English, and the ones that used other languages. Small languages are, more than by proportion, less represented in the training data and gives more unexpected outcomes. Prompting language could be seen as a synonym for prompt engineering, but at the same time as it matters how you prompt the tools, it is hard to see this as engineering. How, clever and iterative prompting could generate a different result is illustrated in the next category.

Category 4: Guardrails.

Without any guardrails at all the outcomes could, depending on the prompting language, be very offending and that the bias reported under 'Gender and Ethnicity' would be much stringer. On the contrary, the guardrails are what makes the outcomes from the image generation more or less useless in educational contexts. However, with smart, clever, or provocative prompting some course participants generated quality and identifiable images of persons without using their names.

Category 5: Training data

Without a substantial data set the AI-models would not perform well, but without a thorough curation of the training data will be biased in aspects such as age, gender, and ethnicity.

Finally, old training data contains a huge amount of historically interesting content, and as an example, guardrails do not stop you when generating images of Winston Churchill.



Image 16. Winston Churchill 1945 generated in DALL-E

5. Conclusion

Despite the poor and frustrating outcomes, the two research questions could be answered:

RQ1: AI-generated images could enrich learning content when it comes to abstract illustrations and historical, no longer living persons. To compare with the frustrating task of trying to depict living persons, or persons that are sparsely represented in the training data. Regarding what the guardrails in DALL-E mentioned as "contemporary political candidates or elected officials, including Greta Thunberg", they can often be retrieved from the Internet without violating any copyrights.

RQ2: The main challenges to consider are the presented categories of Age, Gender and Ethnicity, Language, Guardrails. Since they all are depending on Training data, the brief and generalised solution would be to curate the training data, as suggested in several other studies.

As pointed out by (Zhu et al. (2024), AI-generated images have their own limitations that need to be discussed, and as concluded by Hsu et al. (2024) due to the bias in training data, GenAI is today unable to fully present the nuances of socio-cultural diversity. Addressing biases in training data to ensure fairness in model outputs is essential for the ethical deployment of generative models. Future research should address bias detection and mitigation strategies to promote ethical AI practices as suggested in Sharma et al. (2025). Finally, the pedagogical action research idea of making changes should be considered, and based on the findings in this study, the described assignment and its related activities should be revised in the next course iteration. This paper will also be a part of the additional reading in the next course iteration.

Ethics declaration and AI declaration: Data have been collected with informed consent, and course participants have been kept as anonymous as possible. AI tools were used in the described image generation, but the essays and all parts of this paper, have been written without any use of AI.

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