Diversity, Equity and Inclusion in The Age of Generative AI

Sonja M. Hyrynsalmi[1]

[1]LUT University, Mukkulankatu 19, Lahti, 15210, Finland

Abstract

As generative AI services continue to expand across various industries, especially in the field of software engineering, it is critical to comprehend how these services represent different groups of people. Despite software engineers' crucial role in this industry, limited research exists on how generative AI image tools portray software engineers themselves. This study examines the representation of software engineers in generative AI image tools like DALL-E and Canva. Using qualitative analysis, we assess image outputs to identify representational themes. Our results indicate that while these tools can generate varied images, there are noticeable representation gaps, especially regarding gender and age.

Keywords

Software Engineering, Diversity, DALL-E, Canva, Generative AI, Diversity in Generative AI

1. Introduction

A classic English idiom states that *a picture is worth a thousand words*. In the wake of rapid advancements in artificial intelligence (AI), tools like DALL-E and MidJourney are revolutionizing image creation, making impactful pictures for everyday use more accessible than ever before [1, 2]. Images and narratives play pivotal roles in media, influencing perspectives but also reinforcing stereotypes [3]. However, the representation of software engineers in pictures and talks has long been male-dominated. This has led to a situation where visible role models, such as women in the software industry, are lacking. Furthermore, role models and representation in pictures and talks significantly impact how diverse people get interested in the industry. In addition, role models are essential for retaining and promoting diverse workers in their software industry careers. [4]

Issues related to bias in AI tools can primarily be viewed from two dimensions: data and algorithms. Srinivasan and Chander identify specific biases, ranging from sampling to validation and testing [5], offering guidelines to ML developers. Historically, software engineering has confronted biases, particularly gender bias, with women's crucial yet underrepresented role in the industry [6, 7].

Generative AI image tools like DALL-E have advanced rapidly, becoming widely recognized and used in the industry [8, 9]. Generative AI image tools can significantly influence areas like education and broaden art accessibility [10, 2, 1]. However, as commercial AI tools emerge,

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sonja.hyrynsalmi@lut.fi (S. M. Hyrynsalmi)
0000-0002-1715-6250 (S. M. Hyrynsalmi)

there's an urgency to identify biases in their real-world applications [11]. Furthermore, the correct training data is vital, especially concerning gender biases [12]. It is essential also to note that previous visualizations can perpetuate inaccuracies. For instance, ad display algorithms might inaccurately suggest women aren't interested in software engineering roles, as ads about software engineering roles have been targeted only to male audience [13].

The transformative potential of AI across sectors is undeniable [9], yet its ethical and sustainability implications warrant attention, especially in the context of Sustainable Development Goals [14]. For example, the UN's Sustainable Development Goals address biases, including AI biases. It has also been said that biases remain the main challenge and should be considered in every field [14]. Emergent generative AI tools, providing capabilities from text generation to image creation, demand scrutiny for biases and their broader implications. In this light, we examined software engineering representation in recent generative AI image tools *DALL-E* and Canva's *Text-to-Image*. Our ongoing research poses the question: *How do different generative AI tools, such as DALL-E and Canva's Text-to-Image, vary in their representation of software engineers based on gender, ethnicity, and age?*

2. Research Process

This research investigates potential biases in the portrayal of the software engineering profession by generative AI tools, particularly concerning gender, ethnicity, and age. We employed a qualitative analysis approach to comprehend specific themes related to software engineering diversity [15]. The focal point was the depiction of gender, ethnicity, and age in outputs from sampled tools.

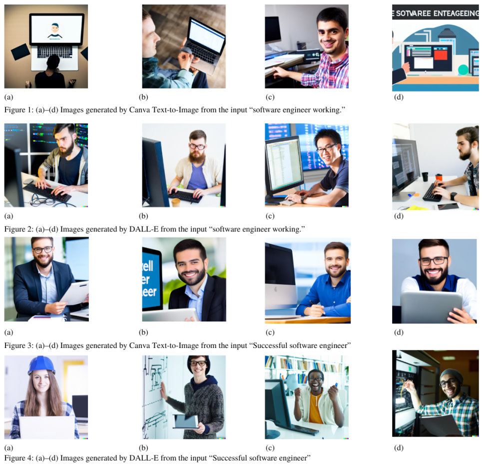
Criteria for tool selection were: (i) accessibility without advanced technical know-how; (ii) widespread usage and media attention, implying diverse user bases; and (iii) standalone operation, meaning outputs are based solely on user commands without any external guiding inputs. Given these criteria, OpenAI's DALL-E, designed to produce visual outputs from verbal cues, was chosen as the first tool. Our second tool was Canva, an established graphic design platform with over 100 million monthly users. Both Canva and Dall-E generate four images per prompt.

The study employed two primary search prompts in DALL-E and Canva's Text-to-Image: *"Software engineer working"* and *"Successful software engineer"*. Additional prompts included *"picture of software engineer for recruitment"* and *"software engineering team"*. Our qualitative analysis was centered on gender, ethnicity, and age which are the most common aspects of team diversity.

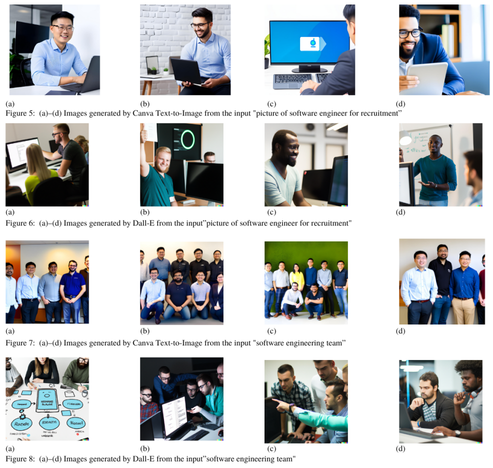
3. Results

Overall, there are 64 persons in these 32 pictures (Figures 1-8); from those 64 people, 5 are women, and 1 is androgyne, or the gender is hard to describe.

When regarding gender, Canva's results are more male-dominant than Dall-E's, and for that, there can be a gender bias in this research phase. In two of sixteen pictures, there is a woman in a picture. In both of those pictures (Figure 7, pictures b and c), where a woman was identified,



(a) Figures 1-4



(b) Figures 5-8

Figure 1: Figures 1-8

are under the input of "software engineer team". However, both pictures describe a big software engineering team, and in both, there is only one woman in the picture. Dall-E provides more diverse pictures regarding gender than Canva. From four different inputs, Dall-E provided women in almost everyone. Only input "software engineer working" does not have any women. Also, in the results of the "successful software engineer," the only woman wearing a helmet would be something to investigate further.

The male gender was underlined in many pictures with a beard, referring to the male software engineer. There were a lot of blue-collar or blue shirts used, and in the one software engineering team picture, where there were a woman (7c), the woman stands out from her male colleagues (wearing blue) as she wears a yellow blouse. Women are also easy to identify even though they don’t look at the camera in some pictures (6a, 8a) as they wear long, nicely cut hair.

Identifying and categorizing ethnicity and age were more challenging for the researchers. Both Canva and Dall-E have diversity regarding the ethnicity in their pictures. However, regarding the age, what was striking was that all the people in the pictures represented people who could be identified as young (30-45 years old). There were no familiar signs of older age, such as grey hair or wrinkles.

3.1. Discussion

While generative AI tools are still in the early stages of their life cycles, it is predicted that the quality of their outputs will improve as they become more widely used. However, as seen from our results, there is a risk that these tools will reinforce and repeat harmful stereotypes.

Overall, our results continue the past discussion around representative pictures, which has been going on digital pictures also regarding ’stack stock photos’. Our advices for the more representaive use of AI image tools would be: 1) Consider carefully the construction of prompts for AI image tools; instead of generic terms like ’software engineer’, specify ’a group of software engineers from diverse age, ethnicity, and gender groups.’, 2) Promote awareness about diverse representation in software engineering within your communities and advocate as an ally for broader inclusivity, and 3) There is a need for ongoing improvements to ensure that generative AI tools produce more representative and inclusive images of software engineers.

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