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AI, Gender, and Politics[1]

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Abstract: The study of gender and politics is about how the multi-level processes that shape institutions, social relations, and individual behavior impact access to rights, representation, and political and economic power. Artificial intelligence (AI) is rapidly changing the landscape of work, social life, and culture. Although in some domains it can level the playing field between men and women by reducing the biases baked into technical education, in others it can be wielded as a tool for sexual harassment and buoy male dominance. This chapter articulates three ways that AI interacts with gender and politics: (1) as a tool of data creation; (2) as a method of data analysis; (3) as a category of analysis, either as a dependent or independent variable. To guide future work, we theorize several arenas where AI will likely reinforce, and several where it will undermine, longstanding patterns of gender inequality.

Introduction

The study of gender and politics, which has normative and empirical dimensions, asks how multi-level processes shape institutions, social relations, and individual behavior, producing access to rights, representation, and power across genders (Boussalis et al. 2021, Cohen and Karim 2022). Many scholars think of gender itself as an institution that is shaped and reproduced by culture, economic systems, and politics. By changing the nature of labor, social life, and culture, artificial intelligence (AI) affects political and economic power (Farrell and Fourcade 2023). Gender dynamics are rooted in these power dynamics. Although there are many definitions and manifestations of power, it is useful to conceive of two forms: "power to" and

[1] All author(s) contributed equally. Our thanks to Divij Sinha, Lisa Keen, Nate Persily, Henry Farrell. We also appreciate the work of the APSA task force on AI, and the leadership of Nate Persily and editorial refinements by Lisa Keen. The views expressed here are those of the authors alone and do not represent the views, policies, or positions of the U.S. Department of War or its components, to include the Department of the Navy or the U.S. Naval War College.

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"power over" (Lazar 2022). AI stands to impact both: AI systems for data creation and analysis have the power to exacerbate gender-based inequality, and dominant groups can use AI to increase their power over others.

This essay outlines three applications of AI to the study of gender and politics: (1) a tool for data collection; (2) a method of data analysis; and (3) a category of analysis, either as a dependent or independent variable. As a tool for data collection and method of analysis, AI has some potential to both further entrench or upend existing gendered power structures and social biases. AI enables gender scholars to reveal inequality in the world around them and, potentially, level the uneven playing field that has hitherto existed because of a history of exclusion of women from technical fields and careers. However, because most of the researchers at the top of the field are men, the largest gains from these new tools threaten to accrue to them. As a category of analysis, gender scholars must consider how AI will shape dominant groups' abilities to exert power over others. The bulk of this essay, therefore, lays out a research agenda for studying AI's impact on gender and power.

AI as a Tool for Data Collection

Applications of AI abound in everyday life. For example, it is being used in generating and analyzing documents by academics, lawyers, and consultants, among others; in individually-targeted campaigns or corporate advertisements; as a consumer-support resource; in image-based healthcare diagnostic support; and in algorithms promoting press coverage or consumer products. By early 2026, AI tools have already been seamlessly integrated into the daily lives of people around the world — especially in the richest countries. Yet researchers are still grappling with how best to harness its potential as a tool of research.

AI algorithms can be written to "web-scrape," that is, extract information from websites or retrieve data from online databases, digital platforms, and social media outlets. AI systems can aggregate and collate information from multiple online sources, such as RSS feeds, newspapers, and journal databases. AI-powered Natural Language Processing techniques can be used for data extraction, classification, and translation from sources such as articles, blogs, comments, historical documents, and government correspondence. Gender scholars already use text-as-data to study gender dynamics in politics – for example, in the manifestos of political parties (Meguid et al., 2025); in the patterns of interruption during political speeches in Congress (Miller and Sutherland 2023); and in the responses of officeholders to constituents (Teele, Kalla, and Rosenbluth 2018). Recent scholarship has used audio recordings of congressional floor speeches to compare 'emotional intensity' – "small changes in vocal pitch that are difficult for speakers to control" – across sexes (Dietrich, Hayes, and O'Brien 2019). Boussalis et al. (2021) use machine learning and computer vision tools during televised debates to extract the emotional expressions

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of male and female political candidates and the reactions of audience members. Studying more than 595,000 observations from German leadership debates, they found that then-German Chancellor Angela Merkel was more likely to express happiness than her interlocutors, and viewers rewarded her for this emotional display while punishing others for non-emotive expressions. These results speak to decades of scholarship in the study of political behavior, showing how candidates adapt strategically to give voters what they want (Boussalis et al. 2021: 1255). We urge gender scholars to utilize AI techniques as a tool for data creation but note that they must take seriously the evidence that AI can be inconsistent and unreliable in the realm of gender-based classification (Schwemmer et al. 2020),[2] particularly given that the data utilized and compiled by AI systems can be riddled with bias.

AI as a Tool of Analysis

AI systems can help scholars identify patterns in large datasets, recognize and classify images and text, and troubleshoot code for statistical analyses and data visualization. However, the use of AI as a tool of analysis for research on gender also runs into the same inherent challenges that produce discrimination and reinforce existing prejudices – a failure to properly conceptualize and delineate between gender and sex.[3] In other words, AI systems carry socially constructed expectations regarding the behaviors and characteristics of individuals on the basis of their sex.[4] Such expectations not only produce social biases but can also dampen the analytical power of scholarly research.

Further, there exists an increasingly widening gender gap in usage of AI among researchers: Male scholars use AI more frequently than their female counterparts, and experience "higher efficiency improvement from its use" — widening the gap in research productivity (Tang et al. 2025, Otis et al. 2024). On the other hand, gender scholars, many of whom are women, can take advantage of AI tools to improve research processes, such as integrating AI tools to assist with coding tasks or web search and scraping, and with writing tasks, improving efficiency, decreasing the costs and time required for large data research, and, at its best, allowing them to be more ambitious in their intellectual projects.

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[2] Gender classification is more accurate in men than women, with highest errors for Asian women over 50 (Ngan and Grother 2015, i). AI systems are increasingly grappling with gender inferences based on physical attributes. Given these challenges, Google removed gender from its image recognition AI algorithm in 2020 (Aggarwal et al. 2022). Schwemmer, C., Knight, C., Bello-Pardo, E. D., Oklobdzija, S., Schoonvelde, M., & Lockhart, J. W. (2020). Diagnosing Gender Bias in Image Recognition Systems. *Socius Sociological Research for a Dynamic World*, *6*. https://doi.org/10.1177/237802312096717.

[3] Sjoberg, L., Kadera, K., & Thies, C. G. (2018). Reevaluating Gender and IR Scholarship: Moving beyond Reiter's Dichotomies toward Effective Synergies. *The Journal of Conflict Resolution*, *62*(4), 848–870. https://www.jstor.org/stable/48597319

[4] Cohen, Dara, and Sabrina Karim, Does More Equality for Women Mean Less War? Rethinking Sex and Gender Inequality and Political Violence, Cambridge University Press, 2022.

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Research on gender and politics can take advantage of AI tools such as Natural Language Processing (NLP) to analyze text-based data like speeches and social media content. NLP can be used in structured or unstructured ways to engage in sentiment analysis and topic modeling. For example, Funk et al. (2022) used supervised tree-based learning to study the drivers of public spending on education, healthcare, and defense. They found that "education and healthcare spending increases sharply after women's representation in the legislature surpasses 20 and 15 percent, respectively, and then flattens after women's representation reaches approximately 41 percent for education spending and 35 percent for healthcare spending." Machine learning thus allowed them to argue that women's representation matters over an interval, instead of at a discrete inflection point, adding nuance to the classic "critical mass" theory.

AI as a Category of Analysis

Much interest in AI stems from its "revolutionary" promise – its potential to transform wealth, welfare, and power structures for the good. However, AI systems also have the potential to reinforce or exacerbate existing inequalities. As a category of analysis, AI can become the dependent variable – where we study the systems themselves and how gender dynamics and hierarchies impact the development or output of these systems – or AI can be studied as an independent variable – where we study how the system impacts other outcomes of interest.

AI as a Dependent Variable

AI algorithms create categories and systematically apply them to new sources of information (Farrell and Fourcade 2023). Typically, the classifications made by AI systems are not visible to the public, yet in many domains of life – from credit allocation to teacher tenure, to sentencing length by judges, to targeted media exposure, to job placement – AI's classification schemes are being used to distribute resources and opportunities. A lack of transparency into AI's classification schemas should be of interest to scholars of gender and politics.

Sociologist Cecilia Ridgeway characterizes gender as a "primary frame" – a simplified cultural-category system that acts as common knowledge – which enables people to classify and interact meaningfully with one another. Given that male-female distinctions are almost universally recognized across societies (albeit with varying degrees of hierarchical ordering), gender binaries have become a routine tool for AI systems tasked with categorizing individuals. This reliance on gender-based distinctions can enhance systemic efficiency, which AI algorithms prioritize. As Farrell and Fourcade (2023) note, algorithms "extend *both* the logic of hierarchy

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and the logic of competition" by using classifications to understand vertical relations between categories and by seeking the fastest ways to make these classifications.

Scholars have begun to study AI as a dependent variable through the lens of "algorithmic bias," by examining how AI choices can further entrench racial and gender-based biases (see Chapter 5 on race in this volume). Often, AI systems rely on massive amounts of data to find patterns and make predictions, informing who health care systems prioritize, which candidates are called for job interviews, and how much credit customers are offered by financial institutions. This data carries biases which are embedded in the geometry of word associations within LLMs (Bolukbasi et al. 2016). By encoding "wrongfully discriminatory social patterns into an algorithm," AI systems can support similarly discriminatory social practices (Vredenburgh 2022, 129). Gender bias in these systems can impact psychological health and economic outcomes, and it can amplify prejudices (Smith and Rustagi 2021). Facial recognition systems, for example, are less accurate from women with darker skin (Boussalis et al. 2021). In healthcare, the downstream effects of biased AI systems contribute to gendered disparities in diagnoses (Aggarwal et al. 2022). The design of biomedical AI algorithms often fail to account for sex and gender, producing not only mistakes but also discriminatory outcomes (Cirillo et al. 2020).[5]

Arguably, algorithms are biased because they are built by humans and learn from large corpuses of information that humans have created (O'Neil 2016). The people who develop AI systems and determine what datasets, rules, proxies, and variables are fed into algorithms play a crucial role in determining whether or not a given algorithm will penalize certain communities or identities (Smith and Rustagi 2021). These biases may result from a lack of diversity in the AI industry or from blind spots of AI researchers preoccupied with improving the performance of models without rectifying the underrepresentation of marginalized populations in the training data.[6] Put simply, the AI workforce is mostly male (Mundy 2017), so the processes that contribute to biased representations are not only algorithmic but also social. Large Language Models (LLMs), such as ChatGPT, often "parrot" the hegemonic worldviews of their training data, propagating, proliferating, and amplifying discriminatory content (Bender et al. 2021), and require manual intervention to fix (Bolukbasi et al. 2016). In other words, the content individuals view and choose to disseminate contributes to and is further entrenched by biased AI. Gender scholars should take up the question of how algorithmic bias can be detected and measured. Scholars could look under the hood by studying algorithmic inputs or, at the point of user contact, for example, by treating LLMs as the site of research and studying how LLMs respond to classic questions about gender and politics (see also chapters 5 and 10 on race and methods). The norms,

[5] Genome-wide association studies (GWAS), for example, tend to rely on white male subjects, overlooking potential sex differences in disease. Whose genomics? (2019). *Nature Human Behaviour*, *3*(5), 409–410. https://doi.org/10.1038/s41562-019-0619-1.

[6] Buolamwini, J., Gebru, T. "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification." Proceedings of Machine Learning Research 81:1–15, 2018 Conference on Fairness, Accountability, and Transparency.

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laws, and institutions that shape how AI is built and utilized can impact how algorithmic biases manifest.

AI as an Independent Variable

Beyond studying the algorithms themselves, we urge gender scholars to conduct research on how the existence of AI tools, the classification and allocation systems of AI, and the labor-substituting potential of AI, impact gender dynamics in institutions and society more generally. A list of potential research questions would include the following:

(1) How does algorithmic bias impact access to resources and opportunities for men and women?

AI has the potential to reduce discriminatory bias. In healthcare, for example, when AI algorithms integrate sex and gender differences effectively, they can enhance our understanding of the differentiation of vulnerabilities for disease among individuals (Cirillo et al. 2020). However, the use of LLMs in health service can also reproduce bias and result in gender-based disparities in service receipt (Rickman 2025). In many domains, algorithms seem to reinforce discrimination against women and minorities.

For example, in the 1970s, St. George's Hospital Medical School's automated assessment program replicated discriminatory policies against applicants on the basis of race and gender (O'Neil 2016, 116-117). Apple Card algorithms granted lower credit to women than men, triggering investigations by the US Senate Committee on Finance and the New York State Department of Financial Services (Crawford et al. 2019, 12).[7] In another case, an online tech hiring platform used social data generated by actions in the digital realm (such as time spent sharing and developing code online) to measure candidate participation in the digital community, failing to account for 1) disparities between the time men and women have to chat online (often due to societal expectations regarding unpaid care for children), and 2) women who adopt male identities online to address gender-specific safety concerns and bias. As a result, the platform created an algorithm that systematically ranked female candidates lower than their male counterparts (Smith and Rustagi 2021). Women and ethnic minorities are often excluded from targeted advertisements for rental listings that rely on personalized algorithms (Spinks 2020). Moreover, the initial salary negotiation offers from LLMs are substantively lower for women, people of color, and refugees (Sorokovikova et al. 2025).

[7] Bowdish, Lawrence. 2012. "American Women's Struggle to End Credit Discrimination in the Twentieth Century." In *The Development of Consumer Credit in Global Perspective: Business, Regulation, and Culture*. Palgrave Macmillan. Such biases shape women's economic rights. In the United States, marital status and gender were used to determine creditworthiness until the mid-1970s, resulting in widespread credit discrimination.

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Algorithmic bias can also perpetuate racial and gender stereotypes. For example, the voices ascribed to AI caregiving devices providing patients with medication reminders, social companionship, and mental health services are often female (Littman et al. 2021, 68). Smith and Rustagi (2021) studied bias across industries using 133 publicly available algorithmic selection procedures from 1988 to present. They identified six domains of algorithmic bias: 1) lower quality of service, 2) unfair allocation of resources, information, and opportunities, 3) reinforcement of existing stereotypes and prejudices, 4) derogatory and offensive treatment, 5) detriments to physical safety, and 6) health hazards. Each of these arenas suggest further research is needed by gender scholars, especially those who study how bureaucracies and street-level officials interact with and allocate resources in their communities.

(2) How do AI algorithms impact political behavior and representation?

Political behavior is a broad concept that comprises an individual's engagement with politics. Certain areas of political behavior – such as volunteering for campaigns, donating money, learning and talking about politics, and voting – are related to the idea that people have confidence that they can get what they need out of politics. However, AI algorithms can undermine confidence in political processes, especially among marginalized groups. The increasing adoption of algorithms *by* political actors, or their broad use across society, represent "what Ridgeway (2011, 40) termed an 'amplification process,' that is, a mechanism through which gender differentials are reinscribed into novel social arenas and social forms." (Schwemmer et al. 2020).

The use of algorithms to target specific people with political content online, for example, may impact political knowledge, participation, and power differently for men and women. AI systems that recommend digital content based on user behavior can promote false beliefs and enhance political polarization (Harris 2017) (see chapter 2 on information ecosystems). News dissemination algorithms trained on materials that suggest that women are less interested in or knowledgeable about politics, may target women with mommy blogs, workout routines, and fluff pieces, and target men, who have been understood as more likely to give larger amounts to campaigns, with more explicit political content. Studying political targeting and its effects will require some sense of a baseline, e.g. understanding what media women and men would have encountered and consumed in the absence of algorithmic targeting. Gender-targeted political advertising may also be part of what is driving the divergence of public opinion between younger men and women.

The advent of image generation capabilities also creates new opportunities for studying – and new risks for – women online. AI-driven microtargeting techniques could also be used to identify vulnerabilities or specific demographics to target with negative campaigning. Deepfakes, for example, are difficult to differentiate from real videos for the regular consumer and primarily

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target women (Wagner and Blewer 2019) and those who identify as lesbian, gay, or bisexual (Lenhart et al. 2016).

Deepfake technology has been used notoriously to create pornographic videos that superimpose the face of a target of harassment onto the body of someone in the video. The technology has also been used to disclose private, intimate videos or images without consent – what is often referred to as "revenge porn" (Franks 2017). The use of AI algorithms to recreate images of real people and adapt photos into highly sexualized images (Conger and Dearden 2026) can further fuel harassment of women (Lazard et al. 2025) and other marginalized groups online, as well as alter individual behavior as they become more hesitant to post photos of themselves. Moreover, the use of AI tools to amplify online harassment and misinformation can create a hostile environment that disproportionately drives female politicians to moderate their behavior (Nadim and Fladmoe 2021) and may affect their willingness or ability to maintain political careers. Deepfakes and tools for visual online harassment may reverse the progress in women's representation that has emerged in recent years. Given the recent turn of social scientists towards the effects of online harassment on gendered behavior (Southern 2026, Wagner 2022), gender scholars should also expand their scope of study to include the effects of LLMs on political behavior, both online and off.

Even when not used for deepfakes or harassment, AI generation models can act as "amplifiers" of stereotypes. Researchers have found that, in text-to-image generation models, AI generation can reinforce traditional gender roles and reflect existing gender stereotypes about women's role in society. When LLMs were asked to generate images of a person during everyday activities associated with traditional gender roles, such as child-care, shopping, or baking/cooking, they generated images of women. When they were asked to generate images of a person smoking, doing car maintenance, or playing football, they generated images of men (Girrbach et al. 2025). Algorithmic image recognition systems already reproduce bias by focusing much more significantly on the appearance of women over men (Schwemmer et al. 2020); and, image generation algorithms likely share the same biases. This bias extends to images of gendered workplaces (Górska and Jemielniak 2023).

AI models overrepresent men when generating images, even relative to the already existent gender disparity in the healthcare space. When asked to produce an image of a physician or doctor, five separate AI models generated images of people who "were more frequently White (82% vs 63%; $P < .001$) and more frequently men (93% vs 62%; $P < .001$) compared with the US physician population." Shockingly, even though women make up 38 percent of physicians in the United States, only *seven percent* of the 1000 images generated were women. (Lee et al. 2024). Scholars of mass political discourse and the political behavior of firms should pay attention to the debates around normative AI behavior. Given that many workforces in the United States are increasingly reaching gender parity, *should* AI reflect the current balance of the workforce? Or

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should AI reflect the workforce as a whole, regardless of the makeup of an individual profession? While these debates are often relegated to ethicists, they are also occurring all across the engineering workforce. The political leanings of the engineers who help to create and train LLMs are reflected in the performance of the models themselves and can magnify social biases given the widespread adoption of AI models in everyday life. Inequality and bias, some scholars have argued, "is not a correctable anomaly but an intrinsic feature of generative AI, rooted in historically uneven data ecologies and design choices." (Kerche et al. 2026). Meanwhile, women across the workforce are slower to adopt AI into their work routines, partially due to their perceptions of the ethics of AI use (Otis et al. 2024). Given the existent gendered data gaps (Criado-Perez 2019) and possible political leanings of design choices, AI could come to represent a primary driver of gendered inequality across the labor and political spheres.

(3) How will AI change jobs and occupational segregation, and how does this impact women's empowerment?

AI is likely to influence how jobs are characterized and the individuals who will populate those jobs (see Chapter 7 on labor and the economy). Occupational segregation, or the concentration of individuals in the workforce on the basis of sex, often occurs when new technologies incentivize employers to recast lower earning positions as suitable for women (Reskin and Roos 1990). However, new technologies can also introduce greater opportunities for groups previously excluded from the workforce. The internal combustion engine, for example, contributed to women's participation in the wider political and economic world. Cars gave women the opportunity to leave the home and work, but they also served to reinforce the gendered distribution of labor primarily via their use as another tool for accomplishing house work – e.g., for running errands and chauffeuring children (Nichols 2024). Morris (2015) argues that steam power and the age of fossil fuels contributed to a substantial shift in gender roles with the decline of the agrarian economy due to a decline in the "need for muscle power" and a rise in the need for "brainpower and services" women could perform "just as well as men" (102).

For large, inflexible organizations with entrenched occupational hierarchies, AI may face resistance if integration requires retraining a workforce that heavily identifies with their current roles and skill sets. Military organizations, for example, tend to be bureaucratically rigid and often stifle opportunities for change (Rosen 1991, 1-3). This is especially true when emerging technologies introduce roles that fail to align with traditional warfighting (Pindyck 2022). Given the salience of AI to military operations, we might expect military organizations to recast individuals within such roles as masculine "warriors" and potentially rethink systems of reward and ascension to attract sufficient talent.[8]

[8] Slayton, Rebecca, What Is a Cyber Warrior? The Emergence of U.S. Military Cyber Expertise, 1967–2018 (Winter 2021)

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A pressing issue is when, and in which occupations, autonomous machines will replace human labor (Korinek and Juelfs 2023). In capitalist systems, women's empowerment is linked to their right to enter the labor force, be fairly compensated, and thereby increase their satisfaction with life. Women's empowerment is likewise linked to their class-position in the economy. AI has already threatened routine jobs more than care-oriented jobs. Haircuts and massages are hard to out-source or automate, but factory assembly has proved amenable to machines and robots substituting for human labor. Thus, in the lower classes, women's employment in some parts of the service sector is likely less vulnerable than men's. In white collar industries, AI adoption originally required skilled employees and, in particular, computer programmers and engineers, a workforce which has skewed male since the 1980s (Abbate 2012).[9] The implementation of AI in hiring and promotion practices can magnify this phenomenon. AI recruitment tools often use a training corpus based on male resumes, favoring 'masculine' language and penalizing mentions of the word "woman" (Dastin 2018). Building on the idea of "breadwinner backlash," one hypothesis is that lower class women will suffer in the household as the men of their class face greater layoffs (Clark et al., 2025), while women in the upper classes may suffer in the workforce if they adapt more slowly to the new technology. At the same time, these returns to technical skills may fall over time, setting into motion a decline in male-leaning technical fields.

Notably, recent research suggests that exposure to generative AI can increase public concern over such disruptive effects (Haslberger et al. 2025). From this perspective, increased use of AI at home and at work can also shape public perceptions of how AI technology should be regulated and activate support for social policy measures. The degree to which such support translates into policy outcomes, however, remains to be seen.

Conclusion

AI has transformative potential for political, social, and economic life. In gender and politics, AI can be used as a tool for data collection and analysis but also must become a category of analysis itself. With this chapter, we hope to galvanize gender scholars into studying AI's impact on gender and power. The scope of potential biases in AI systems and the technology's revolutionary potential introduce a range of research questions that should interest gender scholars. How can we measure bias in AI systems? How do AI algorithms impact political behavior, the nature of work and occupational segregation of labor, gender relations, and gendered organizational structures? Does AI challenge or reinforce men's advantage in agenda-setting and leadership placement and selection in politics? Will AI "feminize" occupations or will its technological uptake exclude women? How will these dynamics unfold in

[9] Notably, this group is most likely to lose jobs to AI as workforce roles shift from routine coding to the orchestration of system architecture and oversight, requiring engineers to manage, test, and refine AI-generated code.

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hierarchical organizations? In politics, is generative AI reinforcing gender role stereotypes in candidate performances? Does selective media exposure polarize men and women? It is too soon to tell whether AI will be a force for gender equality or retrenchment, but research into these and other questions can help guide feminist politics for the next decade.

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