Stereotypical Depictions of Malaysian and Hungarian University Professors Generated by AI

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This article aims to investigate the stereotypical representation of images generated by artificial intelligence in the case of university teachers. This qualitative research used Gencraft software to create pictures of university teachers and researchers in various disciplines in two countries, Malaysia and Hungary. Then, it sought to investigate the stereotypical representations generated by the system. The pilot research is a preliminary exploration of a more extensive study. Following the structure of the disciplinary fields taught at Oxford University, it analyses 44 generated images in 11 disciplines for both countries. Despite the small sample, exciting trends in the images can be identified, which may provide a basis for further investigation. The main results showed that male dominance is undeniable, especially regarding the Hungarian data.

Keywords: Generative Artificial Intelligence, Stereotypes, Image Generating, University Professors, Picture Analysis

Introduction

According to Assmann (2011), visuals are primordial, followed by text. The human brain can build visual references earlier, and then invents textual references. Pictures are autonomous carriers of meaning, but they function as coded texts; they can conserve information about anything depicted. Computer-aided Visual research possibilities and limitations can be seen if we analyse AI-generated images. Therefore, the present research aims to show an example of such research.

Visual analysis of images is perfect for demonstrating certain narratives or tendencies. Visual analysis can help researchers understand information and social relations encoded in images (Kress & Leuween, 2006). Based on this theory, we tried to understand the more profound meaning of these images generated by an AI tool called Gencraft.

An interdisciplinary research project, such as the present one, should focus on several related fields with the admission that these are only some of the possible fields and there could be other perspectives, narratives and fields, depending on the researcher's aims.

The research objectives are to demonstrate the roles and systematic research possibilities of AI-generated images and their analysis methods, possible limits of their usage during the research process and the decoding issues, with limitations and possibilities.

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AI for Image Generation

Technical elements

Artificial Intelligence Generated Content (AIGC) has gained widespread attention beyond the computer science community. AIGC refers to content generated using advanced Gen-erative AI (GAI) techniques, automating the creation of large volumes of content quickly. The technical process of AIGC involves using GAI algorithms to generate content that sat-isfies human instructions. This process typically comprises two steps: extracting intent information from human instructions and generating content accordingly. Training more advanced models on larger datasets and utilising substantial computational resources are among the key elements that propel the advancements in AIGC (Cao et al., 2018).

AI-driven image generation has made significant advancements, enabling producing a wide range of image styles, some closely resembling real photographs. This has been ex-emplified by instances like the Sony World Photography Awards, where an AI-generated image won, showcasing the capabilities of AI in this field (BBC News, 2023).

AI takes image descriptions or random noise as input and generates one or more images for users. Three common frameworks for image generation are neural style transfer (NST) (Huang et al., 2022), generative adversarial networks (GANs) (Karras et al., 2020) and dif-fusion models (Rombach et al., 2022). While significant progress has been made in en-hancing the quality of AI-generated images, computer vision researchers are also explor-ing new technologies to enhance GAI algorithms. These advancements and explorations are seen as ushering in a new AI era with significant societal impacts.

AI-generated images depend on the training images supplied to the algorithm, as these images form the basis for the AI's understanding of creating new visuals. These training images significantly influence the quality and diversity of the generated content (Hossain et al., 2021; Cha et al., 2018).

Image analysis

Iconography was originally a sub-discipline of art history, which concerned itself with the subject matter or meaning of works of art (Panofsky, 1972, p. 3). Iconography as a research method derives from this branch of art history and other visual arts (Géczi, 2010). Erwin Panofsky, who published his theory about image analysis and influenced iconographical studies for decades, declares the stages of iconographical analysis for the history of art. This iconographical analysis is based on three phases of the reception of an image. The acts of interpretation are the pre-iconographical description, the iconographical analyses and the iconographical synthesis (deeper analyses). The iconographical analysis deals with images instead of motifs (Panofsky, 1972, pp. 3–33). To understand the meaning of the painting for another discipline, such as the history of childhood, we need to find another analysing process of images. Although this research focuses on paintings, old prints and woodblock prints, mentioning Mietzner's and Pilarczyk's thesis about categorisation and classification is essential. Their theory is based on photo analysis but also provides a framework for paintings. Mietzner and Pilarczyk have analysed more than 10,000 educational photos so far. They understood the deeper meanings of images representing academic interactions or child-rearing processes in broader contexts (Mietzner & Pilarczyk, 2005). A visual analysis method invented by Bouteaud (1989) focuses on each picture's technical information. A serial visual anthropologic method created by Collier (2010) could be fruitful for researchers who need a comparison method for images with similar topics.

This paper introduces a possible analysis method based on the methods mentioned above.

Depiction of university professors in media

Previous research has shown evidence of stereotypical depictions; Dagaz and Harger (2011) examined 48 popular US movies between 1985 and 2005. Their investigation found that most professors wore glasses, bow ties and tweed jackets. They also compared the actual statistical data of the percentage of gender, race, age and discipline to the data gained from the movies. They found that while African American professors are overrepresented in film, Hispanic and Asian characters are almost nowhere to be seen. Interestingly, no Education scientist was depicted. Regarding gender balance, males were overrepresented compared to the statistical data (Dagaz & Harger, 2011).

If we are searching for the first investigation of the analysis of similar research, we must mention the modified version of The Draw-A-Man test, which made The Draw-A-Scientist Test in 1983. They said scientists were depicted among vials for centuries, with distinct suggestions for connection with alchemy or occult fields. As scientific fields were formed, professional depictions emerged in the media. According to their analysis, the most exciting fact was that only girls draw female scientists (Chambers, 1983). This examination showed similar results by D'Addezio and Basker; however, male dominance was undeniable in the data; females were rarely found among the pictures (D'Addezio & Besker, 2024). Most of these previous researchers underlined the importance of similar research as culture and media shape students, children and people's stereotypes about university professors.

Biases of image-generating AI

Before we started our investigations, we had to understand how generated AI creates or mirrors our biases. Based on previous research, big data or algorithms might not lead to an objective, neutral result since they use limited input data. According to Noble's study, we need to understand how algorithms work, but the data about women are definitely less represented (Noble, 2018). Boulamvini et al. (2018) state, 'Many AI systems, e.g. face recognition tools, rely on machine learning algorithms that are trained with labelled data.' So, in their investigation, they found that facial recognition systems tend to mistake non-binary individuals' gender. They identified that this problem may occur due to inadequate data entry (Boulamvini & Gebru, 2018, p. 1). Monitoring AI software from this angle – seeing stereotypes either in ethics, gender, religion, or other categories- might help to recognise the false pattern and biased inputs by widening the diversity of the implementations.

Gárcia-Ull and Melero-Lázaro, in their research, found that AI can not only repeat but also reinforce stereotypical content. While they saw a 35% chance of stereotypical images referring to gender when using human-made photos, they found a 59.5% chance of stereotypical images when analysing AI-generated images (DALL-E2). According to their investigation, DALL-E2 replicated with 21,6% while generating a picture of a woman and 37,8% when depicting an imaginary man (Gárcia-Ull & Melero-Lázaro, 2023).

Methodology

The research methodology employed falls within the domain of visual anthropology. In this section, we describe the criteria observed and analysed in the generated images. The software utilised for generating these images was Gencraft, selected from among the available free options, known for its emphasis on creating photorealistic depictions. While the hands depicted in the images may not resemble those of actual humans, the facial expressions and other elements appear quite accurate.

These images were generated using Gencraft, with input keywords such as 'University Professor' and the relevant discipline, such as 'Mathematics University Teacher/Professor'. To delineate fields available in higher education, we referenced the faculties and departments of Oxford University, renowned for its top global rankings. Following the identification of possible scientific fields, eleven were selected, and two images from both Malaysian and Hungarian backgrounds were generated for each.

The coding process involved utilising hashtags such as #national (MALAYSIAN or HUNGARIAN), #research field (e.g., BIOLOGY, MATHEMATICS) and #university professor (UNIVERSITY PROFESSOR). Subsequently, categories for analysis were established. Given the focus on stereotypes, the chosen categories included #gender, #facial expression, #posture, #location in the classroom, #clothing, #accessories on the person and #accessories in the background. It was mutually agreed that both researchers would scrutinise and determine the attributes of each analysed image.

Analysis

A total of 44 images were generated, with each set comprising 22 images. Below, we present all the images generated for Hungarian and Malaysian professors.

Figure 1. AI-generated images of Hungarian professors

Figure 2. AI-generated images of Malaysian professors

Our examination revealed notable trends within the generated images. Hungarian images predominantly feature male professors, with a noticeable absence of female representation.

Conversely, the Malaysian set displayed a balanced gender representation. Across both cultures, male researchers dominated fields such as Education, Law, Biology and Chemistry. However, neuroscience emerged as the sole science field where females outnumbered males.

Psychology was the only field where we found balanced results.

In the Hungarian dataset, only six out of 22 images depicted female professors, contrasting with the Malaysian dataset, which featured 11 female professors among the 22 generated images. An intriguing observation within the Hungarian images was the slight resemblances between Hungarian politicians, such as the president of the state and the prime minister and some of the generated professors' images. This similarity can be attributed to the underlying databases upon which the AI model relies. In the following analysis, we picked some fields with interesting observations focused on the stereotypic depictions.

Education Professors

Figure 3. AI-generated images of Hungarian education professors using Gencraft

Figure 4. AI-generated images of Malaysian education professors using Gencraft

Comparing these images reveals a striking similarity: all four depict middle-aged men dressed in formal attire, consisting of white shirts and very formal jackets. This uniformity extends to their overall demeanour, as they exude a sense of formality in every aspect. Notably, three of the four individuals wear glasses, and one Hungarian professor is depicted holding two pens, an anomaly likely attributable to the program's limitations in generating accurate hand representation.

The scenes in these images suggest a focus on scholarly pursuits, with all individuals seemingly engaged in paperwork, likely related to research or documentation. The backgrounds, reminiscent of libraries or museums, further reinforce this scholarly ambience. However, one Hungarian image stands out, featuring a basilica-style apse reminiscent of the Bazilika in Budapest, suggesting a potential deviation from the academic context.

Despite the meticulous attention to detail in portraying formal academic settings, the connection between education research and the depicted image topics remains somewhat ambiguous. This observation highlights the inherent limitations and potential misalignments in AI-generated imagery, underscoring the importance of critically evaluating the context and relevance of such generated content.

Psychology professors

Figure 5. AI-generated images of Hungarian psychology professors using Gencraft

Figure 6. AI-generated images of Malaysian psychology professors using Gencraft

The images of psychology professors exhibit notable differences and similarities between the Hungarian and Malaysian representations. In the Hungarian set, two middle-aged or older men are depicted, with one slightly resembling the prime minister and the other evoking imagery associated with Freud. Conversely, the Malaysian set features two women, presenting a contrast in gender representation.

Despite the gender disparity, all four individuals are attired in formal dress, reinforcing the perception of scholarly seriousness. Interestingly, while the Hungarian professors exude a sense of profundity in their library setting, the Malaysian counterparts appear more youthful and are positioned among what seems to be a group of students. However, all subjects face the camera directly, emphasising a commonality in portraying academic engagement.

Gender biases are apparent in the disparity between male and female representations. Further analysis could delve into the potential connections between academic disciplines and clothing choices, such as the use of traditional folk-style gowns worn by both Hungarian and Malaysian linguists despite the absence of such attire in either culture. This raises intriguing questions about the underlying biases and cultural assumptions embedded within AI-generated imagery.

Chemistry Professors, in contrast with the Biology Professors

Figure 7. AI-generated images of Hungarian chemistry professors using Gencraft

Figure 8. AI-generated images of Malaysian chemistry professors using Gencraft

One interesting observation about the chemistry professors between the two countries is the contrast in attire. In the Hungarian images, the chemistry professor is depicted wearing a brown suit with a green vest, red collar shirt, and red tie, presenting a formal and professional appearance. This attire aligns with the traditional expectations of formal dress in academic settings.

On the other hand, in the Malaysian images, the chemistry professor is shown wearing a white lab coat, suggesting a more practical and laboratory-oriented approach to the field of chemistry. The lab coat symbolises hands-on work in scientific research and experimentation, reflecting a different aspect of the chemistry discipline compared to the more formal attire of the Hungarian professor.

This contrast in attire may highlight cultural differences in the academic and professional expectations within the field of chemistry between Hungary and Malaysia. While the Hungarian depiction might emphasise a formal and scholarly approach, the Malaysian depiction emphasises practicality and scientific experimentation.

However, in chemistry, all depictions are of male professors, yet the gender representation among biology professors between the two countries shows an intriguing difference:

In the Hungarian images, only one of the biology professors is depicted as female, while both are female in the Malaysian dataset. This aligns with the broader trend observed in various fields within the Hungarian dataset, where male professors are more predominant.

In contrast, the Malaysian images portray the biology professor as female, wearing a white lab coat. This depiction challenges the gender stereotype often associated with STEM fields, where male representation tends to be more common. The presence of a female biology professor in the Malaysian images reflects a more balanced gender representation within the academic field of biology, showcasing diversity and inclusivity in the portrayal of scientific professionals.

Overall, the difference in gender representation highlights cultural and societal factors influencing the perception and depiction of academic professions across different countries.

Linguistic Professors

Figure 9. AI-generated images of Hungarian linguistic professors using Gencraft

Figure 10. AI-generated images of Malaysian linguistic professors using Gencraft

One interesting observation about the linguistic professors between the two countries lies in the depiction of traditional attire despite the absence of such attire in either Hungary or Malaysia.

In the Hungarian images, the linguistic professor is portrayed wearing a long-stitched gown, which is described as very elegant. This attire reflects a traditional and perhaps ceremonial style, evoking a sense of reverence or formality that may be associated with academia or cultural heritage. However, it is worth noting that such attire is not typical or commonly seen in Hungary, suggesting a departure from the cultural norm.

Regarding the images representing Malaysian culture, the traditional attire depicted by the linguistic professors does not accurately reflect Malay cultural attire. The attire portrayed, characterised by elaborate embroidery and a scarf worn at the back of the head, closely resembles Indian cultural attire rather than Malay.

The selection of imagery by AI models can sometimes be influenced by various factors, including the data it has been trained on and the patterns it has learned. In this case, if the AI model predominantly trained on or encountered more instances of Indian cultural attire in its dataset, it might have a tendency to associate similar attire with Indian culture rather than Malay culture.

Additionally, the complexity of cultural representation and the nuances between different cultural attires can sometimes be challenging for AI models to accurately distinguish, especially if the training data does not cover a wide enough range of cultural variations. Furthermore, the visual similarities between certain elements of Indian and Malay cultural attire, such as intricate embroidery or the wearing of scarves, might lead to confusion for the AI model when attempting to categorise or identify specific cultural attributes.

This observation raises questions about the cultural representations and stereotypes embedded within AI-generated images. Despite the absence of direct cultural relevance to the attire depicted, it may serve to convey a sense of cultural richness or diversity within the field of linguistics. Additionally, it highlights the potential for cultural fusion or reinterpretation within visual depictions, transcending traditional boundaries and expectations.

Discussion and concluding remarks

Concerns about gender biases have arisen because of the lack of diversity of the input data in previous research (Buolamwini et al., 2018; Gárcia-Ull & Melero-Lázaro, 2023) regarding AI-generated images.

We saw the tendency of biases in the database because the specific software uses AI based on built-in stereotypes. If we give inputs of various images, we need to keep in mind genders and diversity of backgrounds, for example, socioeconomic, religious and ethnic backgrounds. We enhanced specific software to generate a wider variety of images.

We observed in our analysis that generative AI might not recognise the exact cultural background – see the Linguistic professors wearing culturally relevant-looking gowns but not realistic ones. Such creations might generate assumptions or stereotypical depictions.

As for the gender balance, we tend to see male dominance among the whole dataset, especially with the Hungarian creations. Generative AI built in the Gencraft software we used for this investigation recognises a limited range of people as university professors, especially within Hungarian images. It assumes that almost all professors are male and in their 50s or over 50.

Talking about the limitations of our research, we need to mention that we used Gencraft's other features, such as Gemini or Dall-E, which might create different images and biases or balanced results. We also used English for the prompts; in Hungarian, for Male Teachers, we used TANÁR, and for Female Teachers, TANÁRNŐ; however, University Professor is still a unisex word – such limitations of the prompts might also lead to false or biased data. We need to examine further whether the refinement of the prompts influences the reduction of stereotypes. As for the limitation of our research, the examined prompts give one possible limit: the number of images. For more profound research, we need a quantitative analysis with possibly all fields and disciplines regarding any higher institution, or we can continue this analysis by creating pictures based on Oxford's discipline classification or the Frascati index.

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Mesterséges intelligencia által generált sztereotip ábrázolások maláj és magyar egyetemi oktatókról

Tanulmányunk célja a mesterséges intelligencia által generált képek sztereotipikus reprezentációjának vizsgálata egyetemi tanárok esetében. Kvalitatív kutatásunk során a Gencraft szoftver segítségével készítettünk képeket különböző tudományágak egyetemi tanárairól és kutatóiról két országban, Malajziában és Magyarországon. Ezután a rendszer által generált sztereotipikus reprezentációk vizsgálatára törekedtünk. Az itt publikált tanulmány egy kiterjedtebb kutatás része, mely a probléma előzetes, kísérleti feltárását szolgálja. Az Oxfordi Egyetemen oktatott tudományterületek struktúráját követve mindkét ország 11 tudományterületéről összesen 44 generált képet elemeztünk. A kis minta ellenére izgalmas tendenciák azonosíthatók a képeken, amelyek alapot adhatnak a további vizsgálatokhoz. A főbb eredmények azt mutatták, hogy a férfidominancia tagadhatatlan, különösen a magyar adatok esetében.

Kulcsszavak: generatív mesterséges intelligencia, sztereotípiák, képgenerálás, egyetemi tanárok, képelemzés