Gender-Specific Patterns in the Artificial Intelligence Scientific Ecosystem

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Abstract

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Gender disparity in science is one of the most focused debating points among authorities and the scientific community. Over the last few decades, numerous initiatives have endeavored to accelerate gender equity in academia and research society. However, despite the ongoing efforts, gaps persist across the world, and more measures need to be taken. Using various methodologies such as social network analysis, statistical analysis, bibliometrics, natural language processing, and machine learning, in this study, we comprehensively analyzed gender-specific patterns in the highly interdisciplinary and evolving field of artificial intelligence for the period of 2000-2019. This work was completed in two main phases: First, we investigated the collaboration patterns of artificial intelligence (AI) scientists to shed light on team composition characteristics in interdisciplinary research teams from a gender perspective. Next, we identified highly central AI scientists and calculated a multi-dimensional feature vector at the author level that covered multiple characteristics of scientific activities to explore the effects of driving factors on acquiring key/central network positions and explain any possible gender differences.

Our findings suggest an overall increasing rate of mixed-gender collaborations. From the observed gender-specific collaborative patterns, the existence of disciplinary homophily at both dyadic and team levels is confirmed. However, a higher preference was observed for female researchers to form homophilous collaborative links. Our core-periphery analysis indicated a significant positive association between having diverse collaboration and scientific performance and experience. We found evidence in support of expecting the rise of new female superstar researchers in the artificial intelligence field. Moreover, our findings provided a deep understanding of the profiles of highly central AI scientists and revealed that various individual author-level factors could contribute differently to occupying certain strategic network roles in the AI co-authorship network. However, some of the notable and common characteristics of central researchers, regardless of their gender, are their highly collaborative behavior and high research productivity and impact.

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List of Abbreviations

AI	Artificial Intelligence
Athena SWAN	Athena Scientific Women's Academic Network
BC	Betweenness Centrality
CC	Clustering Coefficient
CIFAR	Canadian Institute for Advanced Research
CL	Closeness Centrality
DC	Degree Centrality
EU	European Union
IDR	Interdisciplinary research
ML	Machine Learning
SHAP	SHapley Additive exPlanations
SJR	SCImago Journal & Country Rank
SNA	Social Network Analysis
STEM	Science, Technology, Engineering, and Mathematics

1 Introduction

During the past decades, gender disparity in science has become one of the most focused debating points among researchers (Shen, 2013). Despite concerted efforts to achieve gender equality (UNESCO, 2018), conclusive evidence has revealed that pervasive gender imbalances still exist in academic and scientific practice (Nelson & Rogers, 2003; Shaw & Stanton, 2012; J. D. West et al., 2013). Abundant studies have also shown persistent gender bias in many aspects such as salaries (Shen, 2013), hiring and promoting (Moss-Racusin et al., 2012; Nelson & Rogers, 2003; M. W. Nielsen, 2016), grant funding (Witteman et al., 2019), scholarly authorship (J. D. West et al., 2013), scientific impact (Larivière et al., 2013), peer reviews (Murray et al., 2019), and collaboration (Uhly et al., 2015; Zeng et al., 2016).

Moreover, the complexity and interdisciplinary nature of science motivate scientists to collaborate more and form interdisciplinary research teams in order to overcome challenging issues, produce novel ideas, and enhance their scientific performance (Bennett & Gadlin, 2012; Servia-Rodríguez et al., 2015; Wood & Gray, 1991). Evidence has shown that men and women differ in their collaborative behavior, which could result in gender differences in scientific productivity and impact (e.g., Abramo et al., 2013; Jadidi et al., 2018; Larivière et al., 2013; Sonnert & Holton, 1995). Hence, understanding the role of gender in academic collaboration is vital.

Existing research widely applied social network analysis (SNA) and used network structure variables, primarily centrality metrics, to examine the collaborative behavior of scientists in co-authorship networks, identify most central and influential researchers, and investigate the relationship between different network positions and research performance (Abbasi et al., 2011; Ebadi & Schiffauerova, 2015a; Uddin et al., 2013; Yan & Ding, 2009). Based on the literature, possessing central and strategic roles within the co-authorship network could help scientists to better access various skills and knowledge sources and increase their influence and performance within the scientific network (Abbasi et al., 2012; Freeman, 1978; Zamzami & Schiffauerova, 2017). However, only few studies explored gender disparities in network positioning and found that women are generally underrepresented in strategic network positions such as brokerage roles (Dias et al., 2020; Ebadi & Schiffauerova, 2016c; Jadidi et al., 2018)

As discussed, prior studies emphasized the impact of collaboration and different network positions on knowledge diffusion and academic performance and investigated sex differences in research collaboration and productivity in different disciplines. But to the best of our knowledge, no study hitherto addresses the presence of gender-specific patterns from various aspects in the artificial intelligence (AI) field. As a highly interdisciplinary and fast-evolving domain, AI is constantly influencing many aspects of our life, attracting not only the attention of academic and industrial professionals with diverse knowledge and expertise from broad disciplines but also governments and decision-/policymakers. Currently, AI is facing severe gender diversity gap and growing demand for AI experts to solve unprecedented and challenging global issues (AI Index, 2018; Gagné, 2019). Therefore, it is vital to shed light on gender-related patterns in this field and form more diverse AI teams both in academia and industry to narrow the gender gap.

The aim of this thesis is to investigate gender-specific patterns in the co-authorship networks of AI scientists from 2000 to 2019. In the first part of this thesis, we contribute to the existing literature by exploring the collaborative behavior of AI scientists and team composition characteristics in interdisciplinary research teams through the gender lens. More specifically, we applied social network analysis, machine learning techniques, and statistical methods to analyze disciplinary diversity among AI researchers at the uni-author, bi-author, and team levels and examine the impact of disciplinary homophily or diversity on AI research team formation. We found that AI researchers tend to collaborate with others with similar research profiles, and this tendency becomes stronger among female researchers.

In the second part, we aim to investigate the effects of driving factors on acquiring key/central network positions and explain any possible gender differences. To be more specific, we first considered several author-specific characteristics as independent factors, including but not limited to performance-related metrics, seniority level, and collaborative behavior, etc. We then computed complementary network structure measures, i.e., degree centrality, closeness centrality, and betweenness centrality, as dependent variables, and main proxies to measure the impact and importance of researchers. Next, we leveraged machine learning (ML) techniques to identify the most influential researchers whose presence is essential for knowledge and innovation propagation over the network. Finally, using the model interpretation method, we determined the impact of several influencing factors on possessing highly central positions and examine if such factors differ among female and male AI scientists. Moreover, we shed light on the characteristics of highly central AI scientists and explained any gender differences.The methodology of this work involves different research methods, including machine learning, natural language processing, social network analysis, bibliometric, and statistical analyses.

The remainder of this thesis is organized as follows: Chapter 2 reviews the relevant research work; Chapter 3 presents research gaps and thesis objectives; Chapter 4 discusses the data used in this study; Chapter 5 and 6 discusses methodologies and main findings of the first and second research objectives, respectively; Chapter 7 concludes the thesis; and Chapter 8 presents the limitations of this study and draws some directions for future research.

2 Literature Review

In this chapter, we review the relevant literature in two main sections. First, we will discuss the gender gap in STEM disciplines, particularly AI, and review the literature which assessed the importance of collaboration on scientific output, and examined gender disparity in academic performance and collaboration. Second, the literature which examined the relationships between collaborative behavior of researchers in co-authorship networks with knowledge dissemination and scientific influence and performance, as well as gender differences in network positioning, will be reviewed.

2.1 Women Underrepresentation in Science and Possible Explanations

The pervasiveness of gender inequality in academia is a critical issue which is still not fully addressed (Nelson & Rogers, 2003). Despite significant progression towards gender equality in recent decades (UNESCO, 2018), women yet continue to be underrepresented in academia in many disciplines worldwide (Elsevier, 2017; Huang et al., 2020). As a part of the UNESCO Science Report series, Huyer (2018) noted that although the number of female and male students pursuing bachelor's and master's degrees is almost equal, the women's under-representation starts at the Ph.D. level, and female attrition can be observed across higher levels of the academic hierarchy. This phenomenon, dubbed the "leaky pipeline", was introduced by Berryman (1983) and coined by Alper and Gibbons (1993). Huyer (2018) reported that women account for 53% of graduates and 43% of PhD holders, but women's leakage becomes exacerbated at the researcher level with only 30% female researchers overall and globally. Moreover, females' underrepresentation is more pronounced in science, technology, engineering, and mathematics (STEM) fields (Hill et al., 2010; Holman et al., 2018; National Science Foundation, 2019). Since it has been shown that higher education in STEM fields could drive innovation, social and economic growth, many countries have implemented policies to increase their science and technology capabilities (National Science Foundation, 2012).

On the other hand, the positive effect of gender diversity in facilitating innovation transfer in both science and technology companies and academia has been confirmed (Ashcraft et al., 2016; Duflo, 2012). Hence, scientists are struggling to understand the underlying reasons behind gender inequality, particularly in STEM fields, and address this issue.

Family and caring responsibilities have been noted as the main impediment to female academic trajectories (Stack, 2004). While men follow a linear career path, women are more prone to career interruption or relinquishment due to maternity and family issues (Ramos et al., 2015), which could also lead to a gender gap in scientific performance (Kyvik & Teigen, 1996). In a comprehensive study, Wang and Degol (2017) reviewed research in math-intensive STEM disciplines in the last three decades and pointed that personal preferences, innate individual abilities, and sociocultural factors may explain the two genders' academic career dichotomy. They also suggested that to close the gender gap and attract more women to STEM disciplines, more academic career choices aligned with females' preferences and cognitive capabilities should be provided.

Furthermore, gender differences in choices of an academic career seemed to be also at play in explaining gender imbalances. For instance, some scholars indicated that while women usually tend to be active in people-oriented academic fields, men are generally dominant in thing-oriented disciplines (e.g. Lippa et al., 2014; Paswan & Singh, 2020; Su et al., 2009). However, it is suggested that apart from things-people dimensions, other factors such as the number of available career options and career opportunities to gain higher status or social impact should be considered to explain any gender differences. (Thelwall et al., 2019). Zuckerman (2001) suggested that apart from individual choices, "*social selection*" factors such as gender discrimination, gender differences in academic rank, and resource allocation could also negatively influence women's representation. In light of this, Nelson & Rogers (2003) used survey data and performed a comprehensive analysis on scientists in the top 50 science and engineering faculties in the U.S., and demonstrated that men outnumbered women in higher academic positions across almost all disciplines. They pointed out gender discrimination and the lack of female role models could explain the gender gap. Recent reports have shown that this gap is narrowing but still persists in highly prestigious academic positions across the U.S. (National Center for Education Statistics, 2018), Canada (Government of Canada, 2019b) and Europe (European Commission, 2019). Similarly, other research has also reported gender stereotypes (Ceci et al., 2014), inadequate female role models (Nelson & Rogers, 2003), and the degree of specialization (Leahey, 2006) as potential explanations for the gender bias; however, the extent to which these factors matter for this issue has remained elusive among researchers (Shaw & Stanton, 2012).

Over the last few decades, numerous initiatives have endeavored to accelerate gender equity in academia. Several countries enacted effective policies such as introducing flexible and family-oriented programs in the workplace, e.g. in the European Union (EU) countries, India, and Japan (Bonetta & Clayton, 2008; Jurviste et al., 2016), providing financial incentives for appointment and retention of female scientists (Pearson et al., 2015), and promoting gender-balanced organizational structures (Kamraro, 2014). Moreover, in 2005, the UK government introduced an internationally recognized program called "Athena Scientific Women's Academic Network" (Athena SWAN) to assess and monitor gender parity across British universities. Recently, this program has been widely used across Europe and implemented in other countries such as Australia, the U.S., and Canada (Kalpazidou Schmidt et al., 2020). Canada, as an example, recently initiated the “Athena SWAN” program (Government of Canada, 2018), aiming to enhance women’s career trajectories and adopt an attitude towards gender parity (Ovseiko et al., 2017). Additionally, the Canadian government introduced generous parental leave programs, including extended parental leave for graduate students and parental sharing benefits, thereby fostering greater equality in family responsibilities and facilitating career recruitment and progression for females (Government of Canada, 2019a). Despite these ongoing efforts and policies, gaps persist across the world, and more measures need to be taken on this matter (UNESCO, 2018).

2.2 Gender Gap in the Artificial Intelligence Field

As a highly interdisciplinary and fast-evolving field, artificial intelligence (AI) has dramatically revolutionized every aspect of human life, from the application of AI in medical science to intelligent environments and decision-making processes (Makridakis, 2017; WIPO, 2019). It is widely acknowledged that by broadening the gender diversity of AI research and the industry community, we could include more qualified experts with diverse skillsets and viewpoints, decrease gender inequalities in digital technology, and reduce unfairness and biases in AI development and deployment (UNESCO, 2020). However, women still continue to be underrepresented in academic disciplines stimulating digital revolutions and AI-related industry sectors (UNESCO, 2021). According to the AI Index (2018) report, the share of US female students at the undergraduate level in computing fields and AI and machine learning (ML) courses has noticeably dropped during the past three decades. Additionally, the percentage of women receiving Ph.D. degrees in AI remained constant in recent years, and AI male scientists disproportionately assume prestigious academic positions at US universities.

During the last decades, AI has attracted researchers' attention more than ever since the share of AI research has risen over 300%, and AI papers make up 3% of entire scientific publications (AI Index, 2019). Recent comprehensive analysis based on all AI articles published in arXiv (Mateos-Garcia et al., 2019) confirmed that female scientists are severely underrepresented as they constitute only 16% of AI research. They observed that although the number of AI papers co-authored by female authors has been increasing over time, the share of AI female researchers has stagnated after 2009, and gender gap has been exacerbated in some subfields such as robotics, ML, informatics, and data-related subfields. Regarding the gender gap in AI at the international level, they observed that countries like Norway and Netherlands have a higher percentage of AI female scientists than Eastern European and Asian nations. Moreover, other studies have also confirmed the existence of AI gender diversity gap in both academia and industry (AI Index, 2018; Gagné, 2019). For instance, World Economic Forum (2018) examined LinkedIn data and reported that women formed only 22% of AI professionals worldwide, and the gender gap is by far greater than in any other industry. Based on the report, females tend to have more diverse AI skills than males and assume more research and teaching positions. At the same time, men dominantly occupy management and senior positions, which are generally more highly paid and might result in a gender pay gap. Despite many initiatives to encourage women to the tech world, 41% of females who entered to technology-related profession decided to quit because of the masculine environment, sexual harassment, and other barriers (Hewlett et al., 2008).

As discussed, AI is facing a severe gender diversity gap which could bring many negative consequences. For example, AI is already struggling to find more qualified AI experts, perpetuating this situation by excluding many women (Gagné, 2019). AI technologies are growing rapidly and should serve diverse and inclusive populations, and the lack of diversity in AI development teams might lead to discrimination and bias in AI deployment (S. M. West et al., 2019). Thus, it is critically important to investigate gender-related patterns in artificial intelligence and form more diverse AI teams both in academia and industry to narrow the gender gap in this field.

2.3 Gender Disparity in Scientific Output and Collaboration

This section first reviews existing literature that studied gender differences in quantity and quality of scientific work. Then we review studies that investigated gendered patterns in academic collaborative activities.

2.3.1 Gender Patterns in Scientific Output

There is a significant body of evidence aiming to assess various aspects of gender differences in academic performance. Gender disparities in the scientific world, measured by differences in the number of scientists per gender, number of publications and citations, salary, amount of funding, and recognition, have been widely studied across different scientific fields and countries countries (e.g. Elsevier, 2017; Huang et al., 2020; Larivière et al., 2013; Shen, 2013; Witteman et al., 2019).

The "productivity puzzle," i.e., male scholars are often more productive than females in terms of the number of publications, is the embodiment of gender disparity in science (Cole & Zuckerman, 1984a; Long, 1992). Abundant research used the number of scientific publications as the most common and tangible indicator to measure the quantification of scholastic activities (Okubo, 1997) and demonstrated that males, in general, publish more academic papers compared to females (Abramo et al., 2009; Cole & Zuckerman, 1984a; Ghiasi et al., 2015; Huang et al., 2020; Larivière et al., 2013; Long, 1992; Xie & Shauman, 1998). The productivity puzzle phenomenon in academia inspired many scholars to investigate potential explanations for the gender gap in research productivity. Several studies argue that this gap has resulted from individual choices. For example, female scholars are more likely to interrupt their academic career at an early stage due to parenting and family responsibilities which may leave them lagging behind men in publication rates (Hunter & Leahey, 2010; Kyvik & Teigen, 1996; H. A. Zuckerman, 2001). In a comprehensive study, Xie and Shauman (1998) utilized four large datasets and investigated the trend of gender productivity gap over 24 years, and applied parallel multivariate binomial models to explain the reasons behind the productivity puzzle. They pointed out that the gender gap in research productivity is primarily rooted in differences in personal preferences, academic positions, and available resources. Additionally, they claimed that gender differences in the number of publications would be negligible once mentioned factors are considered.

A recent longitudinal report on the presence of a global gender gap published by Elsevier (2020) also reported that gender disparities reflected in research performance have existed despite significant progress towards increasing women's representation in academia. According to this report, in almost every country, female researchers, on average, publish fewer academic papers, and they tend to have shorter publication careers compared to males. This finding is supported by a global and historical research performed by Huang et al. (2020), denoting that gender differences in academic career lengths is the main factor explaining the research performance gap. However, Van Arensbergen et al. (2012) reported that although gender differences exist in research output, the gender gap becomes a bit narrower among early career scientists.

Moreover, myriad studies have been devoted to analyzing and mapping scientific performance and gender patterns through the number of citations. Citation counts has been commonly utilized as one of the potential indicators of academic recognition of scientists and predictor of their future performance (Long & Fox, 1995) despite its drawbacks (H. Zuckerman, 1988). Nonetheless, the research on this area has produced inconclusive and diverse results. while some studies found a citation bias favoring female authors in few specific fields (Borrego et al., 2010; Long, 1992; Van

Arensbergen et al., 2012), others found no differences for women or men (Bordons et al., 2003; Cole & Zuckerman, 1984b; Mauleón et al., 2008; Tower et al., 2007). Few studies also reported that scientists are more likely to credit writers who are of their own gender (McElhinny et al., 2003; Mitchell et al., 2013). However, some scholars argued that one possible explanation for lower citation rates of women might be due to the fact that male scientists are generally less inclined to cite females' publications and are more likely to cite their own work (Cameron et al., 2016; Dion et al., 2018; Maliniak et al., 2013). For example, Ghiasi et al. (2018) studied over 7 million articles during 2008-2016 and found that gender homophily in citation behavior persists across all disciplines, and men cited other men's work excessively, which might make women's work less recognizable and less visible as a male scientist are generally overrepresented in almost every scientific fields. In a similar vein, King et al. (2017) used reference lists of over 1.5 million publications across a wide variety of scientific fields and applied bootstrapping method, finding that self-citation behavior has followed an increasing trend during the past two decades and men on average cited their work 1.7 times more than females perpetuating gender inequality in research performance.

Moreover, in another study, Dworkin et al. (2020) applied a generalized linear model (GAM) while covering 61,416 articles during the period 1995-2018 to investigate gender-related patterns in neuroscience citations. They found that men-led articles, i.e., articles with men at coveted positions of first or/and last author, tend to be overcited compared to women-led articles, and this bias has mainly resulted from the citation behavior of male scientists. According to the authors, this gender difference in citation behavior might be explained by men's overrepresentation in some disciplines or the existence of unconscious bias among male researchers to underestimate women's work.

Supporting the existence of gender bias in citation behavior, Caplar et al. (2017) examined the gender bias in citation counts of over 200,000 articles published in the field of astronomy between 1950 and 2015. They considered several author and paper specific properties such as gender, seniority, country, number of citations, number of references, etc. Then, they applied machine learning technique to measure gender bias. They found that papers with women as a first author received fewer citations. Still, if a male author has written that paper with exactly the same characteristics, it would accrue more citations. They also concluded that if there was no gender bias in citation behavior, papers written by the primary female author would gain more citations.

Most of the aforementioned studies, except for King et al. (2017), were mainly concentrated in particular scientific disciplines and mostly used small data sets. Regarding large-scale analyses across various disciplines, several studies concluded that female authors, on average, have a lower impact compared to male authors (e.g. Elsevier, 2017; Ghiasi et al., 2015; Huang et al., 2020; Larivière et al., 2013). For example, Larivière, Ni, et al. (2013) studied over 5 million research papers published during 2008-2012 globally and conducted a large-scale and interdisciplinary bibliometric analysis to investigate gender inequality in academia. They provided evidence showing gender gap is still a pervasive issue, and male scientists have higher research output and impact in most countries and disciplines and dominated leading authorship positions. According to their results, papers with women as first or last authors tend to be less cited than papers with male-dominant authors.

In a recent study, Huang et al. (2020) performed a longitudinal and comprehensive analysis on the entire academic career of 7,863,86 researchers during the past 60 years and used bibliometric and statistical analysis to scrutinize gender disparities in scientific performance across 83 nations and 13 main STEM fields. They suggested that although women's participation has increased in academia over the past 60 years, gender inequality in publications and citation rates has been growing in favor of men. They revealed that the yearly rate of publication output is comparable for both genders, and scientists with the same publication output have an almost similar scientific impact, in terms of citations, on their work during their whole career. It is argued that this gap has mainly resulted from greater rates of female scientists' dropping out, leading to shorter academic careers. Based on their findings, gender disparity persists among disciplines and almost all countries and is exacerbated when it comes to highly productive researchers, and future focus should therefore be to maintain females in STEM disciplines and careers.

Another study conducted by Abramo et al. (2021) compared gender differences across various disciplines and academic positions between Norway and Italy. These two countries have different gender equality rankings. While Norway has high gender equality and ranks 2nd, Italy ranks 76 based on the Global Gender Gap Report (World Economic Forum, 2020). They studied over 36,000 professors between 2011 and 2015. They designed a new bibliometric indicator to measure research productivity by considering factors such as the number of publications and citations, academic experience, average yearly salary, and the number of collaborators. Based on their findings, in both countries, women are underrepresented in higher academic positions and have lower academic performance compared to men. Interestingly, they found that this gender difference mainly resulted from male overrepresentation as top 10% of scientists, and for the remaining 90% of scientists, they did not find any gender differences in research productivity.

2.3.2 Impact of Collaboration on Research Performance

With an increasing growth of scientific projects complexity in terms of the scope and processes, it is crucial for researchers to work collaboratively (Katz & Martin, 1997; Wood & Gray, 1991), in diverse and interdisciplinary research (IDR) teams, to better address the challenges (Bennett &

Gadlin, 2012). Scientific collaboration in almost every discipline is mainly driven by the need of sharing knowledge, expertise, and pooled resources since the accomplishment of scientific goals is highly dependent on proper academic competencies, accessibility of research equipment, and other resources (Beaver & Rosen, 1978). Thus, it is not surprising that collaborative efforts are rising and becoming a never-ending phenomenon in "big science" (Hand, 2010) and interdisciplinary fields, which require diverse knowledge base and access to unique resources (NSF, 2005).

The benefits of collaboration are beyond academic publications as it drives innovation and accelerates knowledge dissemination/creation leading to transformative research (Fox & Faver, 1984). As a result, it could positively affect research productivity and impact (Ebadi & Schiffauerova, 2016b; Lee & Bozeman, 2005; Servia-Rodríguez et al., 2015), thereby facilitating academic career advancement (Petersen, 2015) and providing better access to funding sources (Ebadi & Schiffauerova, 2015b). Academic collaboration is a win-win relationship, and its beneficial characteristics have encouraged researchers to adopt more collaborative behavior and made it a topic of burgeoning interest in bibliometric studies (Sonnenwald, 2007). The rising popularity of scientific collaboration has been represented by continuous increasing trend of multi-authored publications in every academic field and across different countries (Moody, 2004; NSF, 2019).

Moreover, in this modern and interdisciplinary science era, collaborative effort in interdisciplinary scientific projects has become more important than ever (Van Noorden, 2015). Van Noorden (2015) pointed out that the current world is struggling with challenging societal and global issues that bridge disciplines. Hence, the complex nature of these issues requires incorporating various fields of expertise, resulting in a growing trend toward interdisciplinary research. Indeed, disciplines such as Artificial Intelligence (AI), as a highly interdisciplinary and fast-evolving field that profoundly affects every aspect of human life, also require academic and industrial professionals with diverse knowledge and expertise from broad disciplines (WIPO, 2019). However, despite the beneficial aspects of interdisciplinary collaboration, it could also pose various challenges affecting the success of research teams. For example, it has been shown that transaction and coordination costs could impede effective collaborative efforts. Particularly in interdisciplinary research teams, researchers with diverse academic backgrounds might have different approaches and viewpoints for problem definition and solution, resulting in communication problems and misunderstandings (Brewer, 1999; The National Academies., 2005).

Additionally, challenges associated with differences in the degree of personal dedication and commitment, the required time to discover other fields, communication barriers, and publishing challenges could negatively impact the success of academic collaborations (Campbell, 2005; Naimen, 1999). Given these challenges, several studies investigated factors influencing the effectiveness of interdisciplinary collaboration. Van Rijnsoever and Hessels (2011), for instance, demonstrated that being women, having longer academic career age, and having a broad range of experience in different universities/industries are favorably correlated with interdisciplinary research (IDR) practices. Some research also showed that individuals with shared prior experience might be better capable of uniting different viewpoints and positively enhance collaboration performance (Cummings & Kiesler, 2008; Guimerà et al., 2005). Several studies found that homophily effect is determining factor in academic team formation. To be more specific, individual researchers tend to collaborate with others with a certain degree of similarity between different characteristics such as gender, affiliation, discipline, age, and ethnicity (AlShebli et al., 2018; Feng & Kirkley, 2020; Holman & Morandin, 2019). However, other studies noted that although an appropriate level of similarity in terms of "knowledge area and expertise," could lead to more efficient communication and better common understanding among team members, too many similarities could also impede knowledge creation and innovation (Boschma, 2005; Nooteboom, 2000). Hence, some scholars examined the level of diversity or homophily in IDR teams by focusing on measuring the degree of similarity or dissimilarity of individuals' disciplines using different techniques, including network homophily measures (Brown et al., 2021), mathematical homophily index (Locatelli et al., 2021), and Shannon's entropy, i.e., one of the common indices to assess diversity (Aydinoglu et al., 2016; Feng & Kirkley, 2020). However, there are still some gaps in this area, and to our knowledge, there is no study to investigate the characteristics of AI interdisciplinary research teams.

2.3.3 Gender Patterns in Scientific Collaboration

Owing to the growing importance of research collaboration and its beneficial effects on academic success, several studies have examined the collaborative behavior of scientists and investigated the presence of gender-specific patterns in academic research. Understanding gender aspects of scientific collaboration is of paramount importance since evidence demonstrates the pervasiveness of gender inequality in scholastic activities (Huang et al., 2020; Nelson & Rogers, 2003). A number of studies reported that men and women exhibit different behavior in collaboration practices, and male scientists are more likely to adopt effective collaborative behavior that could be presumed to lead to higher scientific productivity and impact (Jadidi et al., 2018; Sonnert & Holton, 1995). Sonnert and Holton (1995) found that men tend to develop more informal collaborations and attend various social events, which exposes them to more new and diverse collaboration opportunities. Further, Bozeman and Corley (2004) performed survey analysis and studied academic career of scientists working at American academic research institutes. Their findings showed that females tend to have less-cosmopolitan collaboration compared to males, meaning that they prefer collaborating with others within their own research groups, laboratories, and universities. This collaboration behavior could negatively impact females' research performance as scientists with more cosmopolitan collaboration style could attract more collaborators, access larger grants and funding, thereby gain better academic recognition and performance (Beaver, 2001; Bozeman & Corley, 2004). There are also some studies indicating that female scientists tend to have fewer collaborators (e.g., Boschini & Sjögren, 2007; Ductor et al., 2021; Jadidi et al., 2018) and less-prestigious collaboration network (Fuchs et al., 2001). However, several studies reported that women have generally become more collaborative (Abramo et al., 2013; Fell & König, 2016; Ghiasi, Harsh, et al., 2018; McDowell et al., 2006), while few studies found slight or no sex differences in the amount of research collaboration activities (Long, 1992; Rijnsoever et al., 2008).

Regarding gender differences in the propensity towards interdisciplinary collaboration, Rhoten and Pfirman (2007) used empirical data from different studies and sampled from different IDR institutes in the UK and US. According to their study, female graduates tend to be engaged in more interdisciplinary research than males, particularly early-career female researchers are more likely to adopt an interdisciplinary approach and borrow data, techniques, and tools from other academic fields. Similarly, Van Rijnsoever and Hessels (2011) applied survey and regression analyses to investigate influencing factors associated with interdisciplinary collaboration among Dutch scientists and found a stronger tendency for women towards interdisciplinary research. However, we cannot draw precise conclusions on this matter since not much research has been conducted to assess sex differences in IDR collaborations.

There is also evidence suggesting that scholars favor collaborators of their same gender, identified as gender homophily effect (Holman & Morandin, 2019; Jadidi et al., 2018; Karimi et al., 2019; Lerchenmueller et al., 2019). Comprehensive recent research conducted by Y. S. Wang et al. (2019) covered large-scale bibliometric JSTOR data, studied more than 250,000 articles, applied bootstrapping and logistic regression techniques, and developed a precise method to examine the role of gender in collaborative research relationships. Specifically, they explained that non-gendered attributes (i.e., structural component), different gender proportions across disciplines (i.e., compositional component), and individual behavioral component should be controlled while investigating the gender homophily effect. According to the authors, women are inclined to collaborate with other female researchers in all disciplines, and this tendency becomes stronger when the presence of women increases in the research area. This result is consistent with Boschini and Sjögren (2007) , who previously found a similar pattern among economic scientists. However, since female scientists are underrepresented in primary disciplines (Hamrick, 2019; Holman et al., 2018), the gender homophily effect could create some disadvantages for them, such as less academic recognition, limited access to resources, collaborators, and funding opportunities (Etzkowitz et al., 2000; van den Brink & Benschop, 2013).

In contrast with the above studies utilizing only bibliometric data, Kwiek and Roszka (2021) constructed an integrated dataset, including scholarly articles and their metadata and authors' biographical information. They performed large-scale analysis on all Polish professors in eighty-five universities with at least a Ph.D. degree during 2009-2018 to examine the effect of gender homophily effect among scientists of different ages, academic positions, and disciplines. Utilizing fractional logistic regression method, they found that men have, on average, a 20% higher same-gender collaboration ratio compared to women, and this percentage rises to 36.7% in male-dominant fields. Contrary to previous research, they noted that women show strong heterophillous behavior regardless of career, biological age, and academic positions and often collaborate with other male researchers. At the same time, men exhibit homophilous behavior and predominately collaborate with male researchers.

The study of gender disparities in collaboration at the international level has become increasingly important since scientific international collaborative activities have risen exponentially during the past two decades due to advancements in information and communication technologies (Bornmann et al., 2015; National Science Foundation, 2020). Despite few studies finding insignificant gender differences in international collaborative efforts (Aksnes et al., 2019; Finkelstein et al., 2013), many studies have shown that women are lagging behind men in international research and are generally less active at the international scene (Abramo et al., 2013; Bozeman & Corley, 2004; Elsevier, 2020; Larivière et al., 2013; Uhly et al., 2015).

Abramo et al. (2013) applied bibliometric and statistical approaches and studied Italian scientists between 2006 and 2010, finding that women generally prefer intramural[1] and domestic extramural collaborations[2] and are underrepresented in international research across almost every discipline. Later, Abramo et al. (2019) performed a longitudinal analysis on all Italian scientists, finding the stronger tendency towards international collaborations among top scientists, which might have earned them higher research output, visibility, and reputation. The stronger female researchers' tendency towards domestic collaborations have also been confirmed across most countries and disciplines by studies conducted at a large scale (Elsevier, 2020; Larivière et al., 2013).

[1] Intramural collaboration is associated with collaborating with researchers from the same research centers, departments, and laboratories with commonly shared research themes, objectives, and approaches

[2] Extramural collaboration is associated with collaborating with researchers from different research centers, departments, and laboratories at domestic or international level

However, according to a recent report which studied 28 European countries, although there are no gender-related patterns in international collaborations among early-career scientists, international mobility of female scientists decreases when they become more senior (European Commission, 2019). Presumably, several causes could be attributed to these differences like family and parental responsibilities (Leemann, 2010; Uhly et al., 2015; Vabø et al., 2014), prejudices against women (Hogan et al., 2010), and gender inequality in research funding (Bozeman & Corley, 2004; Jung et al., 2014; Larivière et al., 2011; Stack, 2004). The combination of the aforementioned factors could hamper the situation for women to get involved in effective research collaboration. Additionally, it could isolate them, specifically in male-dominant fields, resulting in gender productivity gap in academia, i.e., male scholars often outperform females in research activities (Astegiano et al., 2019).

2.4 Exploring Academic Collaboration Patterns and Performance through Social Network Analysis

The academic collaborative relationships can be represented by a co-authorship network, in which nodes/vertices indicate authors, and the links/edges between a pair of nodes represent co-authorship relationships. This method is widely used as a meaningful proxy to measure scientific collaboration (e.g., Glänzel, 2001; Newman, 2004; Savanur & Srikanth, 2010) as it could properly manifest mutual direct academic interactions and analyze leading factors to achieve fruitful research, albeit capturing only one main aspect of collaborations (Katz & Martin, 1997). The co-authorship network is known as a dynamic and evolutionary network that could affect nodes' structural properties and, as a result, the position and impact of researchers (Barabási et al., 2002). Hence, several studies have applied social network analysis (SNA) to further explore collaborative mechanisms in co-authorship networks and analyze the role of structural network positions in research activities (e.g., Abbasi et al., 2011; Ebadi & Schiffauerova, 2015a; Eslami et al., 2013).

Researchers within the scientific network can play various special roles according to their positions and characteristics. Possessing strategic roles may enable them to better access different skills and knowledge resources and be involved in diverse communities and potential projects. Also, interestingly, it is shown that their network roles may be changed throughout time (Abbasi et al., 2012). Bavelas (1948) was the first to examine the relationship between strategic and central positions and the importance and influence of actors within the group activities. This notion was later supported by Freeman (1978), who found that some structural properties such as the efficiency of an individual in knowledge transmission, satisfaction, and leadership perception of actor could be strongly influenced by how central a given node/actor is. Therefore, different centrality metrics have been presented to assess actors' importance, role, and influence within the network (Freeman, 1978; Scott, 1988).

Moreover, important and critical researchers within the scientific community can also be characterized by their scholarly impact (O'Boyle et al., 2016; Parker et al., 2013), collaborative relationships (Amjad et al., 2016), and their structural positions in the network (Yin et al., 2006). Hence, network centrality metrics have been utilized extensively by scholars to measure an individual's relative importance and role within the network. For example, one of the key centrality metrics is betweenness centrality which measures the ability of researchers to control information flows between others (Freeman, 1978). Researchers with high betweenness values, known as gatekeepers, are crucial actors who can connect different and separate clusters and transfer knowledge and innovation (Gould & Fernandez, 1989). Additionally, social researchers identified by the high value of degree centrality (Freeman, 1978) in the network can play an influential role as they have many collaborators in their neighborhood. Another important centrality metric is closeness centrality, and researchers with the highest closeness values, known as local influencers (Ebadi & Schiffauerova, 2015a), are more accessible and can transfer knowledge/information efficiently within the network (Beauchamp, 1965). Mentioned network metrics are among the most common network centrality metrics used by scholars.

The existence of central actors appears to have positive effects on knowledge/information dissemination and researchers' performance in the scientific network. Thus, many studies attempted to identify critical and central researchers using centrality measures and investigated the impact of possession of such strategic network positions on research activities. For example, Yan and Ding (2009) studied dynamic and evolving collaboration patterns of scientists in the field of library and information science over 20 years. They found a positive link between centrality measures and researchers' productivity and impact. They also argued that different network centrality metrics could represent researchers' academic career paths and indicate the impact of researchers within their scientific field and community. In a similar vein, Beaudry and Schiffauerova (2011) examined the co-authorship network of Canadian inventors in biotechnology to identify star scientists, i.e., inventors with high quantity and quality of patents, and their associated network roles/positions. They found that star scientists occupy more central network roles, and most of them also assume brokerage roles within the network.

Moreover, the collaboration behavior of Canadian nanotechnology researchers and the role of central actors in knowledge creation/dissemination have been examined by Zamzami and Schiffauerova (2017) using a simulation approach. They categorized researchers into different groups based on their productivity and centrality values and identified top researchers, i.e., top %5 based on centrality values, as gatekeepers (high betweenness centrality), star scientists (high publication rates), popular (high degree centrality), loyal (high weighted degree centrality), and embedded scientists (high clustering coefficient). They confirmed the strong positive impact of gatekeepers, stars, and popular scientists on network performance and knowledge propagation. However, they argued that researchers who formed close-knit groups and repeatedly collaborated with their former colleagues could negatively affect knowledge creation.

Abbasi et al. (2011) applied SNA and regression techniques to explore the role of occupying central positions on importance of scientists within the network of scientists working in the information schools of five American universities. Specifically, they examined four centrality indicators, i.e., closeness centrality, degree centrality, betweenness centrality, and eigenvector centrality, and identified researchers occupying central positions within the network are often the most influential and critical ones. They also found that some properties, such as having a high number of distinct collaborators, possessing central network positions, and locating in close proximity to other authors, are inextricably linked to producing high-impact research. Later, in another work (Abbasi et al., 2012), they studied longitudinal bibliographic data from Scopus. Using SNA and bibliometric methods, they found a significant positive impact of authors' brokerage role on academic performance. Further, other research also confirmed their findings in other disciplines by showing that brokers can play pivotal roles in the network by tapping diverse resources and facilitating knowledge transmission between unconnected groups, bringing them higher research impact in terms of the number of publications and citations (Abbasi et al., 2012; Ebadi & Schiffauerova, 2015a; Gonzalez-Brambila et al., 2013; Uddin et al., 2013).

In a recent study, Fiscarelli et al. (2021) used real data and constructed a collaboration network of researchers working on different scientific projects and publications in a Thai computer and technology research institute. They identified various measures to quantify individual and team performance, utilized centrality and structural measures and applied orbit analysis, which used different graphlets to study local connectivity patterns and compare networks, to explore the collaboration patterns of researchers over time. According to their results, researchers occupying more central and strategic positions are more productive, engaged in multiple projects, and have longer career lengths. However, they are not necessarily producing high-quality work measured by subjective quality indicators based on human judgment. They also suggested that other factors such as team size, density, and turnover should be considered to evaluate the success of research group collaboration. González-Alcaide et al. (2021) utilized a different approach from previous literature and identified key/influential players of the ventilator-associated pneumonia research community during 2006-2017 using cut-points graph theory. More specifically, they considered researchers as influential if their removal caused a minimum of five researchers to break off from the largest component. Then they investigated the individual characteristics of cut-points and found that betweenness was the only centrality metric showing significant differences between influential and non-influential researchers, and degree and closeness centrality were not good indicators to identify critical researchers. They also indicated that critical actors have less cohesion network (i.e., lower clustering coefficient) and more heterogeneous collaborators, diverse research profiles, longer career length, and higher research impact measured by h-index.

Contrary to existing literature, which mainly analyzed the importance of structural network positions or investigated the impact of central and strategic positions on scientific activities, Ebadi and Schiffauerova (2015a) identified characteristics of the scientists possessing strategic positions within a co-authorship network of natural sciences and engineering researchers. They calculated several network variables, including clustering coefficient, betweenness, closeness, and eigenvector centrality, and applied Ordinary Least Squares methods to investigate the effect of various factors at the individual level on assuming different network roles. They noted that highly productive researchers with more funding resources assume more influential and central roles in the network. Interestingly, they argued that younger prolific scientists play crucial roles in knowledge diffusion by occupying more brokerage positions.

2.4.1 Gender Disparity in Network Positioning

Although prior research emphasized the impact of network structural characteristics of researchers on their performance and importance, few studies explored differences between men and women in their positioning and influence in the co-authorship network. In a comprehensive study of computer scientists' collaborative behavior over forty-seven years, Jadidi et al. (2018) investigated gender-related patterns through different network embeddedness indicators, including degree, k-core, clustering coefficient, and structural holes to capture network size, the degree of connectedness, the degree of embeddedness, and brokerage roles, respectively. They found that although the gender gap in degree and k-core has decreased, women, on average, tend to have smaller and tightly clustered networks and seem to possess fewer brokerage roles compared to their male counterparts. Moreover, female scientists’ collaboration networks contain more weak ties while males tend to have more long-lasting and strong ties (Jadidi et al., 2018), interconnected with high-quality research (Petersen, 2015). However, they also demonstrated that while there are no gender differences in collaboration practices among the most successful researchers, women tend to be less involved in effective and potentially fruitful collaborations.

In another study focusing on gender differences in thirty-year collaborations among life science inventors, Whittington (2018) investigated inventors' network locations using statistical and social network analyses. She reported that women are, on average, more reachable and closer to others in terms of closeness centrality, which might be since they are located in more extensive and dense clusters and are less inclined to patent solely. Regarding gender differences in brokerage roles (betweenness centrality), Whittington (2018) observed that men occupy nearly twice as many brokerage positions as women over the course of their careers and acquire more benefits from their strategic roles. According to the author, women's underrepresentation and stronger gender homophily tendency among them might be the main potential explanations for mentioned disparities, and to address this issue, more attention should be paid to build gender balanced research teams and provide incentives to attract and sustain more women in the research community. Similarly, other studies also confirmed the women's under-representation in critical/influential academic network positions (e.g., Ebadi and Schiffauerova 2016b; Karimi et al. 2019).

Recent research studied management and accounting articles published in top-tier Brazilian journals within the period 2003-2016 (Dias et al., 2020). They utilized SNA and a logit regression model to examine the relationships between researchers' gender, affiliation, and academic positions with the probability of assuming central roles within the network. Their results indicated that male scientists are dominant in prominent and central network positions in terms of a number of distinct collaborators and connections with other central researchers, measured by degree and eigenvector centrality, respectively. Regarding the effect of academic degrees on possessing central roles, researchers with higher degrees tend to be more collaborative and less dependent on others. Additionally, they showed that researchers from various affiliations and regions exhibit a similar propensity towards assuming influential roles.

Some research also suggests that career stage should be taken into consideration while exploring gender disparities in networking behavior. Barthauer et al. (2016), for instance, performed survey analysis and analyzed the network structure, including brokerage and cohesion, of ~600 German researchers during their career development from Ph.D. to the postdoc level. Contrary to previous research, they found that female scientists possess more brokerage roles and have effective, larger, and less constrained collaborative networks during their Ph.D. and postdoc stages. They argued that Germany's wide range of initiatives, mentoring, and networking programs supporting female scientists has enhanced women's access to social capital in academia.

3 Thesis Contributions and Objectives

3.1 Research Gaps

Understanding the role of gender in academic collaboration, scientific performance, and research team formation is of paramount importance. Based on the literature reviewed, myriad studies explore different aspects of sex differences in academia and analyzed differences in the gender representation in research, scientific output and impact, salary, grant funding, scholarly authorship, hiring and promoting, homophily effect, and collaborative behavior across various disciplines and countries (Elsevier, 2017; Huang et al., 2020; Larivière et al., 2013; M. W. Nielsen, 2016; Shen, 2013; J. D. West et al., 2013; Witteman et al., 2019)

However, there is still a research gap in existing literature which involves exploration of team composition characteristics in interdisciplinary research teams from a gender perspective. More specifically, to the best of our knowledge, no study hitherto addresses gender differences in the propensity to collaborate with respect to the similarity or dissimilarity of researchers' academic backgrounds. Moreover, most of the previous studies either used limited datasets or applied only bibliometric and statistical techniques for their analysis. In this work, we contribute to current research by investigating the presence of gender-specific patterns in the co-authorship networks and analyzing disciplinary diversity among female and male researchers at the uni-author, bi-author, and team levels, as well as assessing the influence of disciplinary homophily or diversity on scientific research team formation in the field of artificial intelligence (AI), an interdisciplinary field with a significant gender gap (World Economic Forum, 2018). To this end, contrary to previous studies, we utilized multiple techniques, including machine learning, natural language processing, social network analysis, bibliometric, and statistical analyses, and also used large datasets to comprehensively investigate gender-specific patterns in the AI scientific ecosystem between 2000 and 2019.

As discussed in the previous chapter, many studies considered network structure variables, particularly centrality metrics, to explore collaboration patterns in co-authorship networks, identify most central and influential researchers, and assess the impact of different network positions on knowledge/information diffusion and research activities, primarily measured by publication rates and citation counts (e.g., Abbasi et al., 2011, 2012; Eslami et al., 2013; Uddin et al., 2013; Yan & Ding, 2009). So far, all previous works focused on the impact of structural network positions on academic collaborative activities and the research performance of scientists. To our knowledge, there is only one study conducted by Ebadi and Schiffauerova (2015a) who examined the effect of various factors at the individual level on assuming influential network roles. However, they did not consider gender attributes in their study. Additionally, previous studies mostly applied SNA along with simple statistical and regression analyses and considered a small set of variables and/or limited datasets.

Prior research confirmed that academic research and performance is positively influenced by central and influential researchers (e.g., Beaudry & Schiffauerova, 2011; Freeman, 1978; Yin et al., 2006) since they can attract more collaborators, resources and accrue greater recognition, enabling them to parlay their influence into increased career success in academia - a phenomenon dubbed as the "Matthew effect" (Merton, 1988). Despite the prominent role of these critical actors in shaping academic networks and mobilizing resources to develop scientific fields (Bonds, 2011; Serenko et al., 2011), little is known about which characteristics could make them critical.

Moreover, it is vital to identify influential researchers in disciplines such as artificial intelligence (AI) as a highly interdisciplinary and evolutionary field that faces with growing demand for AI experts from diverse research areas to solve unprecedented and challenging global issues (Gagné, 2019). Thus, effective knowledge diffusion can enhance knowledge and expertise sharing among AI scientists and assist them to overcome common challenges and address complex real-world issues. Like many disciplines, it is claimed that AI is also led by a small group of distinguished scientists who are mainly men and form tight clusters together (Yuan et al., 2020a), which makes the examination of the characteristics of influential AI researchers and explore gender-related patterns in their collaboration network essential.

The identified research gaps encouraged us to analyze the collaboration patterns of AI researchers through a gender lens and explore the influence of various factors at the individual author level on achieving strategic and central positions in their surrounding scientific collaboration network. This study aims to extend the current literature in reverse order by investigating the effects of driving factors on acquiring key network positions and explaining any possible gender differences. Indeed, we employed the combination of SNA, advanced ML techniques, and a multi-dimensional feature vector at the author level to analyze the profile of highly central scientists and explore gender differences.

3.2 Research Questions and Objectives

In this research, we aim to scrutinize the presence of gender-specific patterns in the co-authorship networks in the field of artificial intelligence (AI) within the period of 2000 to 2019.

Two main objectives we will address in this research are as follows:.

Objective 1: Investigate the collaboration patterns of AI scientists

- Explore wheather female and male scientists prefer involving in different AI subject areas or focus on limited AI subfields.

- Investigate gender differences in propensity for collaboration with others with similar or different disciplinary profiles.
- Investigate the association between researchers' position in the network and their scientific performance and examine any differences between female and male researchers.

Objective 2: Investigate the effects of driving factors on acquiring key/central network positions and explain any possible gender differences

- Apply a multi-dimensional feature vector at the author level that covers multiple characteristics of scientific activities to identify what factors may lead male and female AI researchers to strategic positions.
- Investigate the profile of highly central scientists in the AI scientific ecosystem, as an example of a highly interdisciplinary, fast-evolving, and collaborative field
- Explore gender differences in the collaborative behavior and characteristics of the most influential AI scientists.
- Investigate the existence of gender homophily effect (i.e., same-gender collaboration tendency) among AI scientists.

4 Data

Data collection and preparation involved several steps. First, the bibliographic data including but not limited to title, abstract, keywords, date of publication, author list, etc. were retrieved from Elsevier's Scopus, filtering in research articles, conference papers, book chapters, and books published from 2000 to 2019. We only included publications for which both title and abstract were available. We used the ("artificial intelligence" OR "machine learning" OR "deep learning") search query to extract AI-related publications where at least one of the mentioned phrases appeared in the title/abstract of the publication or in the keywords section. It should be noted that we used cross-sectional data and considered AI-related papers published between 2000 and 2019. Since the main objective of our research is not exploring historical gender differences and explaining the reasons behind this issue but investigating gender-specific patterns in AI in the current century wherein the number of AI publications has significantly increased (Tang et al., 2020), and AI research has become more application-oriented (Yuan et al., 2020b) due to some technological advances like big data, cloud computing, machine/deep learning, and artificial general intelligence. In the next step, we used a supervised 3-class machine learning classifier to infer the gender of AI scientists. Moreover, we used NLP for data preprocessing and feature engineering, and applied unsupervised machine learning algorithm (LDA) to infer the authors' scientific research themes from scientific publications.

We then used social network analysis (SNA) to build the co-authorship network of AI researchers. For this purpose, we first constructed a bipartite co-authorship network, with authors and articles as the two types of nodes, and edges indicating the publication's authorship (De Nooy et al., 2005). In order to track gender-specific collaborative patterns at the author level, we transformed the bipartite network into a monopartite network wherein nodes represent authors characterized by gender, and two authors were connected if they had a joint publication. The final dataset contains 39,679 publications excluding unknown/unisex only articles as well as those without abstract, and 114,371 authors (30,448 females and 83,923 males). The gender determination method and authors' disciplinary profiles inference are explained in detail in the following section.

4.1 Gender Determination

Using machine learning techniques and natural language processing, we then applied an automatic gender assignment model trained on a large labeled dataset of names to infer researchers' gender from a diverse set of features such as their first and last names, affiliation, and country of origin. The tool trains a 3-class machine learning classifier on a huge labeled data set of names. It benefits from a tailored feature engineering component that expands the initial feature set (e.g., first and last names and authors' affiliations) to boost the performance of the model. In engineering and creating new features, we considered many factors such as linguistic rules in different countries. For example, female last names in Russian, Czech, and other Slavic languages end with the suffix 'ova'. We implemented such rules in the inference pipeline. Moreover, we used natural language processing techniques to enrich the feature set further by focusing on different parts of the first and last names. For example, we created features representing the location of researchers extracted from their affiliation, the last *n* characters of the last names, etc. Also, we calculated locations in which a given first name or last name is very frequent and added features representing this information. The machine learning classifier was trained on this enriched data set and output a label from the set of ['female', 'male', 'unisex/unknown']. From the model output, we classified authors' genders into female (F), male (M), and unisex/unknown (U). We labeled authors' genders as unisex/unknown (U) when our method could not detect the gender and excluded these authors

(~27%, n=41,936 authors) from further analysis. We carefully validated the accuracy of our automatic gender identification algorithm through manual verification on a random sample of 1000 scientists. The algorithm identifies the gender of the researchers with 96% accuracy (94% for females, 98% for males).

4.2 Authors' Disciplinary Profiles

We adopted a topic modeling approach so as to infer the authors' scientific research themes and domains of interest and identify the degree of interdisciplinarity at the author level. The resulted topic vectors from the topic model would represent disciplinary profiles of the scientists in our target dataset, i.e., the AI-related research publications. Whereas journal disciplinary classification and departmental affiliations may be used to recognize the disciplinary profile (Schummer, 2004; J. Wang et al., 2015), they cannot accurately represent the authors' academic backgrounds. For instance, computer scientists who apply their knowledge in various fields of studies like mathematics, physics, medicine, etc. cannot be fully and precisely represented by a merely single computer science discipline. On the other hand, academic publications could properly manifest the interdisciplinarity of individual researchers (Porter et al., 2007). Taken together, we decided to employ the Latent Dirichlet Allocation (LDA) topic modeling technique, developed by Blei et al. (2003), to derive the researchers' disciplinary profiles from their past publications. We first merged the titles and abstracts of the articles. The rationale for this integration is that titles cover specific keywords to index papers, while abstracts contain much more succinct information and represent the research's main idea (Ebadi et al., 2020). To apply the LDA model, several preprocessing steps were carried out on the corpus including the transformation of the textual data to lowercase, tokenization, removal of non-alphabetic characters, removal of the words with length less than three characters and eliminating custom stop words. Next, we created a document-term matrix to prepare the data for topic modeling. We built several LDA models with different numbers of topics and then calculated and analyzed several evaluation metrics, such as perplexity and log-likelihood, to assess the quality of the models (Griffiths & Steyvers, 2004). Besides quantitative metrics, three domain experts evaluated the quality of the model by analyzing top topic keywords and document-topic distributions. They concluded that the optimal number of topics for our research objective is 8, including Natural Language Processing (NLP), Genomics-Drug Discovery, Internet of Things (IoT)-Energy, Decision Support Systems, Computer Vision-Health Informatics, Unsupervised Learning, Machine/Deep Learning, and Cyber Security-Network. As a result of the LDA model, each publication can be associated with more than one topic with a certain probability. Using the document-topic probability matrix generated by the LDA algorithm, we identified the authors' research fields based on average topic distribution over their past publications. Each author was then represented as a topic distribution vector consisting of 8 disciplines, where each component corresponded to the average topic distribution of the author's past articles under the given field. Moreover, we assumed the topic with the highest probability in the topic distribution vector for each author defines the author's primary discipline. For example, assume that author i has two publications P_1 and P_2 with document-topic probability vectors, including 8 research themes, as follows: P_1(0.5, 0, 0.1, 0, 0, 0.4, 0, 0) and P_2(0.6, 0, 0.2, 0.2, 0, 0, 0, 0), where elements in the vector represent the probability that the publication contains the research theme. We calculated the average topic distribution over author i's past publications (P_1 and P_2) and represented author i's disciplinary profile by a topic distribution vector $\vec{x}_i$(0.55, 0, 0.15, 0.1, 0, 0.2, 0, 0), in which each component shows the probability that author i published under the given discipline.

5 Gender-Specific Patterns in the Artificial Intelligence Scientific Ecosystem

In this chapter, we will address our first research objective involving the exploration of collaborative behavior of AI scientists and team composition characteristics in AI interdisciplinary research teams through the gender lens. Moreover, we analyze disciplinary diversity among AI researchers at the uni-author, bi-author, and team levels, and examine the impact of disciplinary homophily or diversity on AI research team formation.

5.1 Methodology

5.1.1 Descriptive Indicators

To examine the impact of network properties on scientific performance and experience, we calculated and utilized several initial descriptive indicators such as the total number of publications published by each author as a proxy for scientific output and the total number of citations received by each article to measure research impact. It is worth noting that publications published in various fields or years accrue citations differently (Waltman, 2016), wherefore, to correct the effects of field and year of publication, we also calculated field normalized citation counts, which is defined by dividing the total citation counts received by each article by the average citation counts for all articles published in the same year and the same field (Paul-Hus et al., 2015). In addition, career length was used as a proxy for academic experience, defined as the difference between the authors' first and last publications' dates in the dataset.

5.1.2 Structural Metrics

Having calculated the set of descriptive indicators, we largely adopted the framework proposed by Feng and Kirkley (2020) to calculate the structural metrics, and modified it a bit to satisfy our research objectives. They presented several metrics to capture the degree of disciplinary diversity among researchers at the uni-author, bi-author, and team levels. In this study, we extended their work by taking the gender aspect into account, aiming to assess the existence of disciplinary diversity or homophily among female and male AI researchers in a larger dataset and investigate gender-specific patterns in interdisciplinary collaborations. Moreover, we improved their approach by applying the probabilistic topic modeling technique (LDA) to better capture the research topics and expertise of scientists based on their research output. Following Feng and Kirkley (2020), we utilized network structure analysis to categorize researchers based on their collaboration patterns and explore how different collaborative behavior could affect research performance and experience. We introduce each metric in detail in the rest of this section.

5.1.2.1 Uni-Author Level Disciplinary Diversity

We applied Shannon's entropy, i.e. one of the common indices to assess diversity (Aydinoglu et al., 2016; Feng & Kirkley, 2020; Gray, 2011) to measure male and female scientists' disciplinary diversity. Shannon's entropy index is used to measure the dispersion among various fields of the individual author's research background. The degree of interdisciplinarity at the single author level is then identified by the diversity of fields represented in his/her publications, which is defined by the topic distribution vector $\vec{x}_i$. Hence, the entropy of each author's publication history is computed as follows:

$$H_i = -\frac{1}{log(n_d^{(i)})} \sum_{d=1}^{N_d} \vec{x}_{id} \ log(\vec{x}_{id}) \qquad (1)$$

where $n_d^{(i)}$ is the number of unique fields in which researcher i published, and $\vec{x}_{id}$ represents the author i's disciplinary profile based on the average topic distribution of all past publications classified under discipline d (the d^{th} entry of topic distribution vector $\vec{x}_i$). We divided the Shannon entropy metric by the maximum possible diversity index to normalize the equation (1) between 0 (no diversity) and 1 (highest diversity) and compensate for the variation in the number of disciplines in which researchers contribute to (Shannon, 1948). One may note that authors who contributed to only one field ($\mathrm{n}_d = 1$) were excluded from the calculation. Accordingly, an author with a high value of entropy would have more equal publication distribution across different disciplines as well as a higher degree of interdisciplinarity and vice versa. To summarize, the uni-author level diversity metric represents the degree of concentration of researchers in different research themes based on the content of their publications.

5.1.2.2 Bi-Author Level Disciplinary Diversity

To explore whether disciplinary homophily or diversity can be observed as a determining factor in forming a collaborative network in interdisciplinary research, we employed a pairwise similarity measure. The relationship between a pair of researchers can be indicated by edges in the scientific collaboration network, and it could be between authors from similar or diverse academic backgrounds; thus, the more disparate the co-authors' disciplinary profiles, the more heterogeneous their relationships are. To represent dyadic interactions between two genders, we classified edges of the co-authorship network into female-female (FF), female-male (FM), and male-male (MM) collaboration. Since several studies (Boschma, 2005; Nooteboom, 2000) confirmed that an appropriate level of cognitive proximity, i.e. the degree of similarities in shared "knowledge area and expertise," could provide more efficient communication and better common understanding among team members, we decided to examine the degree of cognitive proximity among AI scientists in following way. As suggested by Feng and Kirkley (2020), using researchers' topic distribution vectors ($\vec{x}$) as indicators of authors' knowledge area and expertise, we applied the cosine similarity to measure the degree of similarity or cognitive proximity between a pair of authors in terms of shared interdisciplinary profile as defined in Equation (2). Cosine similarity calculates the cosine of two non-zero vectors of n dimensions (Han et al., 2011). In this case, the two vectors contain the disciplinary profiles of authors.

$$S_{ij} = \frac{\vec{x}_i \cdot \vec{x}_j}{\|\vec{x}_i\|\|\vec{x}_j\|} \tag{2}$$

In the equation, $\|\vec{x}\|$ is the norm of the vector $\vec{x}$, and $\vec{x}_i \cdot \vec{x}_j$ denotes the inner product of $\vec{x}_i$ and $\vec{x}_{\mathrm{j}}$. The cosine similarity measure (S_{ij}) indicates the similarity between the research profile of author i and j, and varies between 0 (authors having collaboration only with those from disparate research backgrounds) and 1 (authors having collaboration only with those with the same research backgrounds).

5.1.2.3 Team-Level Disciplinary Diversity

Team-level disciplinary diversity can be characterized by either the variety of team members' disciplines, i.e. interpersonal diversity, or the degree of individuals' disciplinary diversity, i.e. intrapersonal diversity (Bunderson & Sutcliffe, 2002). In different terms, a diverse team can be composed of researchers from various disciplines or different interdisciplinary individuals (Wagner et al., 2011), or a combination of both of them. Given such a definition, to investigate gender differences in the tendency to collaborate in interdisciplinary research, we followed a similar approach as Feng and Kirkley (2020) and considered both primary disciplines and authors' disciplinary profiles as proxies for interdisciplinarity. Additionally, to compare between two gender groups, we considered the authors who publish the same paper as a team and partitioned teams into three categories, labeled as female-only, male-only, and mixed-gender. Then for each team, within-group entropy is defined based on co-authors' primary disciplines to measure team-level interdisciplinarity. The within-group entropy of publication p is defined as:

$$\widetilde{H}_P = -\frac{1}{log(min\{|p|, N_d\})}\sum_{d=1}^{N_d} f_{pd}\, log(f_{pd}) \tag{3}$$

where f_{pd} is the fraction of authors with primary discipline d (the discipline with the highest probability in the topic distribution vector $\vec{x}$) in paper p, N_d denotes the number of unique disciplines within each team, and $|p|$ is the total number of authors in a given paper. As a tight upper bound on the entropy is restricted either by N_d or $|p|$, a normalization factor of $(log(min\{|p|, N_d\}))^{-1}$ was introduced in Equation (3).

Similarly, to Equation (1), a high value of within-group entropy suggests a high degree of disciplinary diversity at the team level. Furthermore, we applied average within-group cosine similarity to measure the level of team interdisciplinarity based on team members' disciplinary profiles, i.e., topic distribution vectors. The average within-group cosine similarity for each publication is expressed as:

$$\tilde{S}_p = \frac{2}{|p|(|p|-1)}\sum_{(i,j)\in p} S_{ij} \tag{4}$$

where $|p|$ is the total number of authors in a given paper, S_{ij} is the cosine similarity between author i and j vectors, and the summation is taken over all pairs of authors in the paper p. Using $2\big(|p|(|p|-1)\big)^{-1}$, we normalized the $\tilde{S}_p$ values between 0 and 1, 1 indicates the maximum team disciplinary homophily. In summary, Equations (3) and (4) help us to explore interdisciplinarity at the team level from two perspectives: (1) based on the diversity of disciplines across team members, utilizing the within-group entropy, and (2) based on the disciplinary diversity of individuals within the team, using the average within-group cosine similarity.

5.1.2.4 Core-Periphery Researcher Decomposition

Researchers' position in scientific collaboration networks could affect their performance (Ebadi & Schiffauerova, 2015b, 2016b). Therefore, we investigated the relationship between researchers' brokerage role and their academic performance and examined how this relationship could differ between men and women. We used betweenness centrality as a proxy for researchers' influence, importance, and their brokerage role in the network. This measure can identify researchers who act as intermediaries between different groups of researchers, called gatekeepers. Gatekeepers can play a crucial role in the network by connecting different clusters and transferring and/or controlling the flow of information/knowledge between communities (Ebadi & Schiffauerova, 2015a). Betweenness centrality of author i is defined based on the number of times that author i connects two other authors via the shortest path passing through author i (Borgatti, 2005). Hence, the betweenness centrality of the given node (bc_{i}) is defined as:

$$bc_i = \sum_{i \neq j \neq k} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{5}$$

In Equation (5), $\sigma_{j\mathrm{k}}$ denotes the total number of the shortest paths between node j and k, and $\sigma_{j\mathrm{k}}(\mathrm{i})$ is the number of those paths containing node i. The betweenness centrality value ranges from 0 to 1, and the higher the value is, the more influence the node has. We performed core-periphery analysis as proposed by Feng and Kirkley (2020) to distinguish researchers based on their influence within the network. We utilized different network measure from theirs and calculated betweenness centrality to determine the most central and influential female and male scientists. More specifically, we built a co-authorship network for the whole period of 2000-2019, including 114,371 researchers. We then ranked researchers based on their betweenness centrality values and categorized nodes into two roles: (1) The upper 5% of authors in terms of betweenness value are associated with the "core" role in the network, and (2) the remaining 95% as the "periphery" role. This helped us to identify core researchers who act as a bridge between different communities and funnel the information in the network. Due to their roles, they may benefit from having more opportunities to collaborate more and produce higher impact research (Abbasi et al., 2012; Yan & Ding, 2009). Figure 1 illustrates the conceptual flow of the study.

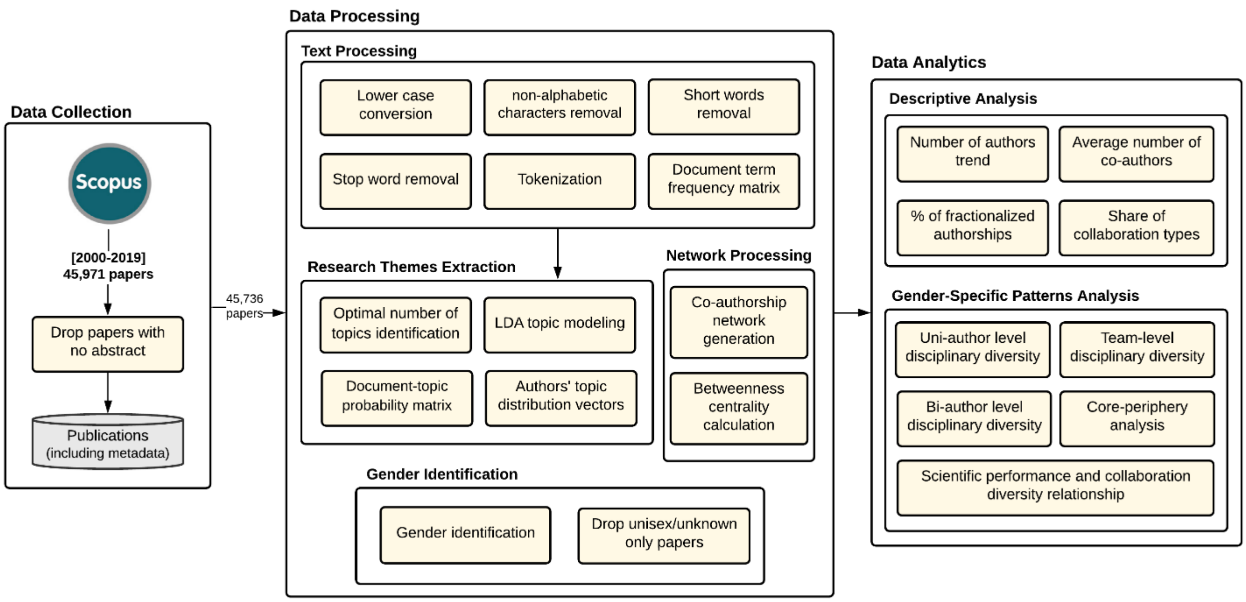

Figure 1. The conceptual flow. The pipeline contains three main components, i.e. data collection, data processing, and data analytics. In the data collection component, publications, and their metadata such as title, abstract, keywords, date of publication, author list, etc. are collected from 2000 through 2019. In the data processing component, first, the text data (publications' title + abstract) is processed and used to extract authors' research themes represented by topic distribution vectors. Next, the gender of the authors is identified, their co-authorship network is generated, and their betweenness centrality measure is calculated. The target data is finally passed to the data analytics component to analyze gender-specific patterns within the co-authorship network.

5.2 Results

5.2.1 Descriptive Analyses

The constructed co-authorship network contained 83,923 men and 30,448 women who contribute to 39,679 publications throughout 2000-2019. As seen in Figure 2-a, the number of both female and male researchers has been increasing steadily over the years, following an almost similar pattern. Despite the growth, female researchers are still fewer, overall making up only ~27%

of the AI research community based on the publications' authorship. We also compared publication outputs of the two genders using fractional authorship counts, where each author is given 1/n credit for the authorship of a given article where *n* is the number of co-authors in the article (Figure 2-b). Although female authors' contribution to published articles is slightly increasing over time, they accounted for less than 30% of fractionalized authorships during the whole period. This partially implies that the gender gap persists in the AI research community. However, AI is a male-dominant field, and the gender gap in research productivity might have resulted from women's underrepresentation in this field.

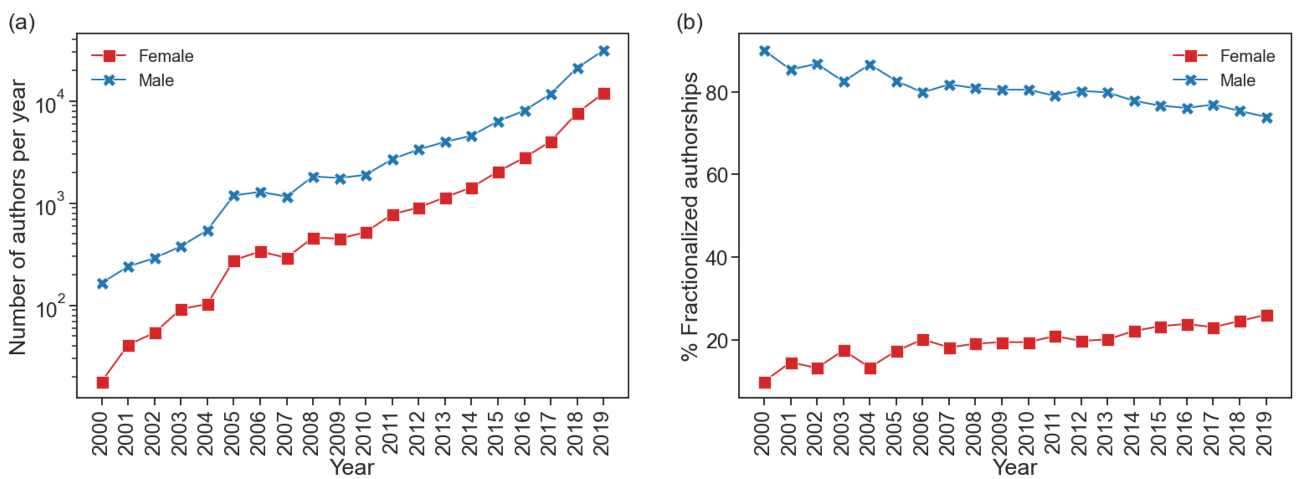

Figure 2. a) The total number of female and male authors per year, and **b)** the percentage of fractionalized authorships for two genders.

Figure 3-a shows the average number of distinct co-authors per paper for each gender (left y-axis) as well as the average total team size trend defined by the number of authors per paper (right y-axis). According to Figure 2-a, females have more distinct co-authors on average than their male counterparts, which is consistent with previous studies reporting that women are more collaborative than men (Abramo et al., 2013; Ghiasi, Harsh, et al., 2018). Figure 3-b shows the trends of different collaboration types. From the figure it can be inferred that the share of male-male (MM) collaboration has followed a downward trend, whereas the shares of female-female (FF) and

mixed-gender (FM) collaborations have been increasing over the years. This implies a change in collaboration preferences among the two gender groups and the increasing role and importance of female researchers in the AI community.

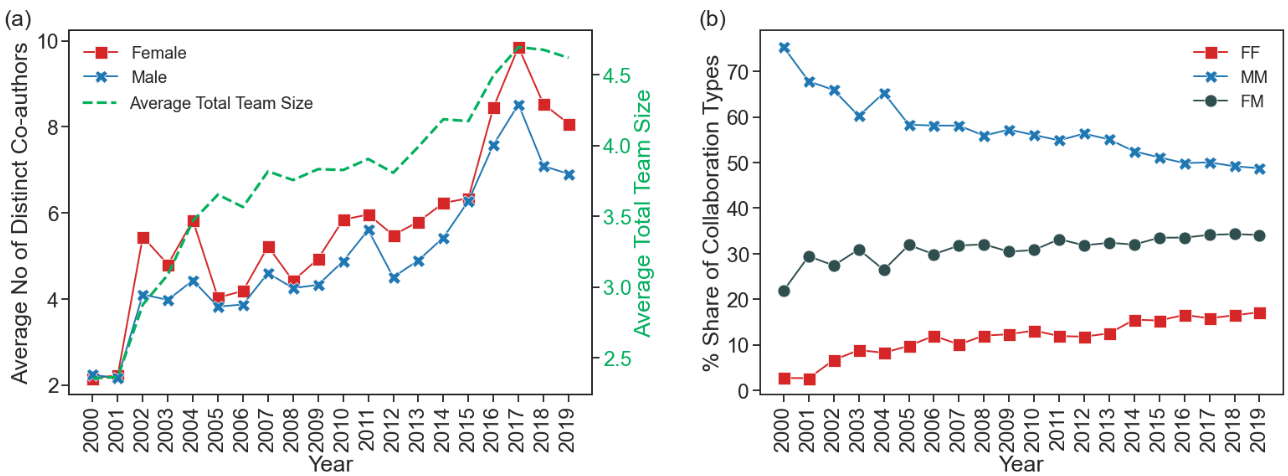

Figure 3. a) The average number of distinct co-authors per paper for each gender (left y-axis) and the average number of authors per paper, i.e. average total team size (right y-axis, which is shown by green dashed line), and **b)** the percentage of share of collaboration types. Note that collaboration types indicate edges in the co-authorship network, classified into female-female (FF), male-male (MM), and female-male (FM) collaborations.

5.2.2 Uni-Author Level Disciplinary Diversity

As an initial step in investigating gender-specific patterns of research background diversity in collaboration, we used normalized Shannon's entropy to examine the extent whereto disciplinary diversity exists in an individual's research background. We excluded authors who contributed to only one discipline and analyzed the disciplinary profiles for a total of 114,313 authors, consisting of 83,880 (73%) men and 30,433 (27%) women. Figure 4 shows the probability density distribution of entropies for researchers' publication history, containing eight main research subfields of AI represented by the topic distribution vector. From the smooth density plot it is observed that all authors, irrespective of their gender, tend to have diverse research backgrounds and almost a balanced publication distribution across different disciplines. However, the number of fields (n_d)

that each author contributes to could negatively affect their ability to equally contribute to all those fields.

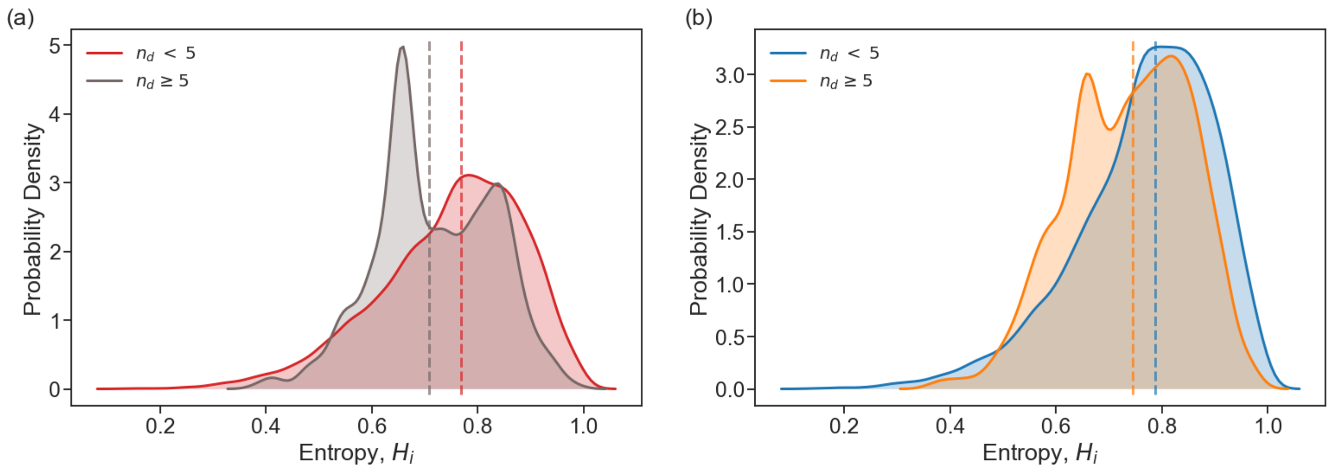

Figure 4. Probability density of entropies for **a)** female, and **b)** male researchers. Dashed lines indicate the median of each distribution, and n_d is the number of unique disciplines in which researchers publish. Note that after examining several thresholds for n_d, we found 5 as the optimal cutoff.

As depicted in Figure 4-a and -b, both female and male scientists who publish in more fields ($n_d > 5$) have lower entropy values, meaning that they cannot have equal contributions to all the disciplines they are involved in. Within the group of researchers active in more scientific fields ($n_d > 5$), the distribution for both genders is bimodal. While the bimodality for the male group is relatively moderate, the gap between the two peaks for the female group is more pronounced, indicating that the female group is neatly divided into two significant clusters. Notwithstanding the mentioned similarities between the two gender groups, male researchers, on average, have slightly more balanced and diverse research profiles (higher entropy values) than their female counterparts. To statistically support this hypothesis, the one-sided Mann-Whitney U test results revealed that female researchers' median entropy is significantly lower than that of males regardless of the number of fields ($n_d > 5$: $\text{Median}_{(\text{female})}$=0.769, $\text{Median}_{(\text{male})}$=0.788, p<0.001); ($n_d > 5$: $\text{Median}_{(\text{female})}$=0.707, $\text{Median}_{(\text{male})}$=0.745, p<0.001). We furthermore performed a permutation test with 10,000 permutations to determine the significance level. This test does not require any distributional and independence assumptions (Edgington, 1980). The results confirmed a significant difference between the medians of the two gender groups.

5.2.3 Bi-Author Level Disciplinary Diversity

As explained in Section 5.1.2.2., in order to examine whether authors of each gender prefer to collaborate with researchers with similar research profiles, we calculated cosine similarity between researchers' topic distribution vectors for a total of 1,998,318 edges in the co-authorship network, consisting of 1,137,245 male-male (MM), 145,339 female-female (FF), and 715,734 female-male (FM) collaborations. Assuming the authors' topic distribution vectors as individual disciplinary profiles, we studied the dyadic interdisciplinarity between female and male researchers. Figure 5 demonstrates the probability densities of the cosine similarity values (S_{ij}) for mixed-gender and same-gender dyads. As seen, cosine similarity values for FF edges are significantly higher than those of MM and FM edges, and mixed-gender dyads tend to have more similar research experience than male dyads. These observations highlight that females have a higher propensity than males to co-author with other researchers who have similar interdisciplinary research backgrounds. Pairwise comparisons using the Mann-Whitney U test (two-sided) indicated that differences between all groups are statistically significant: (for all dyads including FF and MM, FF and FM, FM and MM: Median=1, p<0.001). However, since the cosine similarity values had a left-skewed distribution and all groups had the same median, we used a one-tailed t-test to determine if the average S_{ij} of FF edges is higher than those of MM and FM edges. Results indicated that differences between all groups are statistically significant, suggesting higher disciplinary homophily levels among FF and FM dyads (FF and MM: $\text{Mean}_{(\text{FF})}= 0.986$, $\text{Mean}_{(\text{MM})}= 0.978$, p<0.001); (FF and FM: $\text{Mean}_{(\text{FF})}=0.986$, $\text{Mean}_{(\text{FM})}=0.981$, p<0.001); (FM and MM: $\text{Mean}_{(\text{FM})}=0.981$, $\text{Mean}_{(\text{MM})}=0.978$, p<0.001). Additionally, a permutation test (10,000 permutations) was performed to identify the significance level. The above analysis and our further investigation of team disciplinary diversity in the next section address our research objectives concerning the existence of disciplinary homophily in scientific collaborations.

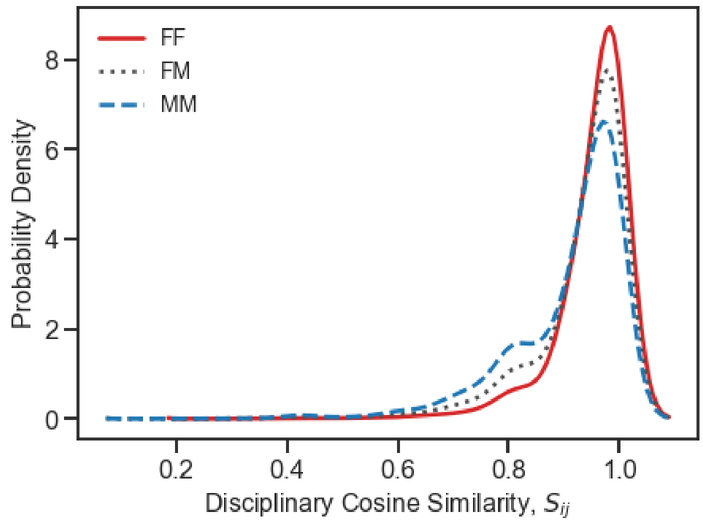

Figure 5. Probability density of cosine similarity (S_{ij}) for female-female (FF), female-male (FM), and male-male (MM) collaboration types.

5.2.4 Team-Level Disciplinary Diversity

In order to study team disciplinary diversity based on team members' primary disciplines, we applied the following strategy: (1) we considered the total number of unique team size (p) as the population and determined an optimal sample size for each population, assuming 95% confidence interval and 1% margin of error, (2) we generated randomized teams by applying random sampling without replacement from all authors in the real dataset, (3) we calculated within-group entropy ($\widetilde{H}_P$) for both real and randomized teams, (4) for each unique team size ($|p|$) in the randomized data, we calculated the average ($\mu_{|p|}^{(H)}$) and standard deviation ($\sigma_{|p|}^{(H)}$) of the entropy values, (5) we compared the real teams with randomized teams by calculating the z-score ($z_p^{(H)}$), which is defined as:

$$z_p^{(H)} = \frac{\widetilde{H}_p - \mu_{|p|}^{(H)}}{\sigma_{|p|}^{(H)}}, \tag{6}$$

and (6) similarly, we replicated our analysis while using $\tilde{S}_p$ instead of $\widetilde{H}_P$ and the z-score ($z_p^{(S)}$) to investigate team diversity based on team members' disciplinary profiles. Thereby,

$$z_p^{(S)} = \frac{\tilde{S}_p - \mu_{|p|}^{(S)}}{\sigma_{|p|}^{(S)}} \tag{7}$$

Figure 6 shows the probability densities of $z_p^{(\mathrm{H})}$ and $z_p^{(\mathrm{S})}$ for female-only, male-only, and mixed-gender teams. In the figure, z-scores indicate how many standard deviations the values of $\widetilde{H}_P$ and $\tilde{S}_p$ diverge from what is expected by random. It is observed that for all collaboration teams, the distribution of $z_p^{(\mathrm{H})}$ is concentrated on negative values, suggesting that $\widetilde{H}_P$ values for most of the teams are lower than what is expected for randomized groups. On the other hand, the distribution of $z_p^{(\mathrm{S})}$ is concentrated on positive values, meaning that teams with high $\tilde{S}_p$ are more common in the actual dataset than randomized. Additionally, the probability density of both $z_p^{(\mathrm{H})}$ and $z_p^{(\mathrm{S})}$ for female-only teams tend to be higher compared to the other groups. These observations highlight that although co-authorship teams, in general, tend to be composed of researchers with more similar disciplinary profiles, this preference is stronger among females, who have more homophilous collaborations compared to their male counterparts.

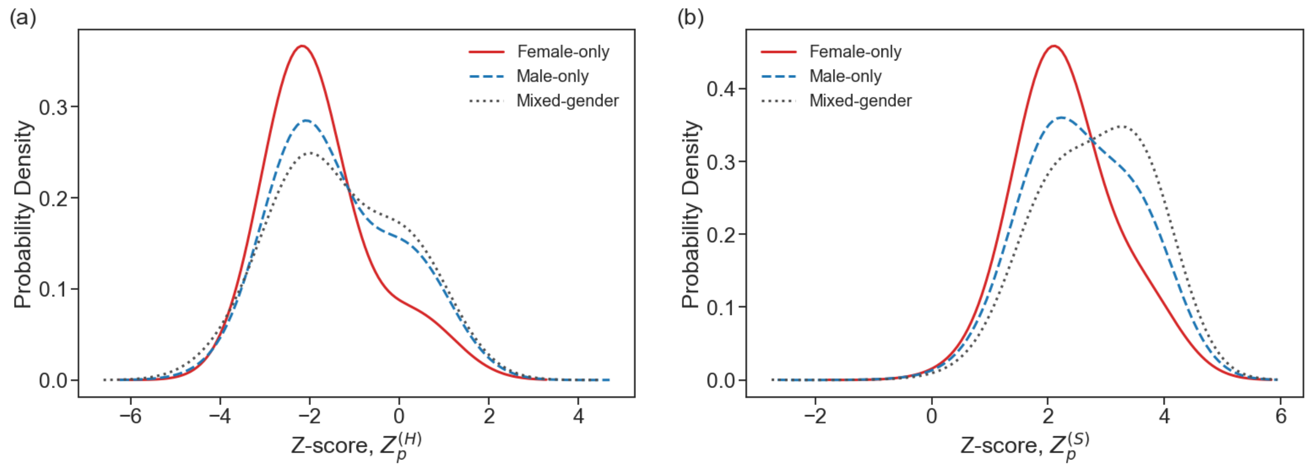

Figure 6. a) Probability densities of $z_p^{(H)}$ for female-only, male-only, and mixed-gender teams, and **b)** probability densities of $z_p^{(S)}$ for female-only, male-only, and mixed-gender teams. The z-scores show the deviations from expected values of $\widetilde{H}_P$ and $\tilde{S}_p$ in the randomized teams.

5.2.5 Scientific Performance and Collaboration Diversity Relationship

In this section, we analyzed the relationship between female and male researchers' scientific performance and their collaboration diversity. First, using core-periphery decomposition, all network nodes, i.e., researchers, were divided into core and periphery nodes (see section 2.2.2. for details). Out of the 114,371 authors, 5,720 researchers (5%) were associated as core researchers, including 4,197 males and 1,523 females. It was observed that male scientists have more brokerage roles in the network as their average betweenness centrality is 1.8 times higher than women's. However, the proportion of core females has increased by over 23% from 2000 to 2019, indicating that women are occupying more influential positions in tandem with men in the AI research community.

Next, we studied the impact of having core roles within the co-authorship network on research performance and experience. Figure 7 shows the distribution of average citation counts, as a proxy for research impact, for female and male core/periphery researchers. As observed, the core researchers' distribution moves above the periphery researchers' distribution, regardless of the gender, suggesting a positive relationship between occupying core positions in the co-authorship network and research impact in terms of citation counts. Notably, from Figure 7-a and -b, it is seen that the curves for core and periphery researchers are almost the same for female and male authors.

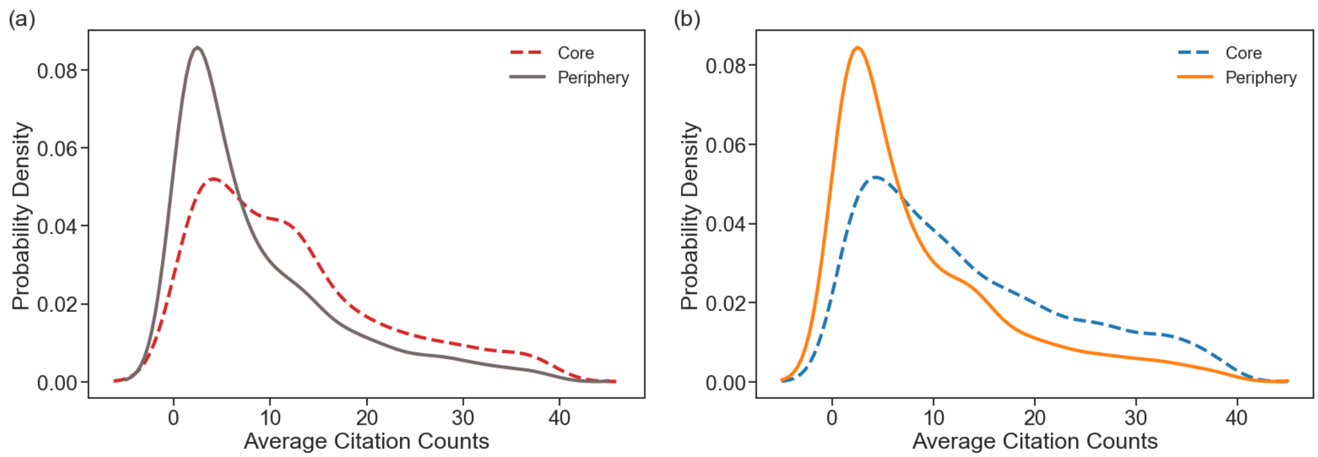

Figure 7. Average citation counts distribution for **a)** female, and **b)** male researchers.

We also investigated the relationship between research output, measured by the number of publications, and researchers' brokerage role in the co-authorship network, measured by betweenness centrality, for female and male researchers (Figure 8). The same patterns were observed here as well, indicating a positive relationship between having core positions and research output for both female and male researchers. Additionally, the core/periphery density curves were comparable for female and male researchers (Figure 8-a and -b).

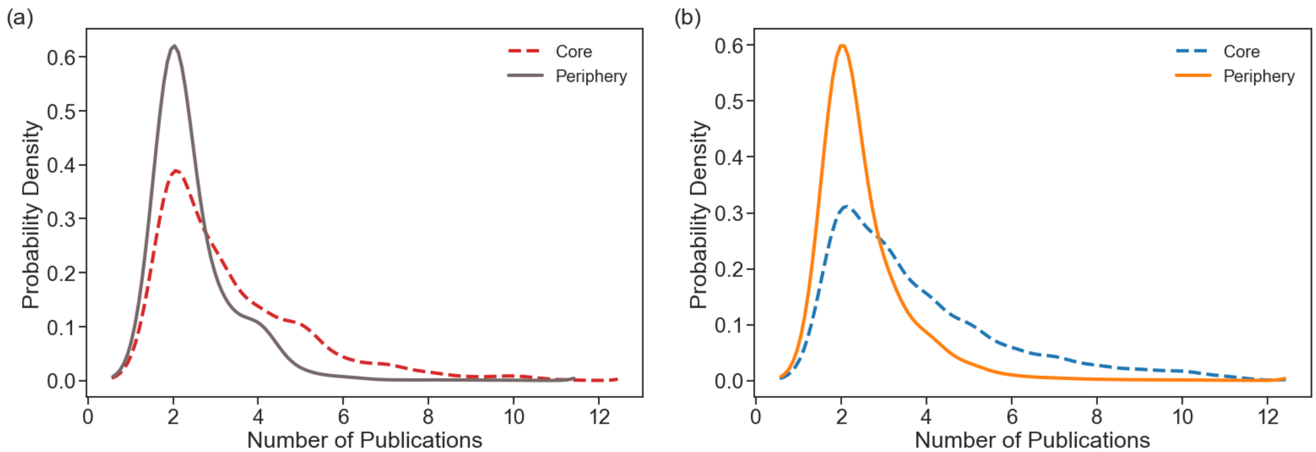

Figure 8. Number of publications distribution for **a)** female, and **b)** male researchers.

Figure 9 shows the probability density distributions of researchers' career length as a proxy for academic experience, measured by the difference between authors' first and last publications' dates in the dataset. As seen, the distributions of the core researchers' academic experience for both female and male researchers place above those of the periphery researchers. This suggests a positive relationship between having a core brokerage position in the co-authorship network and longer academic experience, regardless of gender. We validated our findings by performing the one-sided Mann-Whitney U test which resulted in significant differences in all cases ($p < 0.001$).

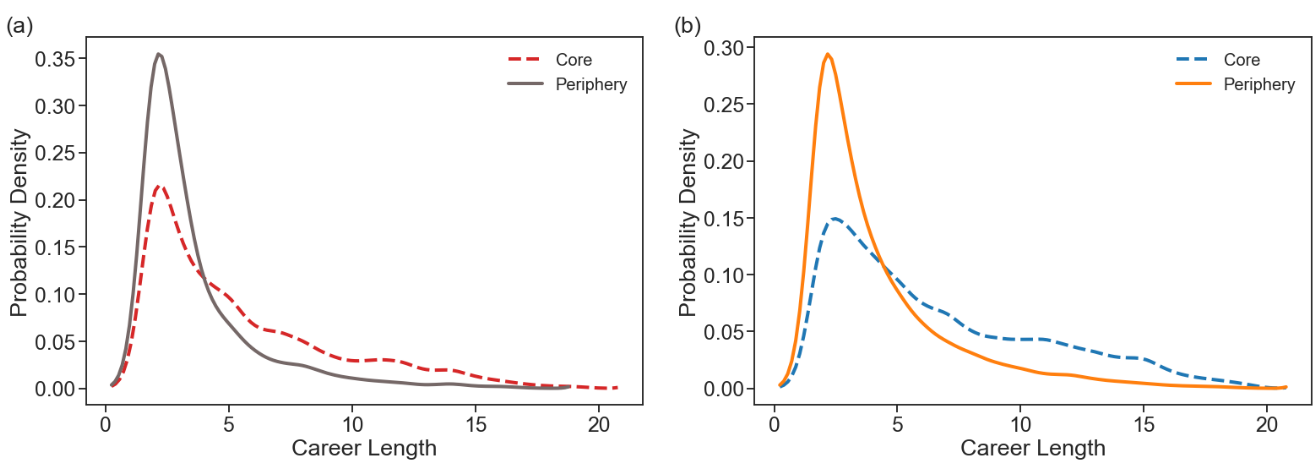

Figure 9. Career length distribution for **a)** female, and **b)** male researchers.

Motivated by these findings, we did further statistical tests to examine whether there are differences in research performance and experience between female and male researchers who are holding core positions in the network. The two-sided Mann-Whitney U test revealed that the difference between men and women in core positions was statistically significant in all cases ($p < 0.001$). Furthermore, the one-tailed t-test was performed to compare research performance between the two groups. Pairwise comparisons between the two groups showed that means of the career length and average citation counts of core females were significantly lower than those of core males, and that women in core positions, on average, publish less than their male counterparts (Average raw citation counts: $\text{Mean}_{(\text{core female})}$=20.584, $\text{Mean}_{(\text{core male})}$=28.236, p<0.001); (Career length: $\text{Mean}_{(\text{core female})}$=4.912, $\text{Mean}_{(\text{core male})}$=6.093, p<0.001); (Number of publications: $\text{Mean}_{(\text{core female})}$=3.462, $\text{Mean}_{(\text{core male})}$=4.126, p<0.001). We moreover calculated field normalized citation counts and observed similar relationships as the ones seen for the average citation count. Our findings show that authors who collaborate with diverse groups are more likely to have higher seniority levels and scientific performance in terms of both quantity and impact. Weaker research performance was observed for core females compared to the core male researchers; however, it is worth mentioning that having shorter career length as well as having a fewer number of female researchers in the AI scientific ecosystem, as suggested by our data, may have a negative impact on the academic performance of female researchers.

Finally, we closely investigated the collaborative relationships among top core AI researchers, defined as the top-0.1% researchers with the highest betweenness centrality (N=114, 15 females and 99 males). Figure 10-a shows their co-authorship network. The red nodes represent female researchers, and the blue nodes represent male researchers. The higher the betweenness centrality value, the bigger the node is in the network. Edges show co-authorship relationships, i.e., if two authors have a joint paper they are directly connected in the graph, and the thickness of edges indicates the collaboration frequency. As seen, not only is the network male dominant, but the top core researchers are also male, i.e., the biggest nodes in the graph. In addition, the gender homophily effect can be observed among both genders meaning that they seem to be collaborating more with researchers of the same gender as theirs. Nevertheless, some female core researchers are creating mixed-gender clusters by joining male-dominant clusters.

Figure 10-b compares the performance of top core AI researchers. As one may observe, top male researchers have more direct connections than their female counterparts, measured by the average degree, however, the gap is negligible. Nonetheless, in terms of the average number of publications, the male researchers produced almost twice the female researchers. Moreover, papers published by males have been more cited, according to their average h-index and i-10 index. These observations are akin to our findings from the core-periphery analysis, indicating the weaker academic performance for women in brokerage roles in the AI community. Regardless of gender, these top core researchers are mostly active in health and biology, partially explaining their high number of direct connections/co-authors. We also compared the ratio of their AI publications in the Scopus database over their total number of publications. The average ratio is slightly higher for men, 4.1% vs 3.7% with 95% confidence intervals of [2.9%, 5.3%] and [2.5%, 5.1%] for males and females respectively.

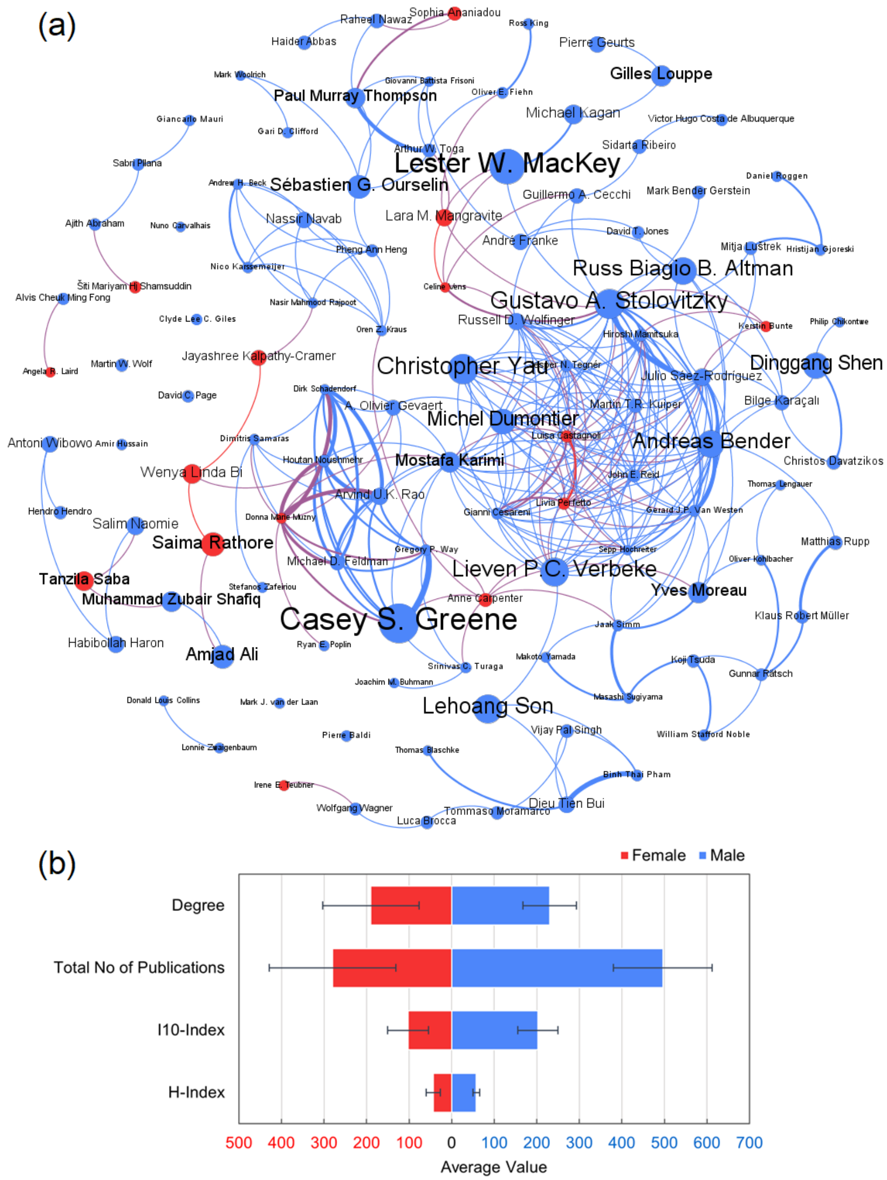

Figure 10. a) The co-authorship network of most central AI researchers, i.e. the top-0.1% researchers with the highest betweenness centrality (N=114, 15 females and 99 males). Female nodes are colored red and male nodes blue, and **b)** comparison of male and female AI researchers based on their degree, the total number of publications, h-index, and i10-index. The error bar represents a 95% confidence interval for the mean value per gender.

5.3 Discussion

Despite notable progress, gender disparity in science and scientific activities remains, calling for a more systematic and comprehensive approach to tackle and investigate the problem. Many initiatives have endeavored over the last decades to fill the gender gap in the academic and research community. As a highly interdisciplinary and evolving domain, artificial intelligence is constantly affecting many angles of human life, attracting the attention of not only researchers but also the governments and decision-/policymakers. This study complements existing literature on gender differences in scientific collaboration by analyzing disciplinary diversity among female and male researchers at the uni-author, bi-author, and team levels, as well as assessing the influence of disciplinary homophily or diversity on scientific research team formation. We applied multiple techniques, i.e., natural language processing, machine learning, social network analysis, and statistical analysis, to comprehensively investigate gender-specific patterns in the AI scientific ecosystem between 2000 and 2019. To the best of the authors' knowledge, this is the first study that addresses gender differences in the propensity to collaborate in terms of the similarity or dissimilarity of researchers' academic backgrounds in a highly interdisciplinary and evolving field such as AI.

In line with general conclusions of a recent report on the existence of a global gender gap in AI published by the World Economic Forum (World Economic Forum, 2018), we also found that the number of male researchers publishing in the AI domain has been constantly higher than their female counterparts in the entire examined period, with an increasing trend observed for both genders. Notwithstanding, our findings suggest that male and female AI researchers are collaborating together more, indicated by the increasing trend for mixed-gender collaborations. This property was recently observed in some other interdisciplinary fields such as nanotechnology

(Ghiasi, Harsh, et al., 2018). This property, along with our observed higher preference of female researchers toward collaboration, may facilitate the knowledge transfer between genders, resulting in generating more female AI superstar researchers that itself could inspire and engage more women at the forefront of the AI domain. Thus, our finding provides new insights into the changing role of female AI scientists and their active involvement in the field, which is in line with the high-level objectives of the frontline countries investing in AI and partially confirms the effectiveness of the policies taken to generate and support women AI leaders. As an example, in Canada, a new initiative has recently been put in place to tackle diversity in AI and foster the next generation of female leaders (CIFAR, 2019), as only 14% of Canadian AI researchers are women (Shelementaicom, 2019). In our dataset, we observed a 22% share for female Canadian AI researchers. This could indicate that women are still underrepresented in the Canadian AI research community despite implementing new initiatives. The possible explanation could be that such initiatives require more time to bear fruit and narrow the gender gap. Of note, the difference between the share of female Canadian AI researchers (14% versus 22%) might be due to using different datasets in each study.

Analyzing male and female scientists' disciplinary diversity revealed that although female scientists have slightly less balanced and less diverse research profiles than males, all authors, regardless of gender, tend to have a wide range of experience in different AI subject areas. In contrast, the tendency to have equal contribution to all fields is decreased as they engage in more research areas. This is in accordance with Feng and Kirkley (2020), demonstrating that individual-level disciplinary diversity is a common indicator of interdisciplinary research collaborations. Generally, several studies reported that researchers prefer working with others who have a certain degree of similarity between different characteristics (AlShebli et al., 2018; Holman & Morandin, 2019). Our findings indicate that while individual AI researchers are generally involved in diverse AI subfields, they are more likely to collaborate with authors engaged in a similar set of AI subfields as theirs. This could imply that the interdisciplinary nature of AI research mainly stems from individual researchers' disciplinary diversity (i.e., intrapersonal diversity) rather than diversity among researchers within the team (i.e., interpersonal diversity). Thus, uni-author level disciplinary diversity plays a significant role in the formation of interdisciplinary collaborations within this field. In other words, a given AI research team is more likely to consist of researchers who have diverse research expertise individually but have a similar set of expertise with other team members. To borrow from Bunderson and Sutcliffe (2002), teams composed of interdisciplinary individuals might be better capable of sharing their knowledge and overcoming common collaboration barriers, e.g. different mindsets, lack of mutual understanding, and communication problems, which could lead to higher team effectiveness. These findings provide insights for both researchers and organizations about team composition characteristics in the AI scientific ecosystem from a gender perspective.

Our analysis of gender-specific collaborative patterns confirmed the existence of homophily in terms of disciplinary profiles at both bi-author and team levels, consistent with previous findings by Feng and Kirkley (2020). Broadly, while AI researchers have, on average, a high degree of interdisciplinarity at the individual level, they are inclined to collaborate with authors who are like themselves in terms of shared interdisciplinary profiles; therefore, our results complement previous studies reporting the presence of homophily in academic collaborations in terms of gender (Holman & Morandin, 2019; Jadidi et al., 2018), affiliation, discipline, and ethnicity (AlShebli et al., 2018). Further, we found that women exhibit a stronger tendency toward disciplinary homophily compared to men in the AI scientific ecosystem. Female scientists tend to form more homophilous collaborative ties, i.e., interacting more with scientists from similar research backgrounds, and this tendency becomes stronger when it comes to female-female collaborations. Several studies (e.g. Brewer, 1999; The National Academies, 2005) indicated that although interdisciplinary collaboration composed of individuals from diverse disciplines could positively impact knowledge and innovation production in science, it could also propose some daunting challenges such as communication barriers, lack of common ground, etc. Given mentioned challenges, we speculate that uni-author level disciplinary diversity, along with homogeneity in AI research teams, may facilitate information/knowledge sharing among team members while maintaining the interdisciplinary nature of teams. This could be in accordance with some literature (e.g. Boschma, 2005; Nooteboom, 2000) showing that if members have an appropriate level of similarities in their knowledge area and expertise, known as cognitive proximity, they could communicate more effectively to exchange their knowledge. However, we also assume that researchers who are primarily collaborating with those of the same disciplinary profile, in a highly evolving and interdisciplinary ecosystem such as AI, might be less exposed to the cutting-edge advancements in the field that could affect the gender gap in time. As suggested by Boschma (2005) and Nooteboom (2000), while having a similar knowledge base could positively affect collaborative activities, too many similarities could also impede novelty. Therefore, it is suggested that researchers of both genders tend to maintain a balance between collaborating with others with similar and diverse disciplinary profiles to benefit from both efficient communication and accessing new knowledge leading to novel research.

Lastly, the core-periphery analysis indicated a significant positive association between having diverse collaboration and scientific performance and experience. In line with the existing literature (Abbasi et al., 2012; Feng & Kirkley, 2020; Yan & Ding, 2009), our findings demonstrated that having core positions within the scientific network could positively enhance scholars' academic performance and, as a result, their success. Core researchers can play an exceedingly important role in developing new collaboration ties with researchers from diverse communities, enabling them to reap the benefits of a wider range of knowledge and experience as well as higher scientific performance. In addition, our findings suggest tangible differences between the two genders occupying core network positions. On average, core female scientists have lower seniority levels and scientific performance in terms of both productivity and impact. We speculate that this lower performance might be due to the fact that women are underrepresented in AI disciplines and they are more likely to leave research careers or pause their scientific activities for a plethora of reasons such as family obligations (Ramos et al., 2015), inadequate female role models (Nelson & Rogers, 2003), masculinist working atmosphere, and professional preferences (M. T. Wang & Degol, 2017). If true, this would aid in explaining fewer influential women in the AI community, impeding females' academic success.

6 The Effects of Driving Factors on Acquiring Central Network Positions and Gender Differences

This Chapter will address our second research objective focused on identifying profiles and characteristics of central/influential AI researchers. To this end, we considered three network structure metrics as dependent variables, calculated several independent variables at the author level, and integrated them into the data described in Chapter 4. The variables and methods used will be introduced in the following sections in more detail.

6.1 Methodology

6.1.1 Dependent Variables

Using social network analysis, bibliometric analysis, and machine learning techniques, we aim to explore the effect of driving factors on acquiring superior network positions and influential roles within the AI scientific ecosystem. Occupying various positions within the co-authorship network may affect researchers’ role, influence, academic performance, and ability to spread or control knowledge/information. Hence, to capture researchers' importance from different aspects, we calculated three complementary network metrics, including degree centrality, closeness centrality, and betweenness centrality, at the individual level of researchers. Similar to other studies (e.g., Abbasi et al. 2011; Yin et al. 2006), we assumed that highly central researchers are inherently more impactful than others due to their network structural characteristics. Hence, we classified researchers into two categories: “core” and “peripheral.” To do this, we first calculated centrality measures for all the authors in the dataset. Next, for each of the calculated centrality measures, we considered the top 5% of researchers with the highest centrality values as “core” and the rest as “peripheral”. We defined three binary target variables for each of the centrality measures in order to capture various roles of AI researchers and explore factors associated with assuming highly central/core roles, that is belonging to the top 5% of scientists with the highest centrality values. Of note, we considered a normalized version of centrality metrics in this work; thus, all of these metrics take a value between zero and one. These dependent variables are briefly described as follows:

Degree Centrality (dc)

Degree centrality measures how well connected a researcher is within its local neighborhood by counting the number of distinct collaborators. Simply, the degree centrality of node i is calculated by counting the proportion of node i's direct ties as indicated in Equation (8) (Freeman, 1978).

$$dc_i = \frac{degree\ of\ node\ i}{highest\ degree\ in\ the\ network} \tag{8}$$

In the co-authorship network, researchers with high degree centrality values have a high number of distinct collaborators and may influence their network by acting as transmitters or receivers of information. The degree centrality can also reflect communicative activities and the popularity of researchers, wherefore we named these researchers as social researchers as they are more likely to actively collaborate with other researchers.

Closeness Centrality (cl)

Closeness centrality estimates the importance of a given researcher based on accessibility and their (network) distance to other researchers. More specifically, this metric is calculated based on the "sum of reciprocal shortest-path distance" between nodes in the network (Beauchamp, 1965). Hence, the closeness of node i can be expressed as:

$$cl_i = \frac{n-1}{\left(\sum_{j \in n-\{i\}} d(i,j)\right)} \tag{9}$$

where $d(i, j)$ is shortest-path distance linking node i and j, and n is the total number of nodes connected to node i either directly or indirectly. The cl_i metric takes values from 0 to 1, where 1 indicates that node i is located only a hop away from any other nodes, and the value decreases as the total distance between node i and other nodes increases. Researchers with high closeness centrality are, on average, close to most of the network members and can exchange information faster and efficiently through the network. Such researchers can be identified as local influencers since, due to their prominent positions, they can exert their influence into at least their local community (Ebadi & Schiffauerova, 2015a).

Betweenness Centrality (bc)

Betweenness centrality is a common proxy to capture a node's ability to pass and control information flows between communities (Freeman, 1978). It measures the extent to which a particular node is in-between other pairs of nodes (Borgatti, 2005). Then, the betweenness of node i is given by Equation (10):

$$bc_i = \sum_{i \neq j \neq k} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{10}$$

wherein σ_{jk} is the number of shortest paths connecting node j with k and $\sigma_{jk}(i)$ is the number of those paths including node i. Researchers with high betweenness, known as "gatekeepers", have pivotal roles in the network since they can bridge unconnected groups of researchers. This could enable gatekeepers to access non-redundant information and control knowledge flows across the entire network.

6.1.2 Independent Variables

To determine the key factors associated with being highly central/influential in the AI research community, we calculated several features, i.e., independent variables, at the individual level of researchers, capturing various aspects of their scientific activities. In the following, we introduce these variables that are used as input to the machine learning model.

Number of publications. The total number of past articles published by each author as a measure of research output.

Average journal rank. The average ranks of the journals where the author's articles have been published, representing research impact.

Average citation counts. The average citations received by the author's articles, as another measure of the author's research impact.

Career age. It is a proxy which indicates the author's academic experience represented by the number of years between the author's first and last publications in our dataset.

Number of distinct co-authors. The number of distinct co-authors of the author, an indicator that measures how diverse the collaborative behavior of scholars is.

Average team size. To consider the effect of scientific team size, we calculated this measure for the individual author based on the average number of authors per article.

International collaboration ratio. To capture the degree of internationalization of scholars' work, we calculated the rate of author's articles that have at least one international co-author, i.e., co-author from a different country (Abramo et al., 2011).

Contribution impact. This metric measures authors' contribution in their publications. There are several methods to measure authors' contribution. We applied the weighted contribution impact technique, which was used in some previous studies (e.g., Ciaccio et al. 2019; Shapiro et al. 1994). This method considers the first and last authors as the major contributors, second and next to last authors as the second-largest contributors to the research, and so on. It assigns different weights to co-authors according to their byline positions in each article, i.e., each author's contribution equals 1/p for a given paper where p is the author's position in the list. Thus, the researcher's contribution impact is considered the sum of weighted contributions over his/her articles.

Funded publication ratio. The rate of funded articles per author, measured by the number of publications for which the funding source was acknowledged in the paper over all publications of a given author.

Multi funding sources ratio. The total number of articles with more than one funding source over all articles published by each author.

Disciplinary profile. As discussed in Section 4.2, we used the topic modeling technique to infer disciplinary profiles of AI scientists quantitatively from the content of their publications. Using topic modeling, we extracted document-topic distributions and then defined each author's research profile based on the average topic distributions over their articles and considered the highest probability topic as the main discipline of the author.

Disciplinary diversity. This metric is calculated based on the Shannon entropy index, which measures the degree of interdisciplinarity of authors and quantifies the diversity of authors' research profiles based on the variation of fields represented in their articles (see Section 5.1.2.1). Researchers with high disciplinary diversity have published in more diverse research fields and have balanced contributions over those fields.

6.1.3 Machine Learning Model

Previous studies widely applied statistical models to explore relationships between variables and network metrics. However, there is only one study conducted by Ebadi & Schiffauerova, (2016a), in which they proposed an intelligent machine learning framework for the scientific evaluation of researchers iSEER system used bibliometric indicators and network metrics to classify researchers based on their collaboration patterns and research performance. They showed that applying machine learning algorithms for the classification of the researchers based on various attributes would be a feasible and proper choice. We decided to apply a machine learning algorithm for several reasons in this study. First, most statistical models work on several assumptions and are generally applied for smaller data with fewer attributes. Instead, ML models have fewer assumptions and perform really well with many attributes and a large dataset. Additionally, we can adjust and tune parameters of ML models, and they can be trained iteratively on data to capture complex patterns within the data. Also, with the help of advanced model interpretation techniques, we can explain what happened behind the model prediction. Therefore, using described independent variables, we trained a machine learning model to classify "core" and "peripheral" researchers. Specifically, we applied a supervised classification algorithm trained on labeled data and categorized researchers based on the defined roles. Therefore, we took each mentioned centrality metric as a dependent variable in turn and formulated the problem as a supervised binary classification problem predicting whether the given researcher belongs to the top 5% of highly central researchers, i.e., the core class. Moreover, we partitioned the data by gender and conducted experiments on two separate datasets, for female and male researchers, to examine gender differences. Overall, we built three classification models for the female dataset as well as three models for the male dataset.

We built several machine learning classifiers such as Logistic Regression as a baseline model, Random Forest, and Extreme Gradient Boosting (XGBoost). After running several experiments on building different supervised ML algorithms, we considered the XGBoost classifier as it outperformed other ML algorithms in our research problem. We trained XGBoost (Chen &

Guestrin, 2016) model, an improved version of the gradient tree boosting algorithm, on the defined datasets to classify researchers. XGBoost has become one of the widely used, high-performing, and popular ML algorithms due to its advantageous characteristics such as efficiency, parallelization, ability to handle missing values, invariance to scaling input variables, and robustness to outliers (D. Nielsen, 2016).

As the first step, the data were stratified and randomly split into 90% training and 10% test sets. The test set remained unseen during training and hyperparameter tuning phases and was used to perform the final model evaluation. For handling missing values, we run experiments using mean and median imputation. Since the percentage of missing values was less than 0.3%, I did not find any differences on model performance between two techniques. Therefore, we used mean imputation for numeric features and mode imputation for categorical features since only three variables, i.e., discipline, disciplinary diversity, and international collaboration ratio, contained null values and the missing percentage was less than 0.3%. In the next step, we normalized input data within the range of [0-1] to ensure that features have the same scales while reducing the computational complexity and run time. Additionally, the resulted dataset was highly imbalanced (5% as core class and 95% as peripheral), which could result in biased predictions towards the majority class. To address this problem, we considered range of different values for "scale_pos_weight" hyperparameter and tuned this parameter of the XGBoost model that is designed for dealing with imbalanced data by considering greater weight for the minority class. For example, regarding our problem which contains only 5% as core and 95% as peripheral class, tuning "scale_pos_weight" hyperparameter helped us to pay more attention to misclassification of the minority class for datasets (i.e. core class)

We then validated the ML model and optimized hyperparameters using repeated stratified 10-fold cross-validation. In this technique, the training data is evenly divided into 10 folds. In each iteration, 9 folds are considered as the training set and the left-out fold as the validation set. This process is repeated 10 times to use each fold as the validation set once. To prevent the bias and obtain a more robust estimated model performance, we repeated stratified 10-fold cross-validation 3 times wherein the training data was split differently. Then the average scores over all repetitions and all folds were reported.

6.1.4 Model Performance Evaluation

To evaluate the classifier's performance, we adopted commonly used binary classification performance metrics as follows:

Confusion matrix. The confusion matrix was first introduced by Kohavi and Provost (1998). This matrix summarizes classification performance. Rows in the matrix indicate samples in actual classes, and columns indicate samples in predicted classes, as shown below figure.

		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

Figure 11. Confusion matrix

Figure 11 shows all possible outcomes of prediction results as follows:

- True Positive (TP): Correctly predicted as positive class
- False Positive (FP): Incorrectly predicted as positive class
- True Negative (TN): Correctly predicted as negative class
- False Negative (FN): Incorrectly predicted as negative class

Recall. This metric indicates the fraction of positive instances (i.e., "core" researchers) correctly predicted by the classifier accounted for actual positive instances (Kohavi & Provost, 1998). For our problem, recall measures how well the model correctly predicted core authors. The high recall value means fewer incorrectly predicted as peripheral class.

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)} \tag{11}$$

Precision. It is the number of positive instances (i.e., "core" researchers) correctly detected as positive over all positive predictions (Kohavi & Provost, 1998). For our problem, precision measures how well the classifier is in predicting core class. The high precision value means fewer incorrectly predicted as core class.

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \tag{12}$$

F1 score. This metric is calculated based on the weighted harmonic mean between precision and recall. F1 score be considered a proper metric when the class distribution is imbalanced, like our problem, meaning that the number of observations in negative and positive classes is not distributed equally.

$$F1\ score = \frac{2(Precission * Recall)}{Precission + Recall} \tag{13}$$

6.1.5 Driving Factors Identification

Since we aimed to identify factors driving researchers' roles in the AI research community, i.e., being influential/core vs. follower/peripheral, we utilized the SHapley Additive exPlanations (SHAP) technique (Lundberg & Lee, 2017) to determine the magnitude and direction of the effect of features on the model's output. Specifically, SHAP is a game theory-based approach that calculates SHAP values to quantify the contribution of each feature on a given prediction and then averages over all observations to estimate the overall feature importance. Since SHAP applies a game-theoretic approach, it demonstrates better consistency, robustness to correlated variables, and capability of revealing hidden relationships Compared to other model interpretation techniques, and it has shown that this method is well suitable for tree ensembles models (Lundberg et al., 2020; Lundberg & Lee, 2017). Using this technique, we provided not only model interpretability but also the potential characteristics of core AI scientists. The conceptual flow of the study is shown in Figure 12.

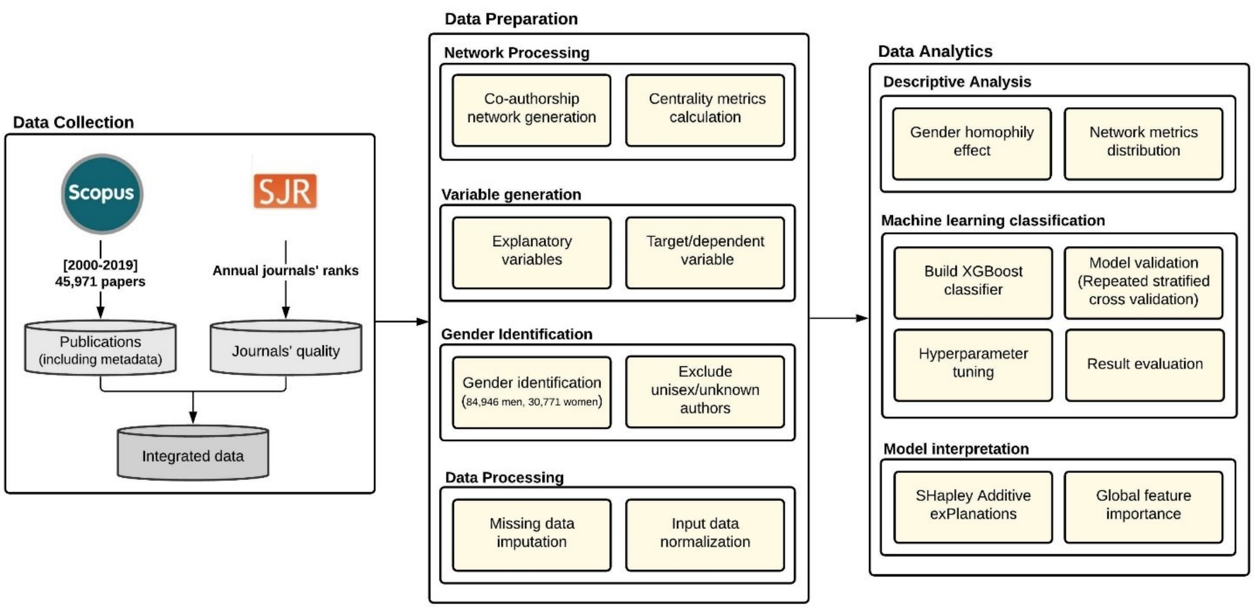

Figure 12. The conceptual flow of the study.

6.2 Results

In this section, we first discuss descriptive analysis results to provide a better understanding of AI researchers' collaboration patterns and dependent variables' distributions. Next, we discuss the results of the machine learning models and investigate the profiles of core AI scientists.

6.2.1 Gender Homophily Effect

To measure the gender homophily effect among researchers, i.e., the tendency towards same-gender collaborations, we used Yule's Q (odds ratio) index. The gender homophily effect could be strongly influenced by the group size from which researchers can connect with others of their gender. Yule's Q indicator takes into account the effect of different group sizes and is defined as follows (Crossley et al., 2015):

$$Q_i = \frac{IY - EX}{IY + EX} \tag{14}$$

In Equation (14), I and E are the numbers of the same and opposite-gender collaborators of author i, respectively. Y and X are the numbers of collaborators of the opposite and the same gender that author i does not collaborate with. Q_i ranges from -1 (perfect heterophily) to +1 (perfect homophily). Figure 13 depicts the changing trends in AI researchers' collaboration preferences. According to this figure, males show relatively homophilous behavior as they have predominantly collaborated with other male researchers. However, their scores decreased steadily, indicating they have gradually started to collaborate more with their female counterparts, specifically in recent years. On the other hand, women had more male collaborators in the early years. This is expected as the share of female AI researchers was very small in the beginning years, and their choices were limited. Nevertheless, we can observe that by entering more women in the AI community, female researchers collaborated with researchers of both genders and formed more balanced or gender-neutral research teams, indicated by a decrease in their Yule's Q scores.

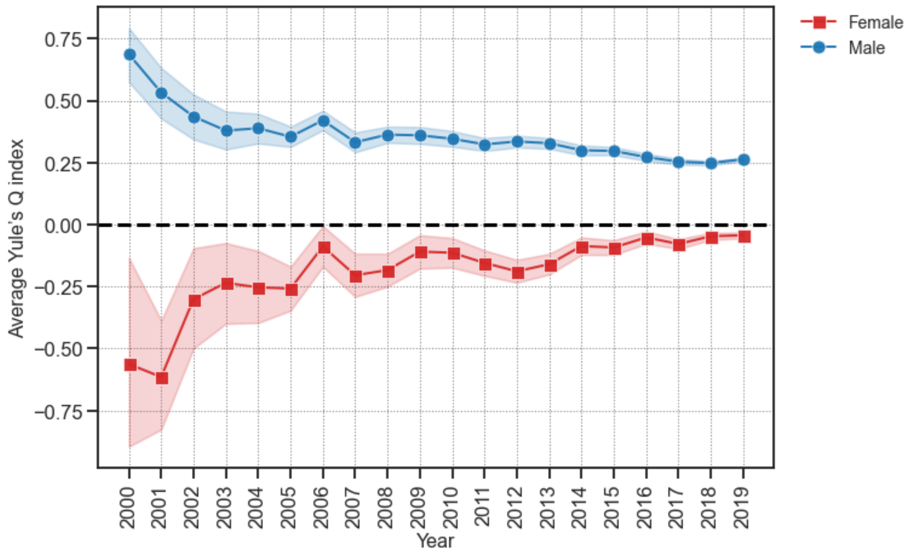

Figure 13. Average Yule's Q scores per year for two genders. Shaded areas show a 95% confidence interval. The high variation in the early years is due to the smaller number of researchers in those years compared to the recent years.

6.2.2 Network Metrics Distribution

We next examine the distribution of centrality metrics, i.e., the dependent variables, among two genders shown by box plots in Figure 14. As seen, centrality values follow right-skewed distribution for both genders, meaning that few researchers occupy highly central positions in the network. Male and female scientists have the same medians and almost the same quartiles for degree and betweenness centrality, but women tend to have higher values in terms of closeness centrality. The descriptive statistics for all centrality metrics are presented in Appendix A. Further, to perform a statistical comparison between network properties of two genders, we used a one-tailed t-test with 10,000 permutations to identify the significance level without any distributional and independence assumptions. Results revealed that the means of the betweenness and degree centrality for males were significantly higher than those of females (betweenness centrality: $p<0.001$, degree centrality: $p<0.05$). However, female AI scientists show significantly higher closeness centrality on average compared to male scientists ($p<0.001$).

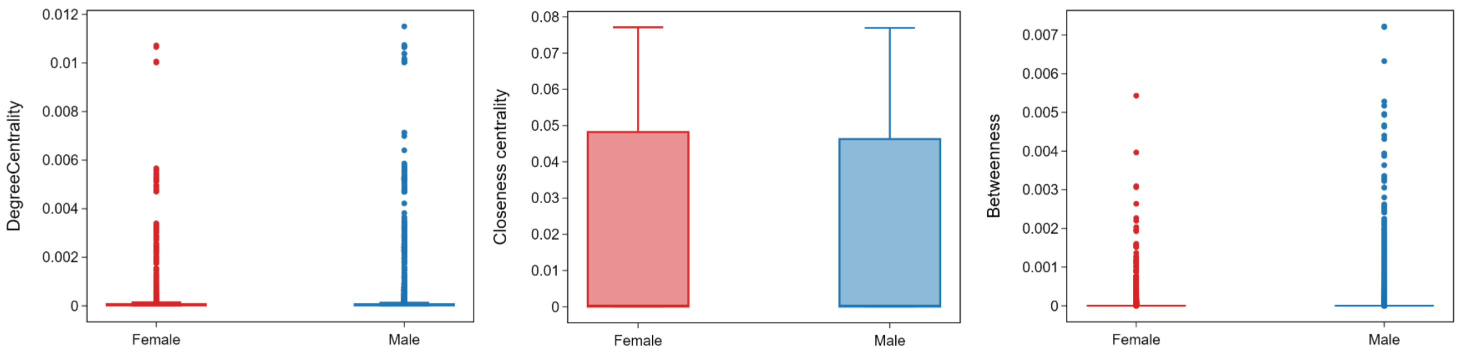

Figure 14. Distribution of network centrality metrics for female and male researchers. The box denotes the first (Q1), second (median), and third (Q3) quartiles. Whiskers specify the variation of values outside of the first and third quartiles, and points plotted individually are considered outliers.

6.2.3 Model Evaluation

As explained in section 6.1.3, we validated ML classifiers by applying repeated stratified 10-fold cross-validation. This validation strategy resulted in 30 disjoint validation sets. We used recall, precision, and F1 score (F1) to evaluate our models. Recall measures the extent to which the model classified researchers as "core" correctly for all researchers who are actually core. Precision indicates the probability that the model detected core researchers correctly out of all researchers predicted as "core" by the classifier, i.e., all positive predictions. F1 measures the accuracy and robustness of the classifier by considering both precision and recall metrics. Table 1 illustrates the quantitative evaluation of classifiers detecting the top 5% of scientists (core scientists) within different influential role categories (ranked by centrality metrics). As observed, almost all models performed well to predict core scientists in both male and female datasets.

Table 1. Model performance validation for predicting core scientists using repeated stratified ten-fold cross-validation. Evaluation metrics were averaged over 30 disjoint validation sets. The table indicates the means and expected variations of performance scores over all repetitions and all folds.

Prediction of core scientists	Validation sets	Precision	Recall	F1 score
Degree Centrality	Female	0.96 ± 0.01	0.93 ± 0.02	0.95 ± 0.01
	Male	0.94 ± 0.009	0.92 ± 0.01	0.93 ± 0.006
Closeness Centrality	Female	0.92 ± 0.02	0.82 ± 0.02	0.87 ± 0.02
	Male	0.87 ± 0.02	0.80 ± 0.02	0.83 ± 0.01
Betweenness Centrality	Female	0.72 ± 0.03	0.81 ± 0.03	0.76 ± 0.02
	Male	0.68 ± 0.02	0.82 ± 0.01	0.75 ± 0.01

After validating our models, we further evaluated the performance of classifiers on an unseen test set using the aforementioned metrics to confirm that the results were reliable and generalizable. As indicated in Table 2, we can notice that evaluation results using the test set are almost similar to cross-validation results shown in Table 1 reflecting the robustness of our models against unseen data.

Table 2. Model performance evaluation using distinct test sets.

Prediction of core & peripheral scientists	Test sets	Precision		Recall		F1 score	
		Core	Peripheral	Core	Peripheral	Core	Peripheral
Degree Centrality	Female	0.97	1.00	0.95	1.00	0.96	1.00
	Male	0.93	1.00	0.93	1.00	0.93	1.00
Closeness Centrality	Female	0.95	0.99	0.84	1.00	0.89	0.99
	Male	0.88	0.99	0.81	0.99	0.84	0.99
Betweenness Centrality	Female	0.71	0.99	0.84	0.98	0.77	0.99
	Male	0.70	0.99	0.82	0.98	0.76	0.99

We further analyzed the confusion matrix to obtain information about all possible outcomes of model prediction (TP, FP, TN, FN) for each centrality metric on the test set. Figures 15-17 show confusion matrices for the degree, closeness, and betweenness centrality for the female dataset on the left and the male dataset on the right, respectively. Rows represent true classes, i.e., the actual roles of researchers in data, and columns represent researchers' roles predicted by the model. As seen, per each centrality metric, the classifier has low false positive (FP) predictions indicating the model could generally perform well to detect core researchers.

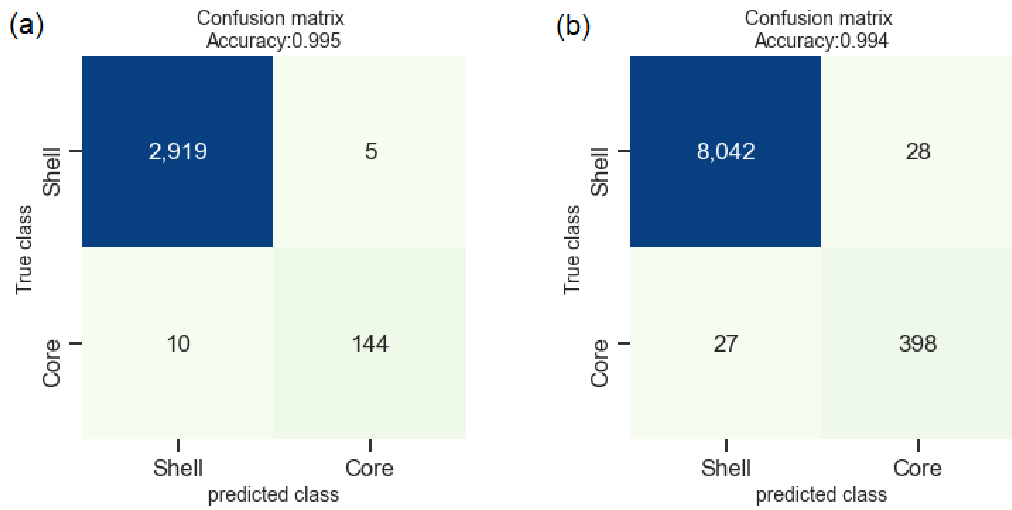

Figure 15. Confusion matrix for degree centrality on the test set for **a)** female, and **b)** male dataset.

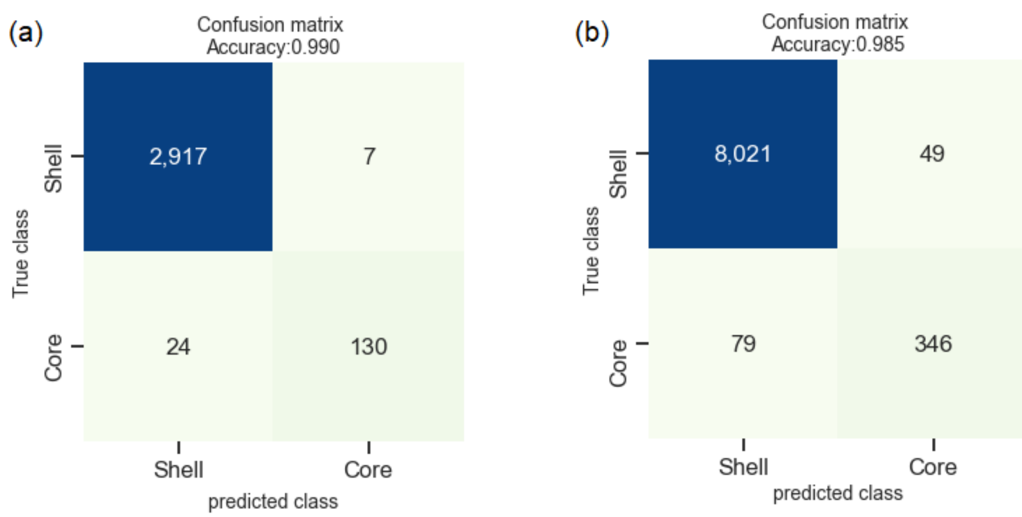

Figure 16. Confusion matrix for closeness centrality on the test set for **a)** female, and **b)** male dataset.

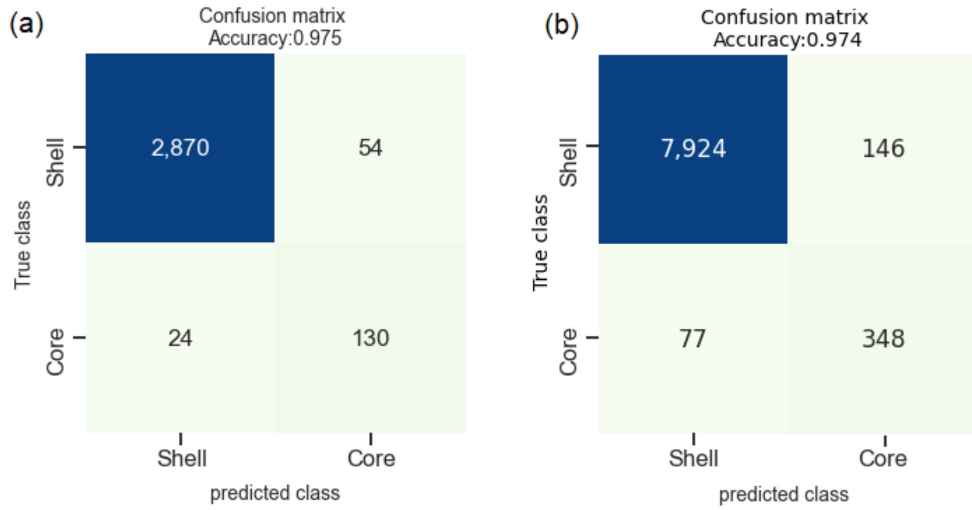

Figure 17. Confusion matrix for betweenness centrality on the test set for **a)** female, and **b)** male dataset.

6.2.4 Profiles of Core AI Scientists

This section addresses one of our primary research objectives, which is to examine the characteristics of the most influential/core AI scientists and explore differences between men and women researchers. As explained in section 6.1.3, using several author-specific characteristics as independent variables, we applied ML classifiers to determine whether a given researcher belongs to the top 5% scientists within each role category, i.e., social researchers, local influencers, and gatekeepers. Then, we utilized the SHAP technique to investigate the impact of driving factors in possessing core positions within the AI co-authorship network. It should be noted that the SHAP feature importance plot cannot be interpreted as causality and it only shows the relationships between features and the predicted target variable (being among the top 5% of highly central researchers). In the following sections, the analysis of characteristics of social researchers, local influencers, and gatekeepers is presented.

6.2.4.1 Social Researchers

Figure 18 illustrates features ranks based on their relative importance for predicting the upper 5% of female and male scientists in terms of their degree centrality values, social researchers. We excluded “Number of distinct co-authors” and “Average team size” features from this analysis as they were highly correlated with the target variable (dc) and could cause data leakage. According to Figure 18, research productivity and scientists’ impact, indicated by the number of publications, average journal rank, and average citation counts, could positively affect possessing core social positions. This may suggest that productive researchers who publish more high-impact publications can attract more co-authors. One possible reason is that having higher research performance might lead to a higher reputation in the AI community, which could attract other researchers and may provide social researchers with more collaborative opportunities.

As seen, a high value of contribution impact, has a great negative impact on the model. In addition, top social researchers have higher disciplinary diversity and balanced contributions to the (sub) fields they are involved in. This is quite expected because having more collaborators could expose them to new knowledge, resulting in publishing in more diverse fields. Moreover, they also benefit from their large collaborative network and access to more (international) co-authors. We can also observe that while career age and funding positively affect possessing core social positions, these factors are the least influencing in the model prediction.

Regarding differences among the two genders, the most pronounced difference is that while the number of publications is the most influential factor for men, this factor is less important for women as it ranked fifth. On the other hand, the average journal rank has the greatest influence on acquiring core positions within female social researchers. We can also see the greater magnitude and importance of the disciplinary diversity factor as a proxy for individual interdisciplinarity among female scientists. Lastly, involving in international collaborations has a greater impact on becoming core social researchers for both genders.

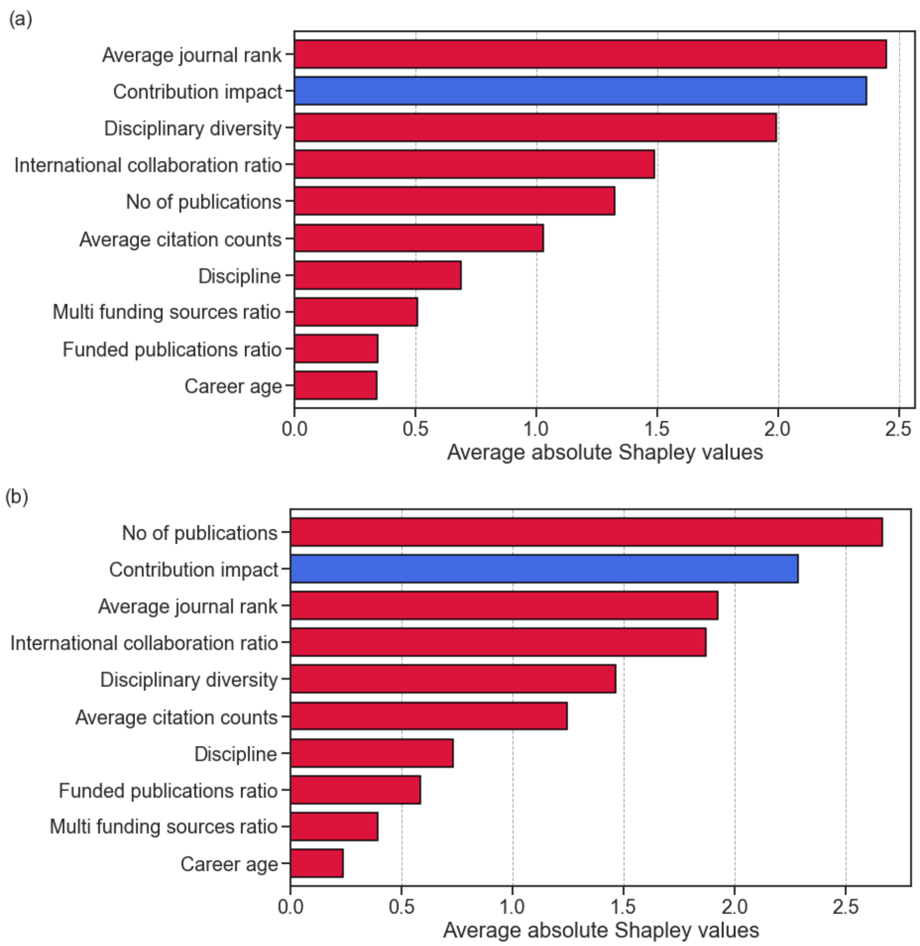

Figure 18. Feature importance in descending order to predict core **a)** female, and **b)** male social researchers. Features that have positive correlations with being core are shown in red color, otherwise blue. The x-axis denotes that by which magnitude each feature contributed to model predictions, which is calculated based on average absolute Shapley values over all observations.

6.2.4.2 Local Influencers

Figure 19 illustrates features' contribution in classifying core/peripheral AI researchers in terms of their closeness centrality. As observed, average journal rank is the strongest predictor for both genders. The positive effect of average citation counts is also noticeable, even though the number of publications has a relatively small positive impact on possessing core roles among female and male local influencers. A large negative impact of disciplinary diversity can be observed from the feature importance ranking plot, which motivated us to perform further investigation. Therefore, we plotted the probability density distribution of closeness centrality values for researchers involved in less or more than 5 research subfields (shown in Figure 20). We noticed that local influencers, i.e., researchers with higher closeness centrality, are mostly involved in diverse AI subfields (more than 5 subdisciplines). As shown in Section 5.2.2, being involved in more research areas may make researchers unable to have balanced contributions to all those subfields, leading to lower disciplinary diversity value.

Interestingly, we can observe that the discipline is the fourth most informative feature driving the prediction of core scientists for both genders. Hence, we further assessed the role of this factor by analyzing the SHAP dependence plot (Figure 21) which indicates the effect of involving in a particular discipline on being a local influencer for a given researcher. We found that while core local influencers generally engaged in some specific AI subfields, such as NLP, Genomics-Drug Discovery, and Computer Vision-Health Informatics, they are less involved in research areas such as Interent of Things (IoT)-Energy and Cyber Security-Network (See the AI subfields Appendix B). In addition, the number of distinct co-authors, average team size, and international collaboration ratio, as proxies to measure collaborative behavior of scientists, contribute positively to the model prediction.

However, there are more commonalities than differences between the two genders. We can see some differences in the collaborative behavior of top local influencers among the two genders. While average team size has a greater effect and importance on prediction core female researchers, this factor is less important for males. Other features, namely funded publication ratio, multi funding sources ratio, career age, and the number of publications, are also ranked as the least influencing factors based on their contribution to prediction scientists assuming core roles.

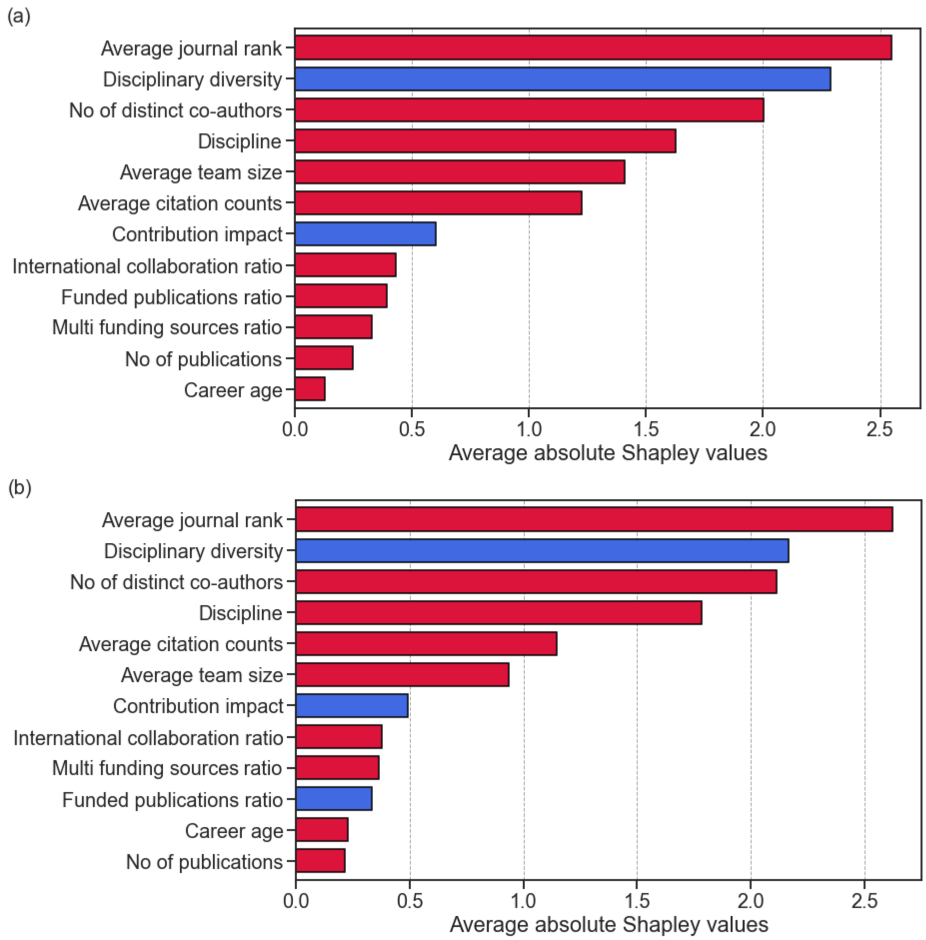

Figure 19. Feature importance in descending order to predict core **a)** female, and **b)** male local influencers. Features that have positive correlations with being core are shown in red color, otherwise blue. The x-axis denotes that by which magnitude each feature contributed to model predictions, which is calculated based on average absolute Shapley values over all observations.

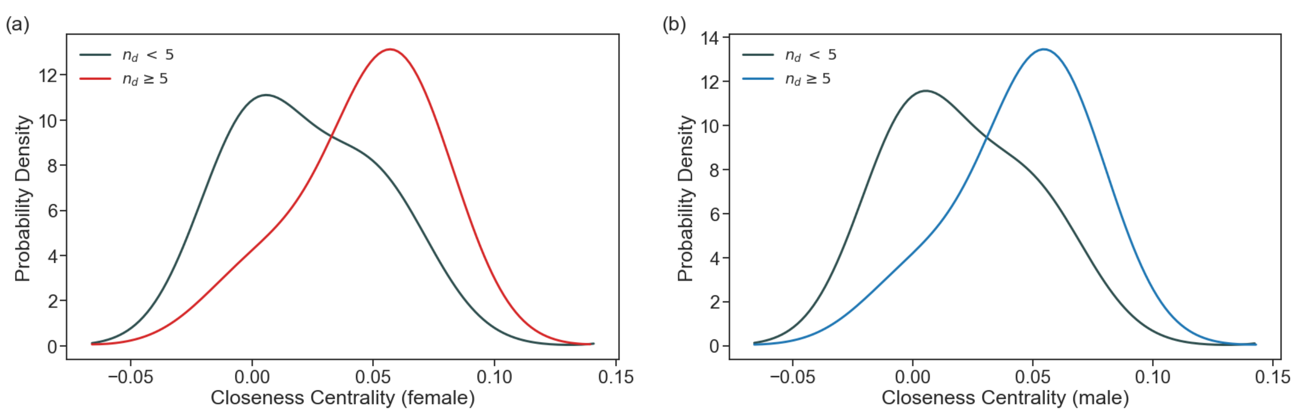

Figure 20. Probability density of closeness centrality values for **a)** female, and **b)** male researchers. n_d is the number of unique disciplines in which researchers publish.

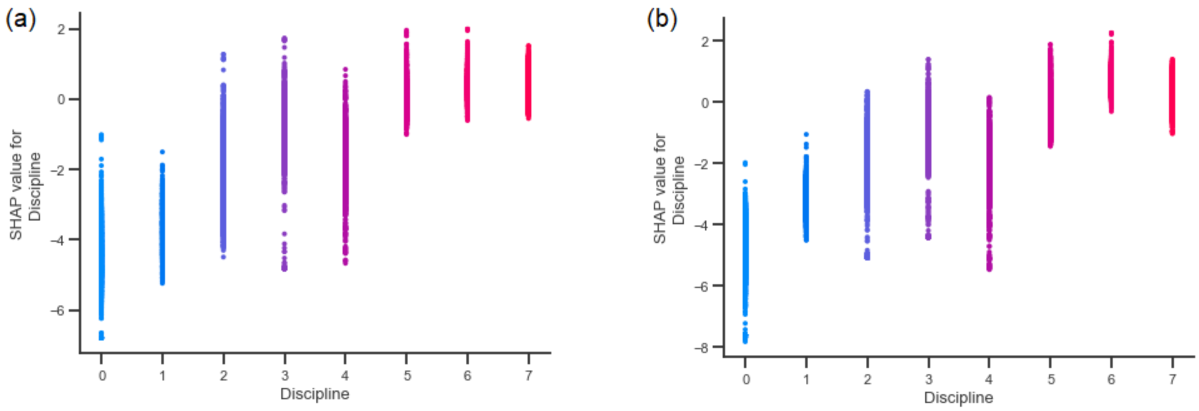

Figure 21. SHAP feature dependence plots for discipline **a)** female, and **b)** male researchers. Each dot indicates the effect of involving in a particular discipline on predicting core class for a given observation. Higher impact is represented by more red, whereas a lower impact is represented by more blue. Note: Since discipline is a categorical variable, it was coded by integer values for machine learning model. The list of discipline codes and names are presented in Appendix B.

6.2.4.3 Gatekeepers

Lastly, we analyzed the influencing factors in occupying gatekeeper roles, measured by betweenness centrality. As seen in Figure 22, the number of distinct co-authors is the most important driving factor that could positively affect the possibility of occupying core positions among female and male gatekeepers. We can also notice that this feature has a bit higher magnitude, measured by SHAP value, for men than women. The next driving feature is the number of publications, followed by the average team size for both genders. Suggested by these findings, highly productive and collaborative researchers are more likely to occupy highly central positions, maintaining influential brokerage roles within the AI community. Interestingly, the high value of average team size has a negative contribution to the prediction of the core class, indicating that top gatekeepers, in general, are involved in smaller teams compared to peripheral ones.

In addition, career age as a proxy for seniority level plays an important role in predicting core researchers, and this factor ranked higher for female core scientists. As observed, although high research performance, measured by average journal rank and citation counts, could lead female and male scientists to possess top brokerage positions, these features are a bit more important predictors for core male scientists. We can also see a positive impact for disciplinary diversity, meaning that the most influential gatekeepers generally have more balanced and diverse research profiles. This is fairly expected because these researchers are in superior network positions and could access a variety of knowledge and skill resources by bridging unconnected groups. Another gender difference is that disciplinary diversity is a more important feature for men. Finally, compared to discussed factors, funded publication ratio, multi funding sources ratio, discipline, and contribution impact have small positive impacts on core class prediction for both genders.

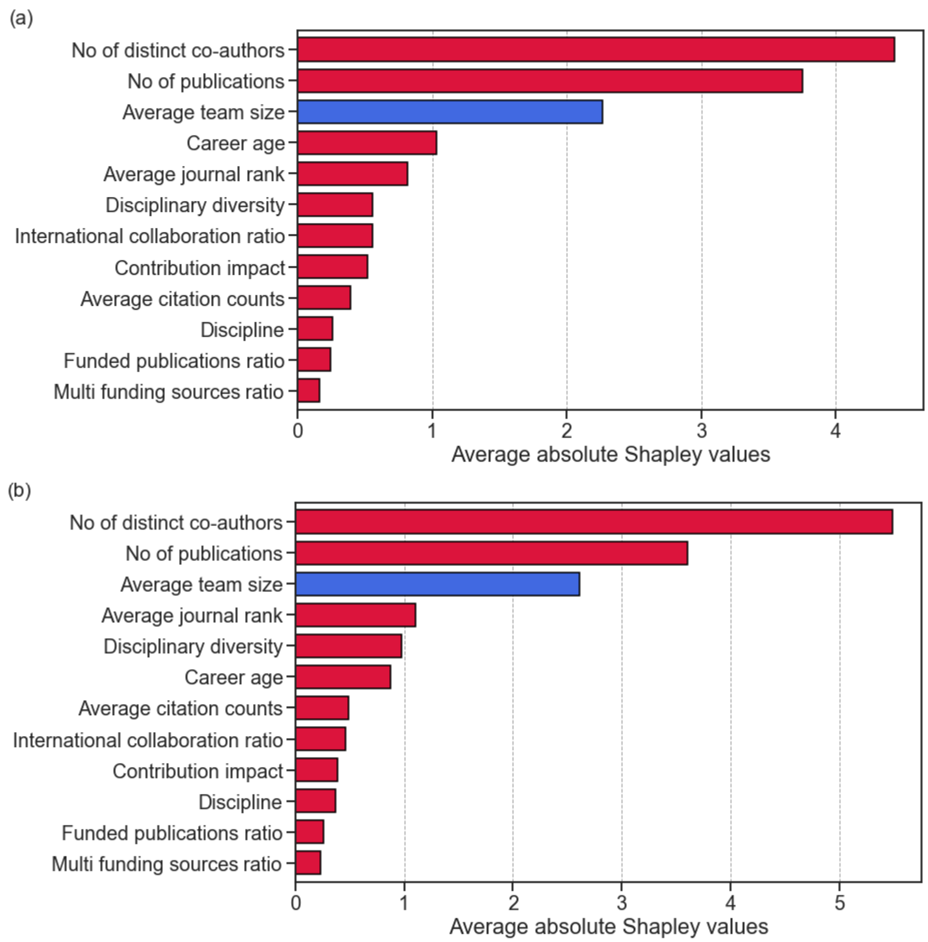

Figure 22. Feature importance in descending order to predict core **a)** female, and **b)** male gatekeepers. Features that have positive correlations with being core are shown in red color, otherwise blue. The x-axis denotes that by which magnitude each feature contributed to model predictions, which is calculated based on average absolute Shapley values over all observations.

6.3 Discussion

As science has become more complex, scientists are inclined to adopt more collaborative behavior, enabling them to benefit from diverse knowledge sources and address perplexing problems. Artificial Intelligence (AI) is a highly interdisciplinary and complex field involving a vast variety of research areas, and its advancement necessitates a diverse set of skills as well as a significant amount of R&D funding. As a key driver of the most current wave of scientific and technological revolution, AI has drastically influenced human's lives and ways of thinking, and considerably affected social, industrial, and economic activities (Howard, 2019). During recent years, AI evolution draws scientists' attention more than before, indicated by increasing trends for the number of researchers, scientific collaborative activities, and AI publications (AI Index, 2019).

Moreover, it is also believed that the AI research and industry community confronts rising demand for AI specialists with diverse expertise and face a significant gender gap and lack of gender diversity. This situation could negatively impact innovation activities and even bring unfairness and discrimination risks in AI development (UNESCO, 2020). Thus, it is vital to form teams with more qualified and diverse AI experts and create collaboration networks with effective knowledge sharing among actors. In this research, utilizing a combination of social network analysis and machine learning techniques, and a multi-dimensional feature vector at the author level that covers multiple characteristics of scientific activities, we first explored the characteristics of influential/central AI researchers as they can accelerate knowledge/innovation diffusion and form more efficient collaborations. Then we investigated any possible gender differences towards acquiring strategic network positions.

According to our findings, regardless of gender, performance metrics, measured by the number of publications, citation counts, journal impact factor, and involving in more diverse research areas and having a higher degree of internationalization play crucial roles in acquiring network positions with a high degree centrality. At the same time, we observed a stronger impact of publishing papers in more diverse research areas and higher-ranking journals on degree centrality among female social researchers, suggesting that they might gain more from their direct and distinct collaborators than male social researchers.

Our results indicated subtle differences between female and male AI researchers when influential researchers were defined based on their number of close collaborators and the degree of reachability (higher closeness centrality). In general, local influencers tend to produce high-impact work and be highly collaborative. Interestingly, we found that discipline is one of the prominent factors that can increase the chance of acquiring influential positions. Local influencers are more likely to be active in disciplines such as NLP, Genomics-Drug Discovery, and Computer Vision-Health Informatics, and they, on average, publish in more diverse research areas.

Lastly, it was observed that a high number of distinct co-authors stands out as the most leading factor affecting the possibility of possessing brokerage roles. Gatekeepers, i.e., researchers with high betweenness centrality, have a high number of distinct collaborators, but on the other hand, they tend to form smaller research teams. This could imply that it is not necessarily needed to be part of big teams to obtain research excellence. Furthermore, our findings suggest that gatekeepers are the ones who are more likely to have higher seniority levels and scientific performance in terms of both quantity and impact.

7 Summary

Undoubtedly being the main driver of many emerging technologies, artificial intelligence is changing the world and many aspects of the way we live, impacting tremendously our future. Within such an evolving and complex ecosystem that is attracting significant investments annually, training leading AI researchers is also complex and costly. In this work, we employed multiple techniques including natural language processing, machine learning, social network analysis, and statistical analysis, to comprehensively analyze gender-specific patterns in the AI scientific ecosystem from 2000 to 2019 and address our two main research objectives: (1) Explore the collaboration patterns of AI scientists; (2) Investigate the effects of driving factors on acquiring key/central network positions and explain any possible gender differences.

Regarding our first objective, we shed light on gender differences in collaborative behavior and how these differences could impact academic success. We also highlighted that disciplinary homophily is one of the main team composition characteristics in the AI scientific ecosystem. In spite of the gap observed between the female and male researchers active in the field, we found promising indications of growth in the number of female scientists in the AI ecosystem. The differences observed between genders in performing scientific activities and collaboration are of crucial importance.

Regarding our second objective, we utilized common network centrality metrics, i.e., degree centrality, closeness centrality, and betweenness centrality, to distinguish the most central AI scientists and categorize them into three groups based on their network positions, including social researchers, local influencers, and gatekeepers. Using ML techniques, we then provided a deeper understanding of the profile of highly central/influential male and female AI scientists. We demonstrated that various individual author-level factors could contribute differently to occupying different key/strategic network positions in the AI co-authorship network. However, some of the notable characteristics of central researchers, regardless of their gender, are their highly collaborative behavior and high research productivity and impact. These central (influential) researchers can facilitate and speed up knowledge flow and exchange across the network and form more efficient and effective scientific collaborations. Moreover, they can assist other researchers in gaining better access to different skills and knowledge resources and, in general, form a more cohesive and efficient collaboration network. Thus, in co-authorship network analysis, it is critical to distinguish between core and peripheral researchers, i.e., between individuals who stand out as core players in network structural metrics such as degree, betweenness, and closeness centrality and others who do not act as intermediaries or nurture overall cohesion and connectivity of the network.

This work represents an important step in using ML algorithms to explore and elucidate network structure variables. Our findings provide new insights to understanding the structure of the fast-evolving AI ecosystem and identify the role of influencing factors to acquire central positions in the AI research community. This work may help policymakers and researchers adjust their strategies to make most of the interdisciplinary collaborations and accelerate innovation and knowledge transfer in a highly interdisciplinary field such as AI. In addition, our analysis provides a comprehensive picture of the gender-specific patterns in AI that could help the policymakers to modify existing or develop new strategies to support female researchers more effectively and efficiently by considering all the aspects of the differences between females and males. This involves taking into consideration not only aspects related to initiating, leading, and maintaining collaboration and scientific activities, but also other influencing factors such as social and family responsibilities that could impact their professional career. We also found the existence of disciplinary homophily among AI researchers. However, we also assume that researchers who are primarily collaborating with others with similar research profiles in a fast-evolving and interdisciplinary field such as AI might be less exposed to the new knowledge that could impede research novelty. Therefore, it is suggested that researchers of both genders maintain a balance between collaborating with others with similar and diverse disciplinary profiles to benefit from efficient communication and accessing new knowledge leading to novel research.

8 Limitations and Directions for Future Research

We focused on gender-specific patterns in the AI field as a highly interdisciplinary male-dominated field (World Economic Forum, 2018), and this characteristic might partially affect our results. Thus, future research could analyze other emerging technologies to compare the results. Moreover, while a recent study (Huang et al., 2020) utilized longitudinal data to investigate gender inequality in academia and reported that career-wise differences could mainly explain gender disparity in research performance, we used cross-sectional data in this work and focused on only researchers' AI-related activities. Hence, future research may consider a longitudinal perspective and examine the entire research activities of scientists to explore gender-specific patterns and find any possiblegender differences. We applied an automatic gender assignment algorithm and excluded authors for which we were unable to assign gender. Future research could explore other gender assignment strategies such as manual and/or semi-automatic. However, manual gender assignment would be time-consuming and not feasible in large-scale data.. In this study, we analyzed collaboration patterns among researchers through a co-authorship network. Although the co-authorship network is regarded as one of the most common and tangible indicators to measure scientific collaboration, it cannot capture all collaboration types inasmuch as collaborative efforts do not always result in a joint publication (Katz & Martin, 1997). Another future direction could be addressing this issue by taking other approaches to measure research collaboration. We used betweenness centrality to measure researchers' brokerage role in the co-authorship network. Future studies may consider other centrality measures such as eigenvector centrality and analyze their relationships with researchers' scientific performance. Additionally, we considered the time difference between the authors' first and last publications as a proxy for their career age as we did not have data on researchers' age and/or seniority level. One may use other proxies for authors' seniority level in future research and compare the results. Since the Scopus database contains funding information for articles that acknowledged funding sources, we could not precisely estimate the funded publication ratio for authors, and future studies may acquire more accurate funding information by performing survey analysis although it may not be feasible for large-scale data. We used articles' abstracts and titles to infer researchers' disciplinary profiles. Future research could further explore the authors' research disciplines by taking the entire publications' text into the account. We applied the weighted contribution impact technique to quantify authors' contributions in their publications. It should be noted that while there are several approaches to quantify authors' research contribution, all methods have their own limitations since measuring research contribution is a challenging task. Thus, future research may consider survey analysis to obtain a more accurate estimation of authors' contributions in their articles. This work identified the most central researchers by calculating common network centrality metrics and categorizing researchers based on their centrality values. Future work may consider other network structural properties or apply other techniques such as unsupervised machine learning (clustering) to identify core and peripheral researchers. Lastly, another interesting future research direction would be expanding our feature space and, for example, investigating the effects of casual mechanisms, psychological, and cognitive properties of authors on achieving certain strategic roles in co-authorship networks.

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Appendices

Appendix A Descriptive Statistics of Network Variables

Table 3. Descriptive statistics of centrality metrics for female dataset

Female Dataset	Degree Centrality	Closeness Centrality	Betweenness Centrality
mean	0.000231	0.022200	0.000007
Std	0.001090	0.025260	0.000074
min	0.000000	0.000000	0.000000
25%	0.000019	0.000025	0.000000
50%	0.000032	0.000092	0.000000
75%	0.000070	0.048230	0.000000
max	0.010722	0.077099	0.005431

Table 4. Descriptive statistics of centrality metrics for male dataset

Male Dataset	Degree Centrality	Closeness Centrality	Betweenness Centrality
mean	0.000248	0.020715	0.000012
Std	0.001252	0.024602	0.000107
min	0.000000	0.000000	0.000000
25%	0.000019	0.000025	0.000000
50%	0.000032	0.000074	0.000000
75%	0.000064	0.046289	0.000000
max	0.000248	0.020715	0.000012

Appendix B Artificial Intelligence (AI) Subfields

Table 5. AI subfields

Discipline code	Discipline name
0	Internet of Things (IoT)-Energy
1	Cyber Security-Network
2	Decision Support Systems
3	Unsupervised Learning
4	Machine/Deep learning
5	Natural Language Processing (NLP)
6	Genomics-Drug Discovery
7	Computer Vision-Health Informatics

Appendix C Definition of the core scientists

As we mentioned in the methodology section (Section 6.1), to measure researchers' influence within the AI co-authorship network, we calculated three commonly used centrality metrics: degree, closeness, and betweenness centrality. We then associated the top 5% of researchers with the highest centrality values as "*core*" and the rest as "*peripheral*" and defined respective roles for these central researchers, including *social researchers*, *local influencers*, and *gatekeepers*. It is worth mentioning that we also tried the 10% threshold to identify the most central AI scientists, and we found 5% as the optimum percentage for our research objective since we aimed to examine the profiles of the most central/influential scientists. However, the results of model evaluation and profiles of the top 10% AI scientist in terms of different centrality metrics are presented in Appendix E. We observed almost similar patterns when using 10% threshold instead of 5% and we discuss minor differences for each role as follows:

Social researchers (top 10% AI scientists): Feature importance ranking is almost similar to the 5% scenario, as shown in Figure 23 (Appendix E). The only difference is that high disciplinary diversity negatively impacts being among the top 10% of social researchers, which makes sense as these researchers may have less distinct collaborators than the top 5% of researchers, which negatively affects their disciplinary diversity.

Local influencers (top 10% AI scientists): Again, for this role, we observed more commonalities than differences. Number of distinct co-authors and average team size are less important features for females when considered 10% as a threshold (Figure 24-Appendix E). One possible explanation might be that top 5% of researchers are assuming more reachable and central positions compared to the top 10% of researchers, which could enable them to collaborate with more distinct authors and form larger research teams.

Gatekeepers (top 10% AI scientists): Like social researchers, feature importance ranking is almost similar to the 5% scenario, and the only difference is that high disciplinary diversity negatively impacts being among the top 10% of social researchers (Figure 25-Appendix E).

Appendix D Model Evaluation (Top %10 of scientists)

Table 6. Model performance validation for predicting core scientists using repeated stratified ten-fold cross-validation. Evaluation metrics were averaged over 30 disjoint validation sets. The table indicates the means and expected variations of performance scores over all repetitions and all folds.

Prediction of core scientists	Validation sets	Precision	Recall	F1 score
Degree Centrality	Female	0.92 ± 0.01	0.93 ± 0.01	0.91 ± 0.005
	Male	0.91 ± 0.008	0.93 ± 0.01	0.92 ± 0.01
Closeness Centrality	Female	0.87 ± 0.02	0.80 ± 0.01	0.83 ± 0.01
	Male	0.85 ± 0.01	0.80 ± 0.01	0.83 ± 0.01
Betweenness Centrality	Female	0.87 ± 0.01	0.93 ± 0.01	0.90 ± 0.01
	Male	0.78 ± 0.01	0.87 ± 0.01	0.82 ± 0.008

Table 7. Model performance evaluation using distinct test sets.

Prediction of core & peripheral scientists	Test sets	Precision		Recall		F1 score	
		Core	Peripheral	Core	Peripheral	Core	Peripheral
Degree Centrality	Female	0.92	0.99	0.94	0.99	0.93	0.99
	Male	0.91	0.99	0.92	0.99	0.91	0.99
Closeness Centrality	Female	0.90	0.98	0.80	0.99	0.85	0.98
	Male	0.86	0.98	0.82	0.98	0.84	0.98
Betweenness Centrality	Female	0.88	0.99	0.93	0.99	0.90	0.99
	Male	0.79	0.99	0.88	0.97	0.83	0.97

Appendix E Profiles of Core AI Scientists (Top %10 of scientists)

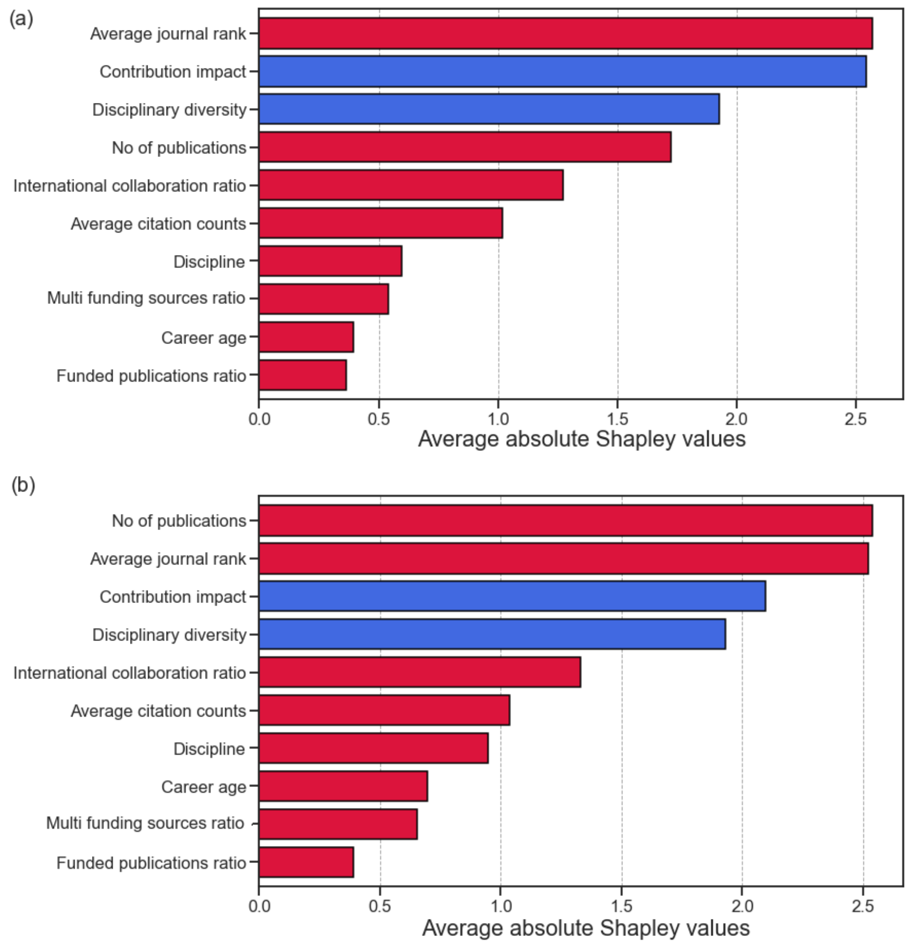

Figure 23. These plots indicate the importance of features, in descending order, to predict core **a)** female, and **b)** male social researchers. Features that have positive correlations with being core are shown in red color, otherwise blue. The x-axis denotes that by which magnitude each feature contributed to model predictions, which is calculated based on average absolute Shapley values over all observations.

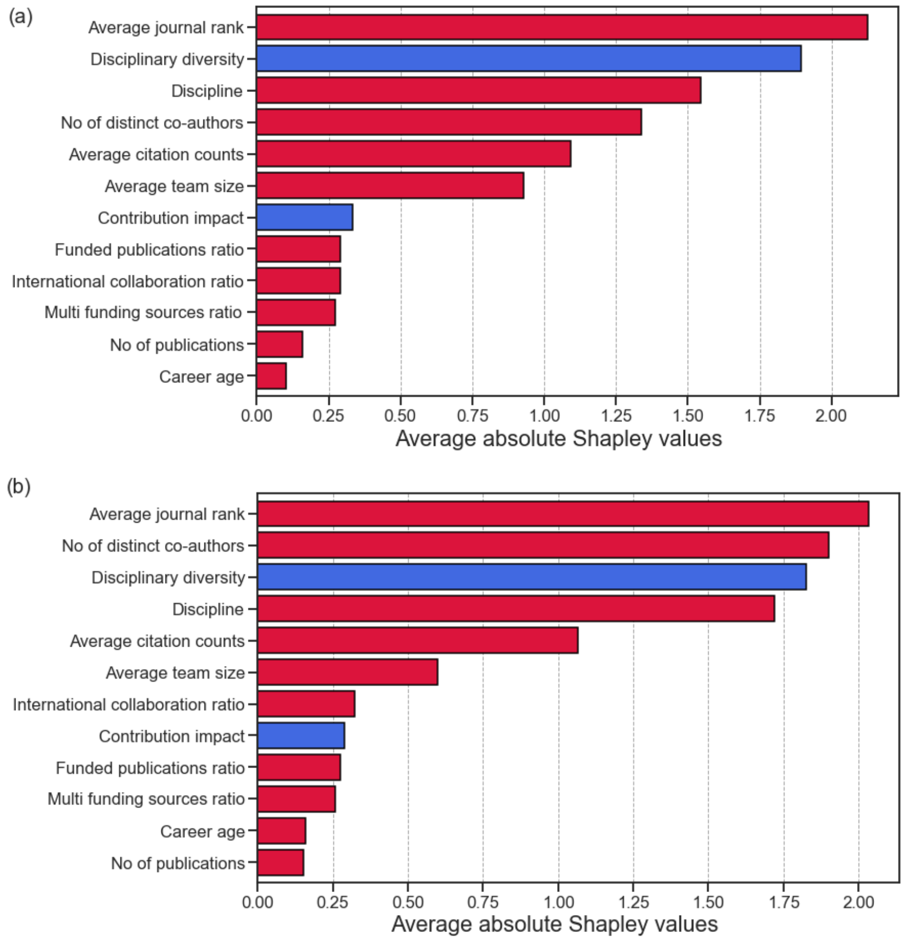

Figure 24. These plots indicate the importance of features, in descending order, to predict core **a)** female, and **b)** male local influencers. Features that have positive correlations with being core are shown in red color, otherwise blue. The x-axis denotes that by which magnitude each feature contributed to model predictions, which is calculated based on average absolute Shapley values over all observations.

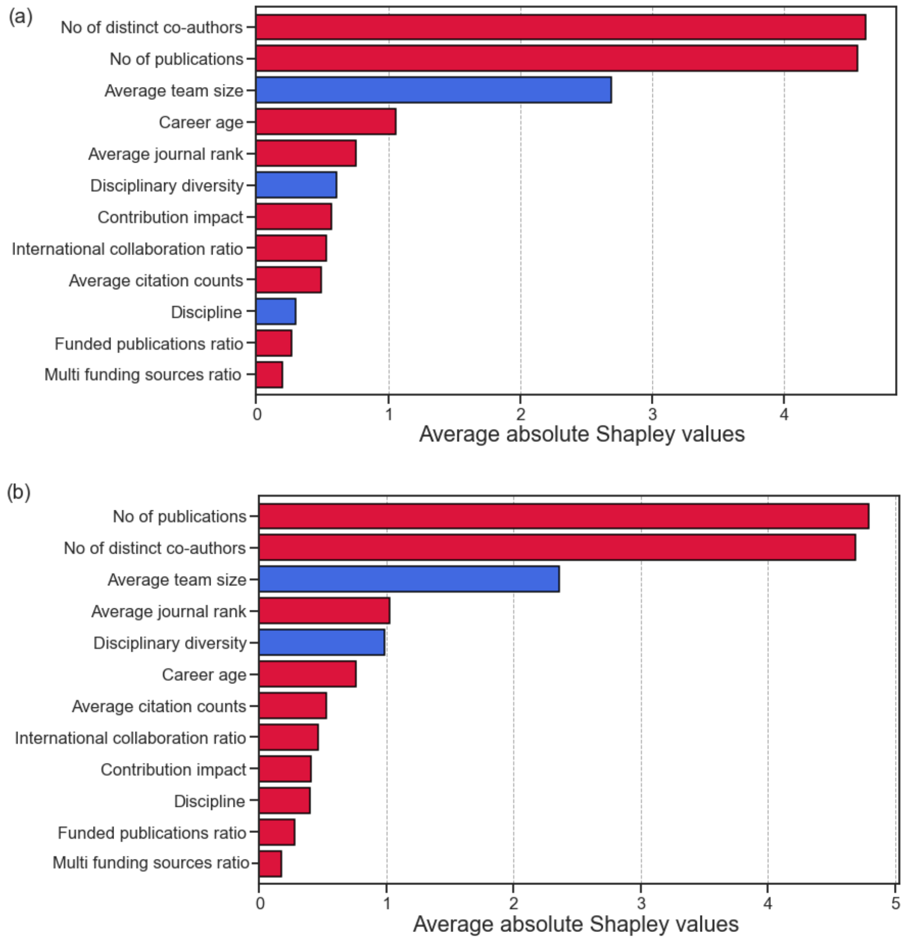

Figure 25. These plots indicate the importance of features, in descending order, to predict core **a)** female, and **b)** male gatekeepers. Features that have positive correlations with being core are shown in red color, otherwise blue. The x-axis denotes that by which magnitude each feature contributed to model predictions, which is calculated based on average absolute Shapley values over all observations.