The Impact of AI on Gender and Work: A Gender Analysis Framework

Navarro-López, Eva M.[a]; Godwin, Eun S.[b]; Yamak, Sibel[b]; Mahmood, Samia[b]; Thelwall, Mike[c]; Ucal, Meltem[d]; Rahimi, Roya[b]

[a] Rochester Institute of Technology, New York, USA
[b] University of Wolverhampton, Birmingham, UK
[c] University of Sheffield, Sheffield, UK
[d] Kadir Has University, Istanbul, Turkey

This paper offers a framework for gender analysis. It investigates whether and how artificial intelligence (AI) might impact gender-related issues in the workplace as regards changes in occupations, processes, and skills resulting from the adoption of AI. We use AI as a general term that includes computer science and engineering tools to automate some tasks, jobs, and our day-to-day lives. There have also been concerns that the impact of AI might be experienced unequally by different groups. There are two main contributions in this paper. First, we review relevant literature on the interrelationships of gender and AI, examining in what way and to what extent AI might have an impact on gender in the workplace. Second, we propose a new framework for gender analysis. We have uniquely combined three methods: 4R, Moser, and Gender Analysis Mix (GAM) to identify gender issues at different levels - micro (individual) and meso (organisation) level. The Moser framework complements them by adding a macro level (the society level) of insights. We propose our gender analysis framework as a multilevel tool to understand the drivers of gender issues at the societal, organisational and individual levels, enabling researchers to assess the issues at work and AI-led workplaces.

Keywords: *Artificial Intelligence; Gender analysis; 4R; Moser Framework; Gender Analysis Mix*

1 Introduction

Artificial Intelligence (AI) relates to "algorithms that give machines the ability to reason and perform cognitive functions such as problem-solving, object and word recognition, and decision-making" (Hashimoto et al., 2018: 70). The goal of AI is to reproduce and formalise some aspects of intelligence in humans and in nature by using computational and mathematical paradigms. In this paper, we will use AI as a general term that includes the use of computer science and engineering tools to automate some tasks in industry, our jobs, and our day-to-day lives. Several studies agree that AI will bring inevitable changes in the composition of occupations, jobs/tasks and skills. Some might disappear, continue, or transform due to AI in the future. There have also been concerns that the impact of AI might be experienced unequally by different groups, although recent empirical studies have shown no evidence of net job loss in occupations due to AI (Lane et al., 2023).

By adopting a Strategic Human Resources Management (SHRM) approach and drawing on AI together with equality, diversity, and inclusion discourses, we develop a model for assessing gender bias in work and workplaces due to AI-related jobs and the automation of jobs.

It is useful to distinguish between biological sex and gender (WHO definition). Biological sex refers to biological and physiological characteristics, from chromosomes to reproductive organs. Gender refers to socialised characteristics associated with biological sex but not determined by it, varying across societies and time. It is based on gender identity: how individuals feel their gender to be. Gender identity can differ from biological sex, as individuals may identify as a gender different from their assigned sex and it can vary beyond the binary male and female genders. In this paper, we look at gender as the main analysis unit, not biological sex.

2 Literature review: Gender bias in AI and beyond

2.1 Gender bias in AI development

Less than 19% of technical workers in the EU are women (EC, 2021), and only 22% of professionals working in AI around the world are female (Bello et al., 2021). The situation is worse when considering other attributes, like race and disadvantaged backgrounds. For example, less than 2% of the workforce in technology are women of colour (Buolamwini & Hedayat, 2019). Moreover, women working in science, technology, engineering and mathematics (STEM) fields are 45% more likely than men to leave within a year (Porter, 2014). Furthermore, according to the report of the European Institute for Gender Equality, women are at higher risk of falling out of work than men due to the increase of AI-related jobs (Thil et al., 2022).

Addressing gender bias at the AI development stage is crucial to reduce bias in recruitment and hiring processes. Proper use and creation of AI-powered talent acquisition tools can help mitigate gender bias and ensure fair practices (Okino & Hussain, 2022). Moreover, diverse teams working on AI solutions may help to mitigate problems at the development stage (Teigland, 2019). If the technology is produced by only 20% of women and with barely 2% of people of colour, algorithms will reflect this imbalance and discrimination (Fefegha, 2021).

Gender biases are further compounded by the challenges faced in retaining women in STEM-related jobs (British Computer Society, 2022). Despite efforts to attract women to pursue computer science and information technology (IT) degrees, the retention rates remain low. Women often leave these fields due to biased evaluations, a lack of sponsors and mentors, and a sense of isolation (Porter, 2014). Women in STEM also face disparities in funding, promotions, mentoring, and support compared to their male counterparts. They not only have lower representation but also often receive lower salaries than their male colleagues, even when they possess more competence, merit, and expertise (Navarro-López, 2014, 2022; Bello et al., 2021).

2.2 Gender bias in algorithms and data feminism.

There is a growing concern that data-driven algorithms will reflect and exacerbate existing gender and racial biases. Currently, biases are masked by the black-box nature of most AI data-driven algorithms. When data fed into algorithms are biased and this is overlooked by the male-dominated fields of computer science, machine learning and AI systems produce biased results (Criado-Perez, 2019). Several recent studies highlight this from computational linguistics and natural language processing to advertising (Thelwall, 2018); from facial recognition (Buolamwini, 2022) to automated recruiting and selection tools (Martínez et al., 2021); from misdiagnosis in medicine (Albert & Delano, 2022) to credit rating (Kelly & Mirpourian, 2021) and internet search algorithms (Vlasceanua & Amodio, 2022).

Over the past years, "data feminism" (D'Ignazio & Klein, 2020) has emerged to counter how "AI is becoming a more powerful force capable of perpetrating global violence through three epistemic processes: datafication (extraction and dispossession), algorithmisation (mediation and governmentality) and automation (violence, inequality and displacement of responsibility)" (Ricaurte, 2022). New paradigms are sought for "ethical machines' ' and algorithms that can be unbiased, transparent, and respectful (Blackman, 2022) so that conditions in STEM fields and society can improve.

It is essential to have transparency in how systems are trained, which data have been used to train the systems, and where their limitations are: that is, transparency is needed in the design, implementation, and deployment of algorithmic systems. Buolamwini & Hedayat (2019) argue that those who are not intentional about being inclusive will perpetuate exclusion and promote algorithmic injustice.

2.3 Gender bias in AI at work

There are three main aspects to consider about gender bias in job automation and AI-based algorithms applied to different work-related processes.

Women are predicted to lose more jobs in the future. As the recent UNESCO report establishes, the digital revolution to be intelligent must be inclusive (Bello et al., 2021). However, the data are not very optimistic:

- Women are at more risk of missing out on future jobs. The United Nations predicts that women will lose 5 jobs for each job they will gain within Industry 4.0, in contrast to men, who will lose 3 jobs per each job they will gain (Bello et al., 2021). An International Monetary Fund (IMF) report has also predicted that women's jobs are more at risk from automation (Brussevich, et al., 2019).
- The digitalisation and the future of work still establish the dominant role of men in the development of technology, and this may impact the future of work in a gender-biased way (European Institute for Gender Equality, 2020).
- OECD (2023) reports gender gaps in terms of the impact of AI on worker productivity and working conditions which is partly attributed to the fact that males are more likely to be AI users than females, while male AI users are more likely to be at management and professional positions than female AI users whose roles are usually clerical support or service and sales workers.

Gender bias in automated work-related processes. Algorithms used in the hiring process, interviews, promotions, and performance analysis have had gender bias (Huet, 2022). On the positive side, there are recent efforts to design AI systems to revert gender bias at work (UNESCO, 2020). An enlightening example is the Startup Pipeline Equity, which has the goal of helping make decisions about hiring, pay, performance, potential and promotion free of bias (Ajao, 2021).

Hidden, unpaid and invisible work behind software and AI systems development. There is an increasing amount of invisible and unpaid work in the development of AI systems (Toxtli, Suri, & Savage, 2021). It is important to know whether this situation is worse for women and other disadvantaged communities.

3 A gender analysis framework

Although existing literature on gender and AI mainly focuses on females and males, our framework offers a scope that could be extended to other genders. Gender analysis is a term primarily used in the context of economic development and can be used to help design interventions in developing nations or organisations to ensure that they are effective, given current gender relations, and/or have gender equity (GDRC, The Global Development Research Centre, 2022). This means fair (not necessarily the 'same') outcomes for all genders.

3.1 Method

We develop a gender analysis framework to identify gender disparities at the meso level (Figure 1). This may allow the users to identify how the increasing adoption of AI affects and will potentially affect people differently based on gender. The aim is to identify and address existing imbalances and in turn, to help ensure equitable participation of all in their jobs and occupations under challenging conditions.

For gender analysis, it is essential to access qualitative and quantitative data and have specialised expertise on gender issues. Gender analysis steps will include (GDRC, 2022):

- Generating a holistic perspective of the topic: For this step, background information regarding the measures and policies adopted by the governments and the relevant organisations, actions of influential pressure groups related to gender issues together, with previous scientific evidence needs to be collected.
- Collecting background information: at this stage, different categories of gender, age, and ethnic origin must be included. Surveys might be used to address their specific conditions. Survey questions need to be designed to fully understand contexts related to gender.
- Collecting gender-related data: Through qualitative research (e.g., focus groups), the analysis can achieve depth by involving women and men from diverse backgrounds in the data collection and identifying different needs to assess key issues in job roles and occupational transition due to AI adoption.
- Analysing relevant current gender information, such as: gender-based characteristics of the division of labour, gendered access to and control over resources; power relations between genders in decision-making, and resource allocation to understand how gender representation problems can be addressed.
- Distinguishing between current and near-future occupational gendered risks.

- Developing remedies against gender inequalities.

For the framework development, we review three different types of gender analysis frameworks, namely the 4R method, the Moser Framework, and the Gender Analysis Matrix (GAM). While they are distinctive frameworks, they are also complementary to each other.

Firstly, the 4R method provides an underlying guide to identify existing gender issues together with their effect on gender inequalities within a given organisation following 4 steps: *Representation, Resources, Realia* and *Realisation*. It is particularly appropriate to use at the project level compared to other approaches (European Institute for Gender Equality, 2020). The 4R method is also useful in designing an action plan to address the issues identified. Its four stages include: 1) assessing gender *Representation*, 2) studying the allocation of *Resources*, 3) investigating the reasons behind gender inequality (*Realia*), and 4) developing measures and targets for gender equality (*Realisation*).

Secondly, the Moser Framework can complement the 4R method for a more holistic solution by offering detailed tools for an actual analysis. We will map the tools that the Moser Framework offers for gender analysis with the first 3 steps from the 4R method. The first tool of the Moser Framework is 'Gender roles identification'. The original tool figures out community-gendered divisions of labour by asking 'who does what' to see whether there is any segregation of 'type of work' or 'role' between genders. Similarly, this tool can be used for mapping how work type and roles are related to AI and whether/to what extent these roles may be affected by current and future job losses or gains. Using this tool at the organisation/workplace level, the first step of 4R, *Representation*, can be analysed with survey data. The second tool of the Moser Framework is on 'Gender needs assessment'. The original tool was developed upon the concept of women's gendered interests because women as a group have needs that differ from those of men due to their given roles and power positions. Using this tool, the second step of 4R, the *Resource* distribution reality, can be explored. The Moser Framework provides the third tool for 'Disaggregating control of resources and decision-making'. Although it was initially designed for household-level analysis, it gives a useful way to analyse the conditions behind gender *Representation* and *Resource* distribution between genders in a comprehensive way, which maps with *Realia* of the 4R. Although the original Moser framework consists of 5 steps, our suggestion focuses on the first three stages which apply to organisational/workplace level together with the 4R Framework.

Here, a survey could be used to collect data for initial analysis of *Representation*, *Resource* and *Realia* through the Moser Framework tools as discussed above. Questions for the surveys can include those on caring responsibilities (e.g., elderly, young), other parenthood issues such as pregnancy, being a single mother, whether the woman is a breadwinner, parental leave, number of children and what prevents/encourages a woman to do the job (e.g., flexibility). The level of inclusion should also be considered to explore gender differences in needs in the workplace. For this, particularly moving from *Resource* distribution to *Realia* analysis, the analysis will require qualitative data to explore these issues in depth. As the Moser Framework distinguishes between practical and strategic gender needs in its gender needs assessment, qualitative data collection through interviews or focus groups will aid in gathering the necessary information for a meaningful analysis. For all these levels, in addition to surveys, interviews and focus groups, the use of secondary data (e.g. employee characteristics data, reports) could also be a valuable source to assess Representation, Resource and Realia.

The qualitative data collection will also be valuable in the post-analysis stage, enabling the development of a training program based on gender analysis results - i.e., *Realisation* step of the 4R method. For this final stage, GAM is a useful additional tool when in-depth qualitative data is available. GAM emphasises community initiation in identifying and analysing gender differences, challenging assumptions of gender roles (March et al., 1999:68). Once the gender-based factors that contribute to the conditions of inequality are identified, GAM is used to determine the actions needed to address the constraints to achieve equitable outcomes. Therefore, by applying GAM, training programs can be designed more effectively. GAM examines tasks, skill levels, time requirements, access to resources, and changes in gender roles among men, women, and the community. These additional data provide comparative insights to survey data and offer practical implications for practices, policies, and interventions.

4 Conclusion and Implications

This paper summarises the gender-related issues generated by data-driven AI tools, and introduces a holistic framework for assessing potential gender inequalities that can be created by the transition to job automation and the use of AI-based algorithms in different work-related processes. This holistic and multilevel framework combines the 4R, Moser, and GAM methods to provide comprehensive tools to identify gender issues. By combining the 4R and GAM methods operating at the micro and meso level (at individual and organisation level) with the Moser method at a macro level (the society level), our proposed gender analysis framework may enable researchers to assess gender issues at the workplace, including AI-led workplaces. This framework creates a multilevel approach to understand the drivers of gender issues at the societal, organisational, and individual levels. This can be recognised as a suitable method for project-level analysis, as compared to the others, which are more useful at a macro policy level. Therefore, Gender Analysis Framework, as described in this paper, provides a comprehensive approach to evaluate gender-related aspects within the division of labour. It examines gendered access to and control over resources, as well as power dynamics between genders in decision-making processes and resource allocation. The framework aims to understand and address issues related to gender representation, identifying existing and potential occupational gender-related challenges. By doing so, it enables the formulation of effective solutions to tackle gender inequalities in workplaces.

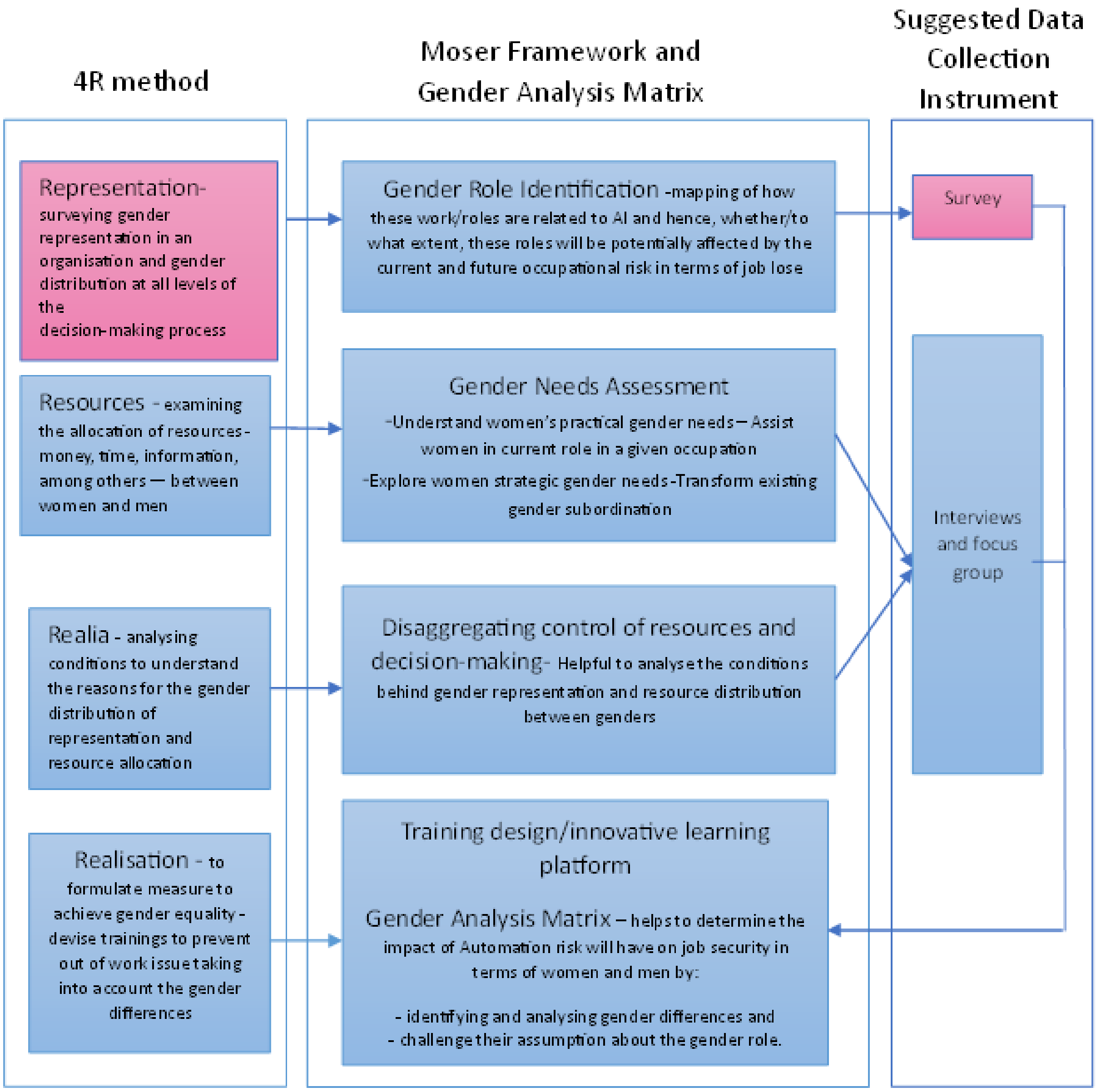

Figure 1. Gender Analysis Mapping.

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Authors

Eva M. Navarro-López is Director of the School of Information (iSchool) and Full Professor in Computing at Rochester Institute of Technology, Rochester, New York. She holds a PhD in Automatic Control and Industrial Electronics from Universitat Politècnica de Catalunya and an MEng in Computer Science Engineering, a BSc in Physical Systems Engineering and a BEng in Systems and Electronics from Universitat d'Alacant/Universidad de Alicante. Her research interests lie in computer science, control engineering, mathematical systems analysis and modelling, systems biology, computational neuroscience, AI, ethics in AI, data science, formal methods and network science (https://orcid.org/0000-0001-8762-6943).

Eun Sun Godwin is a Senior Lecturer and the Master's course leader in International Business and Management at the University of Wolverhampton Business School. Her diverse research interests are driven by issues and topics relating to business and society including Sustainability, EDI in work and workplace, digitalisation and society. (https://orcid.org/0000-0001-7030-1587)

Sibel Yamak is a Professor of Management at the University of Wolverhampton. Her research interests include sustainability and governance with a focus on the relationship between the business elites and the state, governance and democratisation interaction, corporate social responsibility, and gender (https://orcid.org/0000-0001-9468-5546).

Samia Mahmood is a Senior Lecturer and co-leading the Entrepreneurship and Small Business Management research cluster at the University of Wolverhampton Business School. Her research interests in gender and entrepreneurship include women in manufacturing, constraints to access finance, contextual embeddedness of women's entrepreneurship and women in business leadership in the regional context (https://orcid.org/0000-0002-6103-1578).

Mike Thelwall is a Professor of data science in the Information School at the University of Sheffield, UK. He has a PhD in Mathematics from the University of Lancaster, UK. His research interests include bibliometrics, field differences in research, social media analysis, sentiment analysis, and gender differences (https://orcid.org/0000-0001-6065-205X).

Meltem Ucal is a Professor of Economics at the Kadir Has University. She received her BA, MA, and PhD, all in Econometrics. Professor Ucal has coordinated and managed many research projects funded by H2020, UNDP, etc.; as the principal investigator of the AI4labour project funded by MSCA-RISE, she has recently been researching what skills are needed to replace professions at risk of disappearing from the labor market and gender dimension. (https://orcid.org/0000-0003-3707-1948)

Roya Rahimi is a Reader in Marketing and Leisure Management at the University of Wolverhampton Business School and specialises in Consumer Experience, Innovation, and Big Data. She oversees REF coordination for UoA 17 and has published over 50 works on topics like the Sharing Economy and Tourism Education. Roya has edited five books and serves on editorial boards for notable journals. A recognized keynote speaker and member of The British Academy Early Career Researcher Network, she mentors PhD students and secures research funding. (https://orcid.org/0000-0001-7520-3273)

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