AI and Gender Equality: One Step Forward or Two Steps Back?

Maria João Guedes, Ricardo Rodrigues and Dinis Macedo

ADVANCE/CSG[1], ISEG – Lisbon School of Economics and Management, Lisboa, Portugal

mjguedes@iseg.ulisboa.pt
rmrodrigues@iseg.ulisboa.pt
dinis.macedo@iseg.ulisboa.pt

Abstract: This research focuses on potential gender biases in AI algorithms and their implications for gender equality. The recent sudden and unexpected growth in the artificial intelligence (AI) user base has attracted significant attention. It has raised public concerns about AI's impact on jobs becoming redundant in the future, and about the accuracy of AI's content and its power to influence and manipulate users. However, the AI-driven transformation began earlier and yielded several ongoing changes in organizations – for example, enhancing service quality, reducing costs in routine tasks, and improving access to existing information. Nevertheless, from the gender perspective (one of the UN's sustainable development goals), there is a risk that this AI-driven transformation could negatively impact the complex journey toward equality between men and women. This may occur either from women's reduced involvement in the technology development processes (which can lead to developer biases being reflected in the technologies) or because the historical data used to inform and develop AI algorithms may reinforce existing gender biases. We address the challenge proposed by Manasi et al. (2023) to test AI algorithms in this context. Using an experimental approach, our research examines how three popular AI tools (ChatGPT, CoPilot, and Gemini) behave in relation to sensitive gender-related topics and scenarios. This study aims to clarify the associated risks and assist stakeholders, particularly policymakers, in defining guidelines to prevent the replication of gender-biased content. Nonetheless, we believe that AI can serve as a resource to advance the field of gender equality. Given the recent massification of AI use and the recent challenges to progress on gender equality (including the asymmetric impact of COVID-19 and recent armed conflicts), this research is timely and carries direct implications for organizations' managers, policymakers, and the research community. We position it as exploratory research and propose avenues for future research, and we highlight the need to monitor the evolution of AI by regularly conducting similar analyses.

Keywords: Gender Equality; Artificial Intelligence; Gender Gap; AI Gender Bias.

1. Introduction

According to the United Nations, "The world is not on track to achieve gender equality by 2030" (United Nations, 2022, p. 36). And, the World Economic Forum (2022, p. 13) argues that it could take up to 132 years to close the "overall global gender gap". This evidence reflects a failure of strategies, policies, actions, and efforts worldwide to achieve gender equality. However, we must acknowledge that the success of any strategy depends on the ever-evolving external environment, which can either facilitate or hinder the fulfillment of goals, with technology being a significant component of that environment. Since 2015 (the reference year for the UN), various external factors have influenced progress in this field, including Covid-19, which disproportionately affected women, and recent armed conflicts that, in addition to their direct effects on all populations, have shifted several goals to a lower priority and may reverse advances made in previous years (World Economic Forum, 2022; Manasi et al., 2023).

Previous research highlights the significant gender gap in technology-related fields (Manasi et al., 2023). However, looking beyond this existing gap, we need to consider the impact and relevance of technological advances in achieving the sustainable development goal of gender equality (SDG 5), particularly target 5.1, which aims to end all forms of discrimination. This research focuses on a specific application of artificial intelligence (AI), although there are many other applications in fields such as medical, education, and human resources, as noted by Manasi et al. (2023) and Abdelhalim et al. (2024). Thus, in our context, we need to question whether this technological advance will positively or negatively influence the path toward equality. Reflecting on this issue is not only important in enhancing knowledge in this area but also valuable in developing guidelines that assist stakeholder groups to define their future objectives and actions – namely, whether to mitigate negative impacts or to capitalize on the opportunities presented by AI (Abdelhalim et al., 2024). Specifically, it aims to support the development of policies, which remains an open and relevant issue (Manasi et al., 2023).

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In this research, our focus is not on the differences between women and men regarding their use of and contribution to the development of AI (Manasi et al., 2023). These are significant topics, especially since the limited involvement of women in creating AI algorithms may trigger biases (Manasi et al., 2023). Instead, we aim to identify how the use of AI might help perpetuate existing biases. To train and inform the algorithms, AI datasets might be drawn from information and/or content that reflects the historical paradigm of gender discrimination and biases, instead of portraying the ongoing (albeit slow) transformation toward gender equality. To accomplish this, we established the following research objectives: 1) create and apply a simple experiment to identify existing biases in AI-generated content; 2) analyze the content provided by AI to discern the presence of gender-related biases; and 3) identify the limitations of the experiment to inform the development of more advanced approaches.

To address the research questions, we interacted with three different AI tools (ChatGPT, CoPilot, and Gemini) to determine the presence of biases that could negatively influence gender equality efforts. This response answers directly to the call made by Manasi et al. (2023) to perform tests "to eliminate any form of discrimination".

2. Literature Review

Management research has devoted considerable attention to the advantages that diversity can bring to organizations, leading them to higher levels of performance. To take advantage of this diversity, companies are encouraged to implement internal policies that support it. Yet, there are still barriers that need to be overcome, especially regarding the well-known glass ceiling that limits access for specific groups, such as women and minorities, to the top positions. Gender bias is a phenomenon with a history spanning millennia, deeply embedded in the social and cultural frameworks of various civilizations. Societies have long-established norms that favor men over women, shaping their roles and positions within society. These norms became institutionalized, leading to persistent gender inequalities that are still evident today (Bullough et al., 2022; Cheryan & Markus, 2020; Cislaghi & Heise, 2020; Heilman et al., 2024).

Today, gender bias is still subtly manifested in modern life. Disparities in pay, under-representation in leadership roles, and cultural stereotypes endure. Recent studies utilizing data analysis tools have revealed these inequalities, emphasizing the need for ongoing and innovative strategies to achieve true gender parity. In education, gender bias appears early, shaping boys' and girls' perceptions and aspirations. Research indicates that gender stereotypes influence teachers' and parents' expectations, affecting academic performance and subject selection. For instance, girls are frequently discouraged from pursuing STEM (Science, Technology, Engineering, and Mathematics) careers despite demonstrating equal capabilities to boys in these fields (Casad et al., 2021; Ertl et al., 2017; Makarova et al., 2019).

Despite efforts to rectify the situation, women's under-representation in STEM and academic leadership positions remains a significant challenge. Educational policies promoting gender equality, combined with awareness campaigns and mentoring programs, are essential to transform the educational landscape. The progress of these initiatives must be monitored, and strategies adjusted as needed to ensure equal educational and professional opportunities for all children (Prieto-Rodriguez et al., 2020; Tam et al., 2020).

Moreover, the workplace is a crucial setting where gender bias is evident. Research shows that women frequently face significant pay gaps compared to men, even when performing similar roles (Bennedsen et al., 2023; Bishu & Alkadry, 2017; Budig et al., 2021). They are under-represented in leadership roles and face additional obstacles to promotion (Beckwith et al., 2016; Seo et al., 2017). Moreover, these disparities cannot be solely attributed to differences in education or experience; they reflect deeper structural and cultural biases (Yeganeh & May, 2011), which this research seeks to address. Hiring and promotion processes often favor men, whether through informal networking or subjective evaluation criteria that reveal implicit biases (Carlsson et al., 2021; Galos & Coppock, 2023).

The technology industry is a sector where gender bias is evident, influencing everything from hiring practices to product development. Women remain under-represented in technology careers and encounter substantial obstacles to career advancement (Avolio et al., 2024; Eisenhart & Allen, 2020; Onyeador et al., 2021). Consequently, technological products and algorithms created by predominantly male teams may embody implicit biases, leading to systems that inadequately serve the needs of all users. A lack of diversity in development teams can result in outcomes that reinforce gender inequalities, from security devices that neglect women's needs to facial recognition algorithms that are less accurate for female and non-white faces (Hyrynsalmi, 2019; Varma 2018).

Artificial intelligence (AI) tools have the potential to transform many aspects of society, from healthcare and transportation to work and leisure. However, as AI becomes more widespread, significant concerns about biases embedded in these systems have emerged (UNESCO, IRCAI, 2024). These biases can reflect and amplify existing gender inequalities, negatively affecting automated decisions in various areas. Identifying and addressing these biases is essential to ensure that AI promotes, rather than hinders, gender equity (Domnich & Anbarjafari, 2021; Gupta et al., 2022; Newstead et al., 2023; Parra et al., 2021). Gender bias in AI algorithms can have several origins. A common source is the dataset used to train these algorithms, which may reflect historical and cultural prejudices (UNESCO, IRCAI, 2024). In addition, the lack of diversity in AI development teams can result in systems that inadequately consider women's needs and perspectives (Leavy, 2018; Nadeem et al., 2022; Ntoutsi et al., 2020; UNESCO, IRCAI, 2024).

Based on the existing literature, considering the widespread use of AI tools, we formulate the following research hypotheses:

> H1: When discussing career perspectives, AI tools reveal gender biases linked to careers for men and women;
>
> H2: When discussing career perspectives, AI tools reveal gender biases linked to traditional characteristics attributed to men and women.

3. Methodology

3.1 Experiment Design

Based on the literature review and the findings of Project POWER – POrtuguese Women's Equality ObseRvatory, supported by FCT (reference 2022.08793.PTDC), we observe a culture-driven bias in the selection of university-level education programs, which, in turn, affects the availability of men and women for various professional activities. In this context, we prioritize studying the stimuli that lead young people to decide on their field of education. Therefore, to focus on content that AI may provide to young people, we interacted with three AI tools: ChatGPT, CoPilot, and Gemini. We used the same prompt for each tool, asking it to provide a short story (which may perpetuate culture-driven biases) about a boy or a girl deciding on a career path. This approach targeted the possible associations that these AI tools form between gender and professional-role activities.

The literature has already suggested that, when asked directly for advice on careers to pursue, AI models may deliver culturally biased recommendations. However, the influence is not limited to these specific career advising tools. Therefore, we decided to explore the presence of such biases in stories that may be created through AI involvement. In August 2024, using the three tools, we collected data in response to the following prompt 25 times[2]:

1. Tell me one story about a girl choosing her career + university + motivations + characteristics and a full story;
2. Tell me one story about a boy choosing his career + university + motivations + characteristics and a full story.

3.2 Data Analysis

The first step of the analysis focused on content uniformity. It involved checking whether the AI tools represented similar careers and characteristics in varied ways (e.g., Software Engineer vs. Software engineer; resourceful vs. Resourceful) that could be interpreted differently by the data analysis software (SPSS for quantitative analysis) or utilizing any detail that could lead to different classifications (e.g., Entrepreneur vs. Entrepreneur/Startup Founder; problem solver vs. problem-solving skills). We then grouped the careers based on principal characteristics, such as considering an automotive engineer simply as an engineer, an environmental scientist merely as a scientist, or a pediatrician as a doctor. As for the characteristics, no such grouping was needed. The second step focused on the descriptive analysis of the collected data. In the subsequent step, we

[2] We decided to maintain the threshold of 25 stories (which we consider a limited number) because, during the data collection process, we realized that two of the AI tools, after a while, tended to repeat stories rather than create new ones, which we had not anticipated when designing this experiment.

sought to determine whether different careers and characteristics were suggested for girls and boys. However, in order to conduct such an analysis based on the list of careers provided by the AI tools, we needed external benchmarks to evaluate whether the suggestions made by the AI tools were biased.

4. Results

4.1 Descriptive Analysis

The experiment yielded 85 different careers. In the first analysis, we noticed that 55 alternative careers are considered for boys, while 60 alternative careers are available for girls. Following the steps outlined in Section 3.2, we organized similar careers, which allowed us to reduce the total number of careers to 56, with 46 available for boys and 38 for girls. Based on this analysis, the *first takeaway* is that, initially, there was a noticeably larger variety of careers available than after merging similar career alternatives. In a complementary analysis, we checked whether the probability of girls and boys being considered for university degrees differed and found no evidence of such biases. We deem this to be the *second takeaway* from our analysis. In proceeding with our analysis of careers, we report only those with a minimum of four suggestions[3], as shown in Table 1.

Table 1: Selected career suggestions by AI tools for boys and girls

Careers	Boys	Girls	Total
Astrophysicist	1	3	4
Biologist	2	3	5
Chef	**5**	**1**	**6**
Designer	**2**	**8**	**10**
Doctor	3	1	4
Engineer	6	6	12
Entrepreneur	**3**	**6**	**9**
Historian	3	1	4
Lawyer	1	3	4
Musician	2	2	4
Scientist	5	4	9
Therapist	1	3	4
Video Content Director	2	2	4
Writer	2	2	4
Observations	**38**	**45**	**83**
% of the sample	**50,7%**	**60,0%**	**55,3%**

Source: Authors' analysis

The analysis in Table 1 reveals varying levels of proximity between boys and girls regarding the career suggestions provided by AI tools. Careers with no differences include Engineer, Musician, Video Content Director, and Writer. Small differences are observed in the careers of Biologist and Scientist. Other careers show some degree of difference, including Astrophysicist, Doctor, Historian, Lawyer, and Therapist. The remaining cases, which became the main focus of our analysis, reveal intriguing differences. These careers include Chef, Designer, and Entrepreneur. It is interesting to note the existence of several STEM careers for which there is no specific evidence of bias, despite the traditional dominance of men in these fields. Conversely, it is in careers

[3] We recognize that this decision has relevant implications for the analysis. However, we believe this is the minimum threshold that can be beneficial for the analysis. For instance, a threshold of three suggestions, while it would capture a higher percentage of the sample, would raise a debate about whether a distribution of two suggestions versus one suggestion would indicate any biases, which we believe does not add value.

outside these STEM areas that we observe the most significant differences. This is the *third takeaway* from our research.

To better understand the bias, we need to determine whether the careers of Chef, Designer, and Entrepreneur have traditionally been occupied by men or women. Prior research shows that, in top restaurants (for example, those listed in the Michelin guide), the role of Chef is predominantly held by men. The data we collected on this background information is reflected in the stories developed by AI tools, confirming that the data used to inform AI algorithms may be replicated in the algorithms' outputs.

Regarding the Designer career, which includes a diverse range of roles such as Floral Designer, Fashion Designer, Graphic Designer, Interior Designer, and User Experience (UX) Designer, some roles, such as Fashion Designer, are notably associated with women, while others exhibit a balance or even a predominance of men. Considering the specifics of each designer role, it appears that the predominance of girls in our sample does not align with previous data.

Finally, focusing on entrepreneurship, our data reveals a marked association with girls. All represent opportunity-driven entrepreneurship (not reported in Table 1). Existing statistics indicate that the number of female entrepreneurs is lower than that of male entrepreneurs, in contrast to our sample results. Based on this finding, we confirm there are some risks associated with AI tools potentially confirming and replicating existing gender biases. However, we acknowledge that these tools recognize opportunities for women to enter fields that have, until now, been predominantly occupied by men. This represents the *fourth takeaway* of this research. Despite the high number of alternative careers for a relatively small sample (implying a cell count of fewer than 5 in too many cells), we conducted a Chi-Square test with a Monte Carlo simulation to assess the significance of the difference, confirming the reported ambiguity.

4.2 Characteristics Associated With Boys and Girls

In addition to the careers provided, we also analyzed the characteristics that AI associates with boys and girls. Two or three characteristics were attributed to each character in each story. The initial analysis shows that, for 75 individuals, there were a total of 225 characteristics identified for girls but only 194 for boys. This indicates that AI tools struggled to maintain the three characteristics for all boys as effectively as for girls. After implementing some adjustments for content uniformity, we proceeded with the analysis. Focusing on the different characteristics, we noticed that boys are associated with 69 different characteristics while girls are associated with 76 different characteristics. Selecting the characteristics that occur more than three times in the sample, we obtained the information presented in Table 2.

Table 2: Selected characteristics presented by AI tools for boys and girls

Characteristics	Boys	Girls	Total
Adventurous	4	4	8
Analytical	**20**	**15**	**35**
Artistic	2	3	5
Compassionate	7	6	13
Creative	**19**	**21**	**40**
Curious	9	10	19
Dedicated	4	4	8
Detail-Oriented	7	8	15
Determined	4	13	17
Eco-Conscious		5	5
Empathetic	**10**	**12**	**22**
Imaginative	2	3	5
Innovative	3	7	10
Inquisitive	2	2	4
Meticulous	4	2	6

Characteristics	Boys	Girls	Total
Observant	4	2	6
Passionate	11	8	19
Patient	9	11	20
Persistent	1	3	4
Persuasive	3	2	5
Problem Solver	3	3	6
Resilient	2	3	5
Resourceful	3	3	6
Strategic	3	4	7
Tenacious	1	3	4
Visionary	4	4	8
Sum	**141**	**161**	**302**
% of the total	**72,7%**	**71,6%**	**72,1%**

Source: Authors' analysis

Considering the three most popular characteristics, we notice a balance between creativity and empathy. However, regarding the analytical trait, it appears that AI tools perceive boys as more analytical than girls. Expanding the analysis to other characteristics, differences are evident in greater determination, environmental consciousness, and innovation among girls. These differences may be based on underlying biases, which is the *fifth takeaway* from our analysis. To complete the analysis, we focused on characteristics with frequencies of eight observations or more and conducted a Chi-Square test with a Monte Carlo simulation. Based on this analysis, our results reveal that the possible biases are not spread over all characteristics.

5. Discussion and Conclusions

Previous research and public debate have pointed out the potential biases that AI tools may convey, resulting from a scarcity of women developing such tools and the use of historical public information to inform AI algorithms. Considering these concerns and responding to appeals to test existing algorithms, this research envisaged an approach to check whether the outcomes of the AI tools revealed any gender-related biases. Our research hypotheses posited that prospective careers and characteristics for boys and girls would reflect existing, culturally supported biases.

The results reveal that prospective careers – such as one of the proposed careers, chef – may reflect the existing predominance of men in top restaurant positions. However, we must recognize that the AI tools suggest that girls may be suitable and prevalent in other careers that have, so far, been dominated by males. Therefore, concerning Hypothesis 1, we determine that we have mixed findings.

Considering boys' and girls' characteristics, the literature supports the idea that women are more likely to care for others, while men tend to have greater determination and be more rational. In this context, we expect similar biases in our results. The AI tools indicate that men are more analytical, aligning with social and cultural biases, but they also assess girls as more determined and innovative than boys. Therefore, in the case of Hypothesis 2, we have mixed findings.

This research established three objectives. The first was to develop and apply a simple experiment that could help identify existing biases in AI-generated content. The experiment focused on content that may influence young people in learning about the roles of men and women in society, thereby impacting their own career and education decisions. While the experiment was successful, we acknowledge several limitations, including those related to the diversity of the outputs. The second objective pertains to the identification of gender-related biases, which we have noted. However, we recognize that the AI tools also provided interesting outputs to combat existing biases. Finally, we identified the limitations of our experiment to facilitate future efforts in this field.

Regarding our research's contribution – as highlighted in the presentation of our results – there are five key takeaways to note:

1. The number of suggested alternative careers is greater for boys than for girls;
2. Both boys and girls are considered equal in terms of enrollment in university degrees;
3. The most significant differences in terms of prospective careers for boys and girls are found outside the STEM areas;
4. AI tools recommend careers for girls that are currently dominated by men, although the chef career seems to replicate existing biases;
5. AI tools perceive boys as more analytical than girls but, as in prospective careers, they also perceive girls as currently having characteristics more associated with men.

6. Limitations and Recommendations for Future Research

Despite existing calls to check whether AI delivers biased contributions, we recognized during this research the importance of establishing a comprehensive instrument that can be regularly deployed to assess whether and to what extent AI offers biased suggestions. Without such a tool, it will be challenging to support arguments about potential existing biases. However, we still need to establish a common understanding of what constitutes a biased perspective or not.

In this research, we have not considered language-induced biases. There are languages where words (for instance, “doctor” in English) provide no information on gender (e.g., female or male doctor). There are also languages where such distinctions are the norm. For instance, the word “doctor” in Portuguese, as in other widely spoken languages, translates into two different words, one for a woman and one for a man). Furthermore, there may be an expectation based on the popularity of particular professions for women and for men (for example, male doctors and female nurses), which can influence AI outputs. In this context, recognizing pre-existing issues in Natural Language Processing (Manasi et al., 2023), we must acknowledge efforts to develop AI tools that can interact with users in their native languages. These often employ automatic translation features that may or may not be sensitive to the topic of gender equality. For example, in writing this paragraph, we used Google’s translation tool to translate the word “doctor” from English to French. Immediately, we received an appropriate translation (“médecin”) as well as an example of a sentence using the word (“Elle voulait devenir médecin"). We could not help but wonder whether the gender-specific sentence was generated by chance or represented an effort to mitigate biases. Therefore, in future research, researchers should replicate the same analysis in languages other than English (e.g., Romance languages) and determine whether the findings are affected.

A future topic to explore is the background. We noticed while conducting the analysis that the AI tools deliberately assigned names from Romance, Asian, and other language regions. However, we have not analyzed the extent to which this reflects the diversity of people or if there is a connection between those origins and the types of career suggested. In addition, we have only addressed one specific form of bias related to sex. However, we acknowledge that other forms of gender-related biases need to be assessed.

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