Computational and relational understanding of gender inequalities in science and technology

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Researcher declaration

I, Orsolya Vásárhelyi, certify that I am the author of the work "Computational and relational understanding of gender inequalities in science and technology". I certify that this is my own original work, except parts where I have clearly indicated, in this declaration and in the thesis, the contributions of others. The copyright of this work rests with its author. Quotation from it is permitted, provided that full acknowledgement is made. This work may not be reproduced without my prior written consent.

Statement of inclusion of joint work

I confirm that Chapter 4 is based on a paper which was written in collaboration with Dr. Balázs Vedres, and published at EPJ Data Science in 2019 [1]. We developed the idea of quantifying gendered behaviour based on users' online activity together. I managed the data preparation and modelling. Dr. Vedres and I developed and implemented the manuscript together. Dr. Vedres endorses this statement with his signature below.

I confirm that Chapter 5 is based on a working paper which was written in collaboration with Emőke-Ágnes Horvát, Staša Milojević and Igor Zakhlebin. I conceived the idea to explore the gender differences in science dissemination online. Besides data collection done by Igor Zakhlebin, and research area identification done by Dr. Milojević (a method used based on her previours work [2]), I conducted the entire research under the supervision of Dr. Horvát. Dr. Horvát endorses this statement with her signature below.

I confirm that Chapter 6 is a result of a collaboration with Dr. Balázs Vedres. Dr. Vedres and I collaborated on developing and improving the methods used in this chapter. The original dataset was provided by Dr. Vedres. Dr. Vedres endorses this statement with his signature below.

Signature of PhD Candidate: Orsolya Vasarhelyi
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April, 2020

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April, 2020

Abstract

Women are still a minority in Science and Technology, and gender discrimination persists, even though recent research suggests gender diversity can be beneficial in teamwork: female members increase the overall intelligence of teams, gender-diverse scientific teams are more creative and produce higher quality science, and diversity enforces objectivity, helps to process information more carefully and can reduce unconscious bias. However, in male-dominated fields, gender diversity has been associated with worse performance and lower success. Most diversity advocates agree that diversity without inclusive work practices will not help teams to perform better. As our lives rely heavily on scientific and technological innovation, the lack of diversity has high societal costs: unintended consequences of non-diverse scientific teams range from not developing proper medical interventions for women to not ensuring that technological innovations profit women and men equally.

Since success is a collective measure that captures a community's reaction on one's performance, (unconscious) gender bias can impact one's reputation. For women, successful role models are crucial to envision a potential career in STEM, therefore identifying the micro-, meso- and macro-level behaviour patterns that hold women back is crucial for better female representation. This work presents findings on how gendered behavior and gendered network formation influence women's success in three male-dominated STEM fields which serve as gatekeepers for future STEM careers: Open Source Software Development, Academia and the Video Game Industry.

The purpose of this research is to use computational methods on large-scale data to explore how gender inequalities are embedded into social networks. This dissertation has three major contributions. First, the main contribution is applying data and network science methods on large datasets to uncover the relational complexity of hidden gender inequalities. The second important contribution is moving beyond the typical gender inequality research, which conceptualizes gender-based discrimination as categorical discrimination with quantifying gendered behaviour based on users' online activity. Third, a key contribution is introducing a new approach with relevant findings to the ongo-

ing debate on positive and negative effects of team diversity.

Findings suggest that gendered behaviour and gendered network formation are key drivers of online inequality, although the negative consequences of categorical gender stereotypes might still be present as well. Since the segregation of women is the product of a masculine culture in STEM fields, I argue that we cannot overcome gender inequality as long as a cultural shift does not happen.

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CHAPTER 1

Introduction

1.1 Background

The way that science and technology has changed our lives over the last two decades is remarkable: smartphones, big data, artificial intelligence, self-driving vehicles, social media, personalized medicine – just to mention a few life-changing innovations. Science, Technology, Engineering and Mathematics (STEM) has become the driving force of innovation, which enables economic growth and welfare [5, 6, 7]. Technological entrepreneurs and scientists are celebrated as rock stars, and the Silicon Valley is considered to be the epicentre of geniuses who are creating the future of humankind. However, as many times before in human history, women seem to be left out of this historical movement[8, 9, 10, 11, 12, 13, 14]. Recent years' scandals in the technology industry brought into the spotlight the low representation of women, and the negative consequences of the widely present masculine culture: discrimination, unbreakable glass ceiling, sexual harassment, and a significant gender pay gap [15, 16, 17, 18, 19].

Feminist scholars argue that initially women had important roles in the technological revolution; however, the masculine culture in engineering decreased women's importance, and made femininity incompatible with technical occupations [20, 21]. This cultural shift has had long-lasting consequences. Women are still less likely to pursue STEM careers, and more likely to leave their STEM-related jobs behind [22, 23, 24]. Low female representation in STEM occupations is a global phenomenon: according to UNESCO, only 30% of STEM researchers were women in 2015 [25]. The ratio of women in the industry is even lower: in 2017, 25.4% of employees in computer and mathematical occupations were women in the United States [26, 27]. Considering the fact that the demand for qualified STEM workers is growing every year by approximately 200,000 new job postings only in the United States, it is a luxury to leave women out of the world of technology [28]. A recent study by the World Economic Forum estimates that the gender pay gap will not close for another 257 years, and the low representation of women in STEM occupations has enlarged the wage gap between men and women [29]. It would be a rational decision to attract more women to STEM fields to decrease already existing wage inequalities, although unconscious gender bias can block these endeavours: it is historically shown that if a large number of women move into an occupation the prestige of the field drops and it becomes less paid [30]. Moreover, underrepresented groups are very likely to be embedded into highly homophilous interpersonal networks, blocking their access to power, information and promotion [31]. Thus, increasing female representation in STEM fields without changing the cultural context can be counterproductive.

Since hierarchical gender relationships are present in most Western societies, men are usually more dominant in powerful institutions [21], the gendered aspects of inequalities are deeply embedded into everyday work processes, norms, and societal values [32]. According to *Hegemonic Gender theory*, men and women are both penalized by society if they do not follow the accepted rules and norms of their gender [33, 34]. For example, women in powerful positions are often criticized for being too aggressive and not feminine enough [33]. That is why women in highly masculine occupations face a paradoxical visibility problem: they are highly visible as being female, but many times overlooked as experts, as they do not fit the stereotype [35].

However, there is ample evidence that gender diversity is beneficial in teamwork: female members increase the overall intelligence of teams [36], gender-diverse scientific teams are more creative and produce higher quality science [37], and diversity enforces objectivity, helps to process information more carefully and can reduce unconscious bias [38, 39]. As our lives rely heavily on scientific and technological innovation, the lack of diversity has high societal costs. Unintended consequences of non-diverse scientific teams range from not developing proper medical interventions for women to not ensuring that technological innovations profit women and men equally [40, 41, 42, 43]. To make sure that newly developed algorithm-driven solutions are not sustaining, or at least not magnifying already existing inequalities, is a high-priority scientific objective. Even though a new field of computer science has emerged which focuses on algorithmic fairness and ethical data science, our current knowledge of how unconscious gender bias manifests itself in teams, and creates structural and cultural barriers that can marginalize women, is still limited.

Most empirical studies focus on why women do not choose STEM occupations and on what the systematic challenges are that make them leave their chosen field [44, 45, 22]. Gender studies scholars have made significant progress in mapping the cultural aspects of why women are underrepresented and less successful in highly male-dominated industries; however, their studies are based on small sample size case studies, therefore the generalizability of the results is limited [33, 30, 46, 20, 47]. The availability of large-scale interaction data allowed scientists to analyze systematic gender inequalities in science and engineering helping to understand the macro-level patterns that can make women less successful [48, 49, 50, 51, 52, 4, 53, 54, 55].

Since success is a collective measure that captures a community's reaction on one's performance [56], (unconscious) gender bias can impact one's reputation. For women, successful role models are crucial to envision a potential career in STEM [57, 58, 59, 60, 61, 62], therefore identifying the micro-, meso- and macro-level behaviour patterns that hold women back is crucial for better female representation. My dissertation presents findings on how gendered behaviour, and gendered network formation influence women's success in three male-dominated STEM fields: Open Source Software Development, Academia and the Video Game Industry. Although there are contextual differences between the three analyzed fields, they share common problems: low female representation, especially in higher positions [63, 64, 65, 66, 67, 68], a highly masculine culture which defines who is considered to be successful [64, 69, 70, 71, 72, 73] and a project-based environment which increases the significance of interpersonal networks [66, 55, 74]. Furthermore, these fields serve as gatekeepers for future STEM careers. Playing video games has been shown to increase young girls' interest in science [75], thus creating gender-inclusive games that do not marginalize girls, and allow them to express themselves can increase female representation in technical fields in the long-term. Making sure that we have gender equity and an open culture in academia is crucial for training the next generation of female technical professionals as well. As technology is interwoven into our lives and programming skills become a necessity in many professions the *gatekeeper* function of platforms, where beginner programmers and early-stage professionals can ask questions and receive feedback increases. GitHub serves as a portfolio site for early-stage career professionals [76, 77], therefore keeping women active in open source software development can also have long-term positive impacts.

The purpose of this research is to use computational methods on large-scale data to explore how gender inequalities are embedded into social networks. Since the segregation of women is the product of the masculine culture in STEM fields, I argue that we cannot overcome gender inequality as long as a cultural shift does not happen.

1.2 A new computational and relational understanding of gender inequalities

My dissertation has three major contributions. First, the main contribution of my dissertation is applying data and network science methods on large datasets to uncover the relational complexity of hidden gender inequalities. The second important contribution is that I move beyond the typical scope of gender inequality research, which conceptualizes gender discrimination as categorical discrimination, quantifying gendered behaviour based on users' online activity. Third, a key contribution is introducing a new approach with relevant findings to the ongoing debate on positive and negative effects of team diversity.

First, I apply data and network science methods on large datasets to uncover the relational complexity of hidden gender inequalities. Using big data to analyze (online) inequalities is part of the recently developed research field of Computational Social Science. There are significant case studies analyzing the relational aspects of gender inequalities in technology and science [78, 79, 80, 81, 82, 83, 84, 85, 74, 55], but our knowledge is still far from being comprehensive. All below presented papers aim to understand how gender-specific behavioural traits and network formation patterns predict success in the given context, using predictive models and machine learning techniques. My research aims to extend the literature of computational social science, the social sciences, and gender inequality research from the methodological and conceptual perspectives.

By focusing on the relational perspective of career building, the path-dependency of structural and cultural inequalities becomes visible. The first two case studies (Open Source Software development in Chapter 4, and Academic Research in Chapter 5) analyze the role of gendered behaviour and gendered network formation in individual success. While one's career success is analyzed, it is important to keep in mind that all careers are linked and influence one another. The study on scientists' popularity online shows that offline gender inequalities in scientists' networks perpetuate, or even reinforce women's offline disadvantage. Both studies deal with individual careers that are embedded into collaboration networks, and present that gender homophily is a key driver of collaborations, even though women are significantly more underrepresented than men. Due to the subordinate role of women, lower ranking positions and prestige in technical fields [13, 14], the marginalization of women is especially harmful and slows down the progress towards gender equality [31].

Second, I operationalize gendered behaviour in an online setting (Open Source Software Development) by predicting with a machine learning model whether a user's inferred gender is female. The model takes into account variables covering behavioural choices in the level of activity, specialization in programming languages, and the gender choice of collaborators. An important methodological consideration is that the variables that capture one's behaviour are theoretically under the control of the individual. However, since these traits are probably not fully under the control of the individual, it is likely that the reasons behind the predictable nature of gendered behaviour is due to constrained choice and deep-rooted stereotypes, rather than free choice. Results show that women's disadvantage in success and survival is mainly due to the gendered nature of their online behaviour.

Similarly to open source software development, we found evidence that the negative consequences of gendered choice of interest is present among academics. In fields with a higher female ratio (Social Sciences and Psychology), traditionally feminine topics are significantly more common among female than male scientists, and receive systematically less coverage online. However, in fields with very low female representation (Physics) we found that there are very few significant associations with either gender. This indicates that in male-dominated fields the successful strategy for women is to follow less female-like behaviour. Although female scholars chose non-stereotypically female topics, they are still associated with lower levels of coverage than the ones chosen by their male colleagues. Likewise, in Open Source Software development, men who followed highly female-like behavior were still more successful than women with the same extent of female-like career traits. This indicates that gendered behaviour is a key driver of online inequality, although the negative consequences of categorical gender stereotypes might still be present as well.

Third, I introduce a new approach with relevant findings to the ongoing debate on positive and negative effects of team diversity [36, 38, 39, 78, 86, 87, 88, 89, 90, 91, 92, 93, 94]. As a response to the harsh criticism of academia and the technology industry being too white and male, employers started to invest more into attracting diverse talent [16, 15, 17, 95]. However, these endeavours were not fully welcomed by employees, resulting in huge scandals such as the case of the Google Memo[1] [96]. Until a consensus is reached that diversity is indeed (economically) beneficial, only moral considerations can guide companies towards gender equality. Moving from individual careers to the meso-level by

[1] In July 2017, Google engineer James Damore started to circulate a document among Google employees called "Google's Ideological Echo Chamber" which was a critical essay on Google's diversity policies. In his memo, Damore argued that Google's positive discrimination towards women is harmful, and the company is not aware of the biological reasons that explains difference in men and women's interest in technology. The memo was leaked on August 7, 2017, and attracted huge media attention. In August 2017, Damore got fired for violating Google's Code of Conduct [96]

analyzing production teams allows me to explore how diversity can improve teams' creativity and success. Even diversity advocates agree that diversity without inclusive work practices will not help teams to perform better[97], although, arguably, no widely accepted inclusion metric has been developed. In the third case study of my dissertation, we introduce a data-driven inclusion metric quantified on team networks and analyze how the interaction of diversity and inclusion predicts teams' creativity and success in the video game industry.

Findings indicate that investing only in diversity without inclusion is not beneficial: a high level of diversity with a low level of inclusion predicts the lowest level of creativity. Teams need both high inclusion and diversity to create an environment where creativity can flourish. In addition, we found supporting evidence that inclusion is negatively related to success in the video game industry, indicating that as long as a cultural shift does not happen, the gender diversity of a production team itself will not be a valuable asset to a game's success. This case demonstrates that even though well-integrated, gender-diverse teams can create more innovative products, as long as the cultural norms and values are defined by a non-diverse pool of stakeholders, the positive effects of diversity cannot manifest themselves in success.

1.3 Structure of the dissertation

My dissertation is structured as follows. Before presenting my three cases, I summarize the current trends in gender inequalities in technology and science (Chapter 2). Beyond a statistical description of current female representation in STEM fields, this chapter describes the reasons why young girls are less likely to choose STEM careers, and outlines the structural difficulties that women face throughout their careers, focusing especially on the three previously introduced fields.

In Chapter 3, I introduce the theoretical foundations of my research and introduce recent findings in network and data science. Since gender discrimination is closely related to the concept of gendered behaviour and gendered organization, I start this chapter by discussing these two key concepts. Then moving to the meso-level, I discuss findings on the impact of gender diversity on team performance and success. Social networks can block women's access to crucial information to advance in their careers, therefore I also give an overview on the role of networks in women's careers. I finish the last introductory chapter with a short overview of recent literature on how gender discrimination manifests online.

The first case study (Chapter 4) analyzes 7 million users' entire career data on the most popular Open Source Software development platform, GitHub. This chapter investigates why women are less successful, and drop out at higher rates than men in open source software development. Findings suggest that the disadvantage is more due to gendered behavior than to categorical discrimination: women are at a disadvantage because of what they do, rather than because of who they are. Men are also at a disadvantage if they follow female-like behavior, and users who hide their gender drop out at higher rates than those who reveal their gender. Results suggest that fighting categorical gender discrimination will have a limited impact on gender inequalities in open source software development, and gender hiding is not a viable strategy for women.

The second case study (Chapter 5) explores differences in the dissemination of articles of 537,486 scientists who had at least one article shared online in 2012. Literature supports that science dissemination is a crucial first step in exposing scholars' work to other scientists and the public, therefore it might be an important channel for female scientists to overcome gender-related inequalities in academia. It is unclear, however, whether the online sharing of scientific articles mitigates, perpetuates, or reinforces known gender-related inequalities. This chapter uses a unique data mash-up that combines detailed traces of the online sharing of scholars' articles, their publication histories, collaboration networks, scientific fields, and research topics. Findings provide evidence that factors related to social capital are the most important in predicting online popularity: in particular, the gender diversity of coauthor teams and gendered patterns in the authors' previous collaborations determine online success, which makes it harder to overcome gender inequalities that exist offline among scholars. Interestingly, traditional measures of scientific merit, such as productivity, the prestige of publication venue, and citation impact, matter the least across fields in predicting online popularity, regardless of the author's gender.

The final case study (Chapter 6) focuses on the role of gender diversity and inclusion in the video game industry using data based on 15 years of video game development from a video game repository website, called Moby Games. We analyzed the collaborative career of 8,617 video game production teams consisting of 630,420 unique developers. Since our database goes back to the very beginnings of the video game industry, we are able to infer each individual's full career path; connecting unique user accounts with the games they had worked on in a consecutive order. In this chapter we conceptualize inclusion from a network science perspective, then test two hypotheses on how diversity and inclusion influence team success and creativity. Our findings indicate that investing only into gender diversity without inclusion is not beneficial: a high level of diversity with a low level of inclusion predicts the lowest level of creativity. Teams need both high inclusion and high diversity to create an environment where creativity can flourish. Although diversity and inclusion turned out to be a positive predictors of creativity, we did not find a significant relationship with team success. We measure success by the average evaluation of game reviewers, who are almost exclusively male. This suggests that the masculine culture of the video game industry does not reward ideas developed by gender-diverse teams.

I conclude by synthesizing our findings together, presenting policy implications of the interpretations, and suggesting future avenues of research.

CHAPTER 2

Current trends in gender inequalities in technology and science

My dissertation aims to explore how network and data science can help us understand stubborn gender inequalities in technology and science. As I outlined in my Introduction, I analyze three cases of inequalities: open source software development, the video game industry, and science. In all three cases I start from a relational understanding of path-dependent network structures reproducing inequalities. This introductory chapter discusses the problem of inequality, current trends in gender inequity in technology and science. The aim of this chapter to give an overview of female representation in technical fields in general then focus on each field which are the subjects of my case studies: open source software development, video game industry and academia.

2.1 Women's representation in STEM

When one imagines the greatest scientists of humanity, Galileo Galilei, Francis Bacon or Albert Einstein come to our minds. However, the word *scientist* was first used in connection with a woman, Mary Somerville. When William Whenwell was writing a review on Somerville's best-selling book, the *Connexion of the Physical Sciences* in 1834, he realized that people working in scientific disciplines needed a more specific but inclusive term than ″men of science″. Based on terms like ″economist″ and ″artist″ he created the word ″scientist″ [98]. Although the most known computer programmers and entrepreneurs in technology are mostly men; Bill Gates, Steve Jobs, Elon Musk [99], the first computer programmer was a woman. Just a decade after Somerville published her best-selling book, another outstanding lady published the first algorithm specifically implemented for a computer – Ada Lovelace (1843) [100]. These two are widely-known cases of women contributing in the early ages of the field of Science, Technology, Engineering and Mathematics (STEM). Feminist historians argue that women had important roles in the scientific revolution, but they have been omitted from the story-telling [101]. Long-lasting invisibility still holds it marks. It is a widely held view that men are more suited for STEM and it is believed that men can pursue science more successfully than women [102].

Despite the remarkable progress of women entering the job market in the twentieth century, gender inequality still persists. Women in highly masculine professions are facing a paradoxical visibility problem: they are exceptionally visible as women, but are often not regarded as experts [103]. This ignorance has crucial consequences. Due to the lack of female role models and non-welcoming organizational cultures, women are less likely to pursue STEM careers, and more likely to leave their STEM-related jobs behind [22, 23, 24]. There is no overall statistics available about the ratio of women working in STEM fields globally. Estimates are based on indicators: for example, the ratio of women enrolled in undergraduate education in STEM fields, employment statistics of national surveys and diversity reports of companies. According to UNESCO, 30% of STEM researchers were women in 2015 globally, but there are significant differences among fields and geographical regions [25]. Table 2.1 shows that except for life sciences, fewer women earn STEM degrees in every level of higher education in the United States [8]. Women of colour are even more under-represented in the United States: Asian women earned only 5%, Latinas 3.8%, and Black women 2.9% of all Bachelor's degrees in all STEM fields in 2015-2016 [104]. According to Eurostat, women are better represented in the natural sciences in the European Union: 53.3% of all post-secondary education degrees were earned by women in natural and life sciences, mathematics, and statistics, but only 27.7% in engineering, manufacturing and construction [105].

The ratio of female first-year students with STEM majors has increased in the Unites States, although women are less likely to choose math-intense majors and are over-represented in less math-intensive STEM majors, especially in life sciences (eg.: Biology, Medical sciences). As Figure 2.1 shows, the ratio of women in computer science has been declining from 36% in 1985 to 18% today; however, in other scientific fields female representation is steadily increasing [9, 10, 11, 12]. The fact that computer science was a much more popular choice among young women in the eighties than today is alarming, and indicates that the cultural aspects of a career choice cannot be overlooked.

As a result of women's low representation in computer science education,

Field	Bachelor	Master	PhD
Biological and biomedical sciences	59.9%	57.3%	53.0%
Mathematics and statistics	42.5%	41.7%	28.5%
Physical sciences and science technologies	38.8%	37.8%	32.2%
Engineering and engineering technologies	19.7%	25.2%	23.5%
Computer and information sciences	18.7%	30.8%	20.1%
All STEM Fields	35.5%	32.6%	33.7%

Table 2.1. *Percentage of degrees earned by women in higher education in the United States (2015–2016)*

their representation in the technology industry is also very low globally. In 2017, 25.4% of employees in computer and mathematical occupations[1] were women in the United States. Similarly to education, in general, women of colour are extremely under-represented in science and engineering (6.5% Asian women, 1.6% Black women, and 1.8% Latinas) [27].

The low representation of women in entry-level careers in STEM has long-term consequences for female leadership. In technical fields, women are even less represented on corporate boards than in any other industry [13]. According to a 2017 global report by the consulting company MSCI, 28.5% of Information, Communications, and Technology (ICT) companies had no women on their board. Most companies with no women were from East Asia, and the majority of companies with at least 3 women among board members were based in Western markets [14].

2.2 Why don't girls choose math-intensive careers?

Many explanations have been developed by feminist scholars as to why women do not pursue math-intensive careers, and especially computer science. Good mathematical ability is generally a good predictor of a future STEM career. Even though research on standardized math tests suggests no difference between young girls' and boys' performance on average [24], girls are less likely to par-

[1]This occupation category contains the following professions: Computer and Information Research Scientists; Computer Systems Analysts ; Information Security Analysts; Computer Programmers; Software Developers, Applications; Software Developers, Systems Software; Web Developers; Database Administrators; Network and Computer Systems Administrators; Computer Network Architects; Computer User Support Specialists; Computer Network Support Specialists; Computer Occupations, Actuaries; Mathematicians; Operations Research Analysts; Statisticians [26]

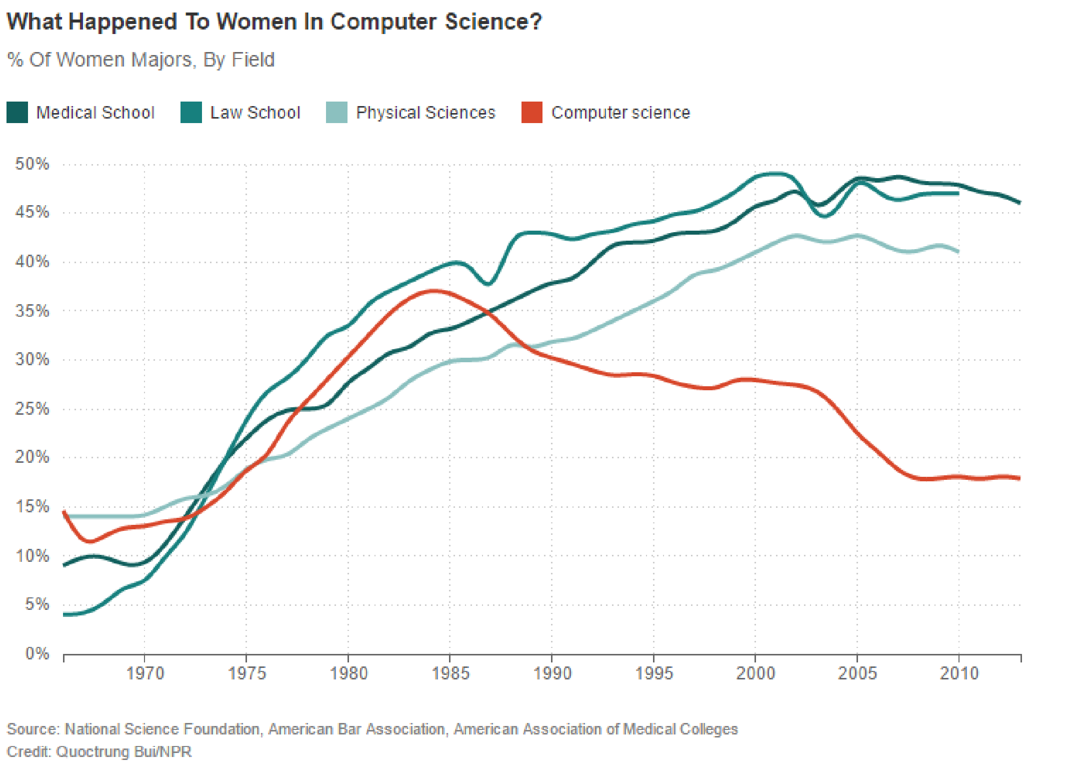

Figure 2.1. *The ratio of women by undergraduate degrees in computer science*

ticipate in science and engineering courses in high school [106]. It is also known that boys' math scores have a higher variance, and even in primary school there are more boys than girls among the top 1% of students, and this gap grows by the end of high-school [24]. Although on average there is no difference between young girls' and boys' mathematical abilities, the top-performing students are more likely to be boys, which can influence later career choices and personal attitudes towards science.

Attitudes towards mathematics and beliefs in gender stereotypes in the social environments of young children (family, school, friends) can play important roles in future career choices. Cvencek and Meltzoff found that by the end of second-grade children associate boys with "maths" and girls with "reading" [107]. Eccles and Wang found that teenagers with confidence in their own mathematical ability are more likely to pursue a STEM career within the next ten years [108]. Eccles and Jacobs showed that children's beliefs on how valuable maths is influenced their future performance [109]. Eccles and colleagues showed that if mothers had negative gender stereotypes about the math ability of women, their daughters' perception of their math ability was lower than what their teachers' assessment of their abilities would predict [110, 109]. It has also been shown that parents have lower math expectations for girls than boys [111] [106]. Parents' growth mindset towards sciences positively impacts children's beliefs that they can learn mathematics, which is twice as important for girls as for boys. Having a parent employed in STEM increases children's probability of majoring in STEM, especially for girls. A maternal role-model in STEM increases the likelihood of girls choosing a career in the hard sciences [112]. Children's confidence in mathematics is highly influenced by their family members: supporting parents with less gender bias, and approachable role models are already very important at an early age to keep young girls interested in the sciences.

Various studies have shown that girls who had primary school teachers with negative stereotypes about girls' mathematical ability took fewer math courses in high school, and were less likely to major in STEM fields in college [113, 114]. Positive role models are not only important in the family: having female STEM teachers in high school makes it more likely that girls choose STEM majors in college, especially if they have high mathematical ability [115]. Many studies have indicated that in college, female role models are even more important for majoring in STEM [59, 60]. Scholars have found that having at least one female faculty in engineering [58] and a higher ratio of female graduate students in research-intensive fields can increase the probability of women majoring in STEM [57]. Having female instructors helps female students to get better grades and makes them drop out with lower rates [61, 62]. Visible female role models are crucial in every educational level to increase the ratio of women in STEM, which is why the under-representation of female faculty in higher education is especially concerning (See Chapter 2.4.3. Gender Inequality in Academia).

2.3 The leaky pipeline and its criticism

The process in which women in STEM leave their chosen careers behind is very often illustrated with the so-called *"Leaky Pipeline"*. This concept describes career-building as a linear process, where women go through different educational and professional stages. Figure 2.2 shows an example of the most common concerns women have in STEM throughout their careers. This framework emphasizes mainly structural factors of why women do not enter the STEM pipeline, and why more women than men drop out at transition points (e.g., high school to college, or STEM major to the job market) [116]. As a result, there are fewer and fewer women as times goes on. It is called "leaky" because women choose different paths than the "optimal" STEM path at a higher rate than men at every stage. Among STEM fields, Computer Science has the most

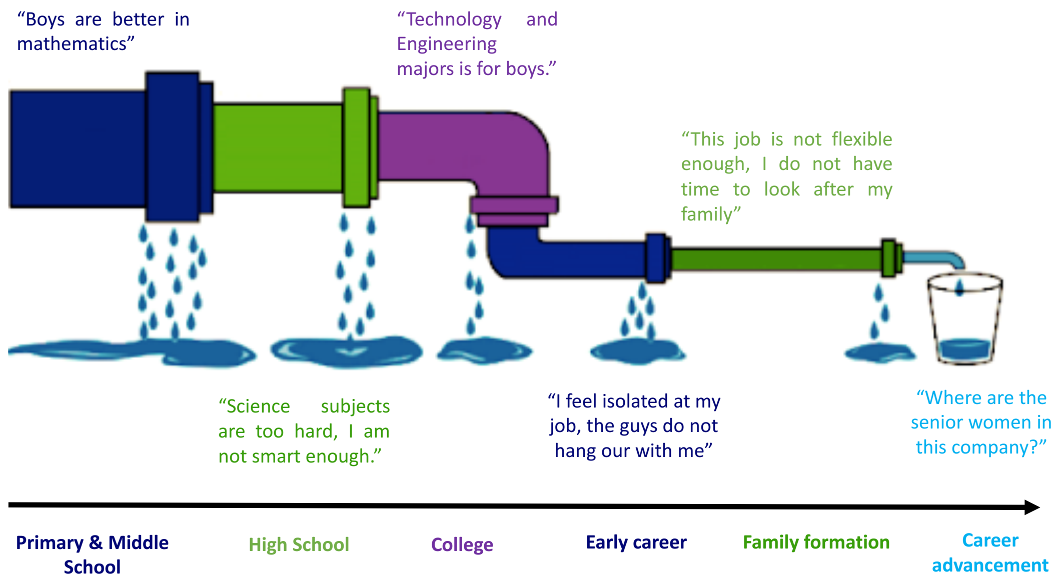

Figure 2.2. *The leaky pipeline Source and inspiration: https://twitter.com/medickinson*

"leaky" pipeline, where the ratio of women shrinks at every stage [117].

Middle school (age 11-13) has been identified as a very sensitive period, and scholars believe that this is the time when most girls develop a disaffection to computing, which leads to not choosing computer science tracks in high school [24]. It has been shown that stereotypes against computer science hold among both genders, but influence girls' career choices more than boys' [44]. Vitores & A Gil-Juárez grouped the main factors behind girls' "disaffection" to computing into four main categories: 1) the stereotypes about people working in IT (nerdy, antisocial), 2) image of computer science (male-dominated, lack of human interactions), 3) lack of knowledge about what computer science is, and 4) lack of interest or perceived ability in computing-related subjects (Mathematics, Physics) [45]. A great body of research has examined the role of social factors that makes girls not choose technical careers, including the role of socialization [118, 119, 120], family values [121, 122], and stereotypical peer pressure [120, 123]. In addition, researchers have argued that the low representation of women in technical roles in popular culture and media can also influence girls' lack of interest in computing too [124, 125]. Negative stereotypes, cultural factors and the low visibility of women related to technology, both in popular culture and education, can make computing a less attractive career choice among 11-13-year-old girls.

If girls choose a technical track in high school it does not mean they will persist, as there are several decision-making moments during the beginning of a career when women are more likely to leave than men. Ahuja argued that the leaky pipeline has many cultural aspects that make women consider leaving the field multiple times during their careers. The first important decision happens during university, when female students make a decision on whether or not they would pursue a career in IT. Studies have found that social expectations and potential work-family conflicts related to the field (such as long working hours, traveling and the demand for continuous updating of skills) and the lack of female university professors (role models) make computing less attractive for female students [22]. In addition, scholars suggest that women suffer from a lack of confidence in male-dominated areas. It has been shown that when a task or a job requires knowledge that is outside of women's perceived expertise, they are less likely to participate than men [126, 127]. Therefore, women are less likely to apply to technical jobs that require a long list of skills and that makes it harder for women to land a job in IT. The competitive environment of the tech industry can make women less interested in pursuing a career in the field. Researchers have found that young girls perform worse in competitive settings, especially when they compete against men [24]. However, stability and positive feedback can help women build confidence and persist. Cotton et al. analyzed a series of math competitions and found that girls performed worse than boys in the first task, but if time pressure was removed, girls performed as well as boys, and in the long term (after gaining confidence) girls outperformed boys [128].

The next risky point in time for women to leave the field is around the time of starting a family. Women experience higher work-family conflict, which causes higher occupational stress and reduces the probability of staying in IT. The lack of female mentors also has a negative impact on female professionals' persistence in IT, and research has shown that for women, educational and career encouragement is more important than for men [129]. At the career advancement phase, social (female-friendly informal networks) and structural factors (organizational culture, lack of women leaders) start to play important roles. If women find organizations with welcoming culture and can build social connections, and achieve success or appreciation, they stay; but if they do not get positive feedback they rather switch to other, non-technical fields [55].

The pipeline model has been criticized from various perspectives. One of the main criticisms is that the framework assumes a linear career-building process, where women decide as young girls to pursue technical careers and keep preparing for it. Another important criticism is that the pipeline assumes that STEM workers pursue related education. However, as computing has become one of the highest-paid occupations, many have migrated from different fields (for example economics, sociology, biology) and many of these professionals take non-academic training to pick up the required technical skills. In addition, a major criticism by feminist scholars is that the pipeline emphasizes the supply-side of the problem. They argue that this framework focuses mainly on how to recruit more women to fill the pipeline without asking about the cultural, social and institutional barriers that make women not enter or leave the pipeline in the first place [45].

The leaky pipeline is a descriptive framework about the key career moments when women are more likely to leave their technical occupations behind. It does not offer solutions or strategies to overcome these barriers. The simplicity of the framework allows a broad application and helps to draw attention to systemic deficiencies, but it overlooks field-specific cultural aspects. Therefore, the second part of the chapter will give an overview on the field-specific challenges that women face in the three industries my research focuses on: open source software development, the video game industry and academia.

2.4 Field-specific trends

2.4.1 Open Source Software development communities online

According to opensource.com, *"Open source software is software with source code that anyone can inspect, modify, and enhance"* [130]. Source code is a collection of programs that operates the software. In the case of open source software development, the code is freely available and any programmer can improve that program by adding new features or fixing bugs. The most known examples of open source software are Mozilla Firefox, WordPress, Linux Operating System, OpenOffice and 7-zip. Open source software is often created publicly using online collaboration tools, such as GitHub. GitHub is the most popular online hosting service, providing a version control service with Git for developers all around the world. GitHub provides features for collaborative development, source code management, and has traditional social media functionalities (e.g., following) as well.

According to Octoverse, the annual statistical report of GitHub, the platform had more than 40 million non-spammy user accounts on September 30, 2019, regardless of their activity status. GitHub users are very diverse: 80% of them are not from the US, however, there is no official data about the gender and racial composition of the user base. GitHub is becoming more popular and collaborative every year: last year alone, 10 million new accounts were created. In 2019, more than 44 million repositories (projects) were created. In 2019, 44% more developers created their first repository at GitHub. The number of developers collaborating through pull requests (the technical protocol with which developers code into each others' repositories) has also risen by 28% between 2018 and 2019. [131].

The rising popularity of Open Source development has been explained with intellectual gratification, enjoyment of creativity and almost artistic contribution, but there are also conscious career decisions behind it. These projects provide success through visibility and prestige, which helps developers to be noticed by potential employers [76]. From an economic point of view, it is an investment into knowledge and social capital. A qualitative study on developer career-building behaviour by Dabbish et al. found that users invest in the social side of the platform and combine these social interactions with effective career strategies for social and human capital-building and reputation management [77].

Analyzing the role of gender diversity in teams' performance in Open Source software development became a popular research area. Open Source software development has the lowest ratio of women among all engineering fields: recent empirical studies have found that the ratio of women is around 9% on GitHub and 5.8% on Stack Overflow [66, 132]. In one of the first studies conducted on data from GitHub, Vasielescu et al. found that both the gender and tenure diversity of project teams had a positive effect on productivity [66]. Ortu et al. also found that a higher gender diversity indicated higher productivity (faster issue-fixing time) [133].

To date, several studies have investigated the presence of gendered behaviour, and the role of gender diversity in teams' productivity in online source development communities. Imtiaz et al. tested several hypotheses on the gendered behaviour of female developers on GitHub. They did not find significant evidence that women would provide more information on their profiles about the expertise or write more detailed pull requests to demonstrate competence. Women's pull requests got accepted faster than men's; however, this might be the consequence of women working on fewer projects, with people they are already familiar with. Social expectations work online too: women communicate more politely and avoid profanity more than men [134]. Wang et al. demonstrated that visibly female users attracted more attention if they sent a pull request to a new repository. After initiating a pull request, the number of followers increased for women, but not for men [135]. This phenomenon can put women into an uncomfortable situation: women might question whether they are really competent or if they are only interesting because of their perceived gender. Wang et al. argued that this discomfort could contribute to the competence-confidence gap between men and women. However, drawing a causal conclusion based on such a data-driven study might be somewhat premature.

Stack Overflow is one of the biggest online communities for developers to ask and answer questions about programming-related issues [136]. Ford et al. investigated why female contributors had a very low representation online and found that women had more doubts about their level of expertise, found the environment too competitive and were not aware of the features of the site (eg.: reputation, gamification tools) [132]. May et al. observed significant differences in men's and women's reputation (success) on Stack Overflow, which could be mainly explained with different activity patterns. They found that men were more active in answering questions, but even after controlling for users' activity, men were more rewarded for their answers than women [71]. Vasielescu et al. compared the participation and engagement of women in three main online developer communities: Stack Overflow, Drupal and WordPress. They found that gender representation was unequal regardless of how gender-friendly the community was, but female-friendly culture could positively influence engagement. Their results suggest that Stack Overflow had the least female-friendly culture [48].

Open source software communities, such as GitHub and Stack Overflow, are important educational platforms, where self-taught developers and less experienced programmers can ask questions and gain feedback. Hence, it is crucial to make sure that the culture and the norms of these communities are safe, inclusive and do not penalize beginners or under-represented groups. The low representation of women can reinforce existing gender stereotypes and increase the practice of gendered behaviour. Non-inclusive norms can harm women's confidence, resulting in leaving such platforms. Since these platforms play gatekeeper roles in early career development in technology the negative consequence of "dropping out" is significant on the societal level.

2.4.2 Video game industry

Women being a minority in software engineering and its consequences is a widely discussed topic in the media [137, 138, 139, 140, 141]. Statistics indicate that it is a world-wide phenomenon; according to a study which focused on female representation in technology, in 41 countries in the OECD and EU only 17.5% of the technological workforce[2] was female, ranging from 9.3% in the Slovak Republic to 30.3% in Bulgaria in 2018 [63]. The ratio of female software engineers in Silicon Valley is estimated to be around 20% [142]. However, it is less discussed how particularly low female representation is in one of the most

[2] Sub-major group of the International Standard Classification of Occupations (ISCO-08), Information and communications technology professionals. [63]

financially successful sectors of the decade: the video game industry. The video game industry is currently the most popular entertainment sector, which was predicted to generate 152.1 billion USD revenue in 2019, from 2.5 billion games around the world [143]. LinkedIn estimated the ratio of female engineers in the media and entertainment industry to be around 16% [65].

Bailey et al. analyzed the credit lists of 27 video games by the seven most prominent game publishers' top selling games over the last 30 years. They found that overall the ratio of female employees grew over the last three decades, but women were still under-represented, especially in higher-paying positions, such as engineering and leadership. The ratio of women ranged between 0% (Super Mario Bros, 1983) to 22% (Super Mario Odyssey, 2017) and 23% (Super Mario Galaxy, 2007) [69].

Video games are famously stereotyped as as "male-centric" products. In 2010, Greenberg et al. argued that women were not as engaged as men with games because video games were designed by males for males. They suggested that the industry should focus on developing more gender-inclusive games to expand the market size [144]. One of the first qualitative studies in 1998 by Dietz et al. found that 41% of video games did not have female characters, and among those which had female characters in 28% women were portrayed as sex objects [145] In the 2000s, multiple other studies using bigger datasets found that women were under-represented [146, 69] and portrayed in a hyper-sexual way [147], for example exposing more skin than male characters [148]. Research by Hayes suggests that playing video games increases the interest of children in STEM fields, therefore making games attractive for young girls can be an important step towards women's better representation in technical fields [75]. However, it has been shown that the sexist attitudes of the online video game community drive women away more than the sexist content [149]. Industry culture does not value inclusivity: in 2013, Near found that video games with a central female character were negatively correlated with sales, indicating that the expectation of the main user-base was still male-focused [70].

Nevertheless, in the 1990s an entire genre of "Pink Games" emerged, targeted to appeal to young girls. These games are usually centered on stereotypical female characters and activities, such as cooking or talking about relationships. As more studios try to attract a larger female audience, they even change the hardware to look like girly accessories. For example, Nintendo's 3D console is available in multiple colors and patterns (e.g., pink, purple, tiny ponies) [150]. Feminist scholars criticize pink games for being sexist and reinforcing already existing stereotypes (such as focusing on appearance and emotions) [150]. Cassel argued that the ghettoization of women's games strengthened the belief that women need "special help and products" to deal with technology [151]. This market segmentation and sexist marginalization allows video game publishers to keep the cultural status quo. Moreover, this over-targeted product design can create a low-prestige subculture for women in an already highly-masculine and segregated industry.

A few video game companies exclusively focus on games targeted for young girls, without falling into the stereotypical gender pit [150]. The first American software company which designed games for girls was established in 1999 by Brenda Laurel, called Purple Moon [152]. Through user experience research with young girls in Purple Moon, Laurel learned that young girls preferred complex characters and narrative-based games, which was not too common among mainstream studios producing competition-based games [150]. Megan Geise, the CEO of a company with a similar approach, HerInteractive, also pointed out that girls, similarly to boys, preferred complex characters, and added that they did not like to be portrayed as victims and found violent games boring [153].

But times are changing, and the marginalization of female gamers cannot persist any longer. Recent studies indicate that almost 50% of gamers are women [154, 155]. However, considering the fact less than 30% of women who work in the video games industry have creative roles, where they can influence games' content, it is not surprising that moving towards better representation is very slow [155]. Still, in 2018, five times more video games featured male characters than female ones [156].

At least in other entertainment sectors increased female representation pays off. It has been shown in the film industry that strong female characters positively influence box-office sales [157]. The same study also pointed out that if women were portrayed in gendered roles (which did not pass the Bechdel-Wallace test)[3] the revenue would be lower. A debate has started recently whether the video game industry should introduce a similar method to the Bechdel-Wallace test to improve gender inclusivity, however, no such metric has been created, nor tested so far [159, 160].

As the video game industry has become the most popular entertainment sector, the pressure on employees has grown tremendously. 100-hour working weeks, obligatory overwork, mental illness and discrimination is common in the video game industry [161]. According to a survey taken by the International Game Developers Association, 48.5% of industry employees agreed with the statement that *"There is no equal treatment and opportunity for all manner of people in the video game industry"*. Women also reported that sexism was highly accepted and part of the everyday culture of the industry [162]. Female game

[3]Bechdel-Wallace test: two named female characters having a conversation not about a man [158]

designers organized a couple of online campaigns (1ReasonWhy, womenaretoohardtoanimate,) to raise awareness of the lack of diversity, harassment and discrimination against women in the game industry [150]. But unfortunately, these pursuits generated a backlash and resulted in publicly harassing female game developers [163].

2.4.3 Gender Inequality in Academia

Gender discrimination in academia is well documented: women scientists earn less [72, 73], have access to less funding [164, 165, 166, 167], their work receives fewer citations [168], and their careers benefit less from co-authorship [126]. These inequalities persist, even though it has been shown that gender-heterogeneous scientific teams are more creative and produce higher quality science [169].

Despite the remarkable progress of women entering higher education in the last century, female professors are still under-represented in more senior positions: women held nearly half of tenure-track positions in 2018 in the United States, but only 39% of tenured ones [67]. Female professors are also a minority among senior faculty in most European countries (e.g., Netherlands (18.7%), Germany (19.4%), France (21.9%), Switzerland (23.3%), Sweden (25.4%) and the United Kingdom (26.4%)) [68]. As Figure 2.3 shows, there are important differences between scientific fields: generally, women are underrepresented in math-intensive fields and over-represented in life sciences. The ratio of female assistant professors is the highest in Health Sciences(73%) and Psychology (66%) and the lowest in Mechanical (8%) and Electrical engineering (9%). As this chart also indicates, female professors are less likely to become tenured and hold senior academic positions [170, 171].

There is ample evidence that women publish less than men, which influences the total number of citations their work receives. Awareness of the productivity gap between men and women is not recent, having possibly first been described by Cole [172], and has been shown in various research fields [173, 80, 174]. Although women publish less than men, the average number of citations per publication has been shown to be equal or higher for female than for male scientists [175, 176]. Huang et al. demonstrated on data from 1.5 million authors over 60 years that this productivity gap had increased between men and women: on average, male scientists published 13.2 papers, and female scientists published only 9.6 during their entire career. However, this gap was almost fully accounted by the fact that women had shorter careers than men, since the average number of annual papers published does not differ by gender [177].

Weisshaar argued that only a portion of the tenure gap can be explained by

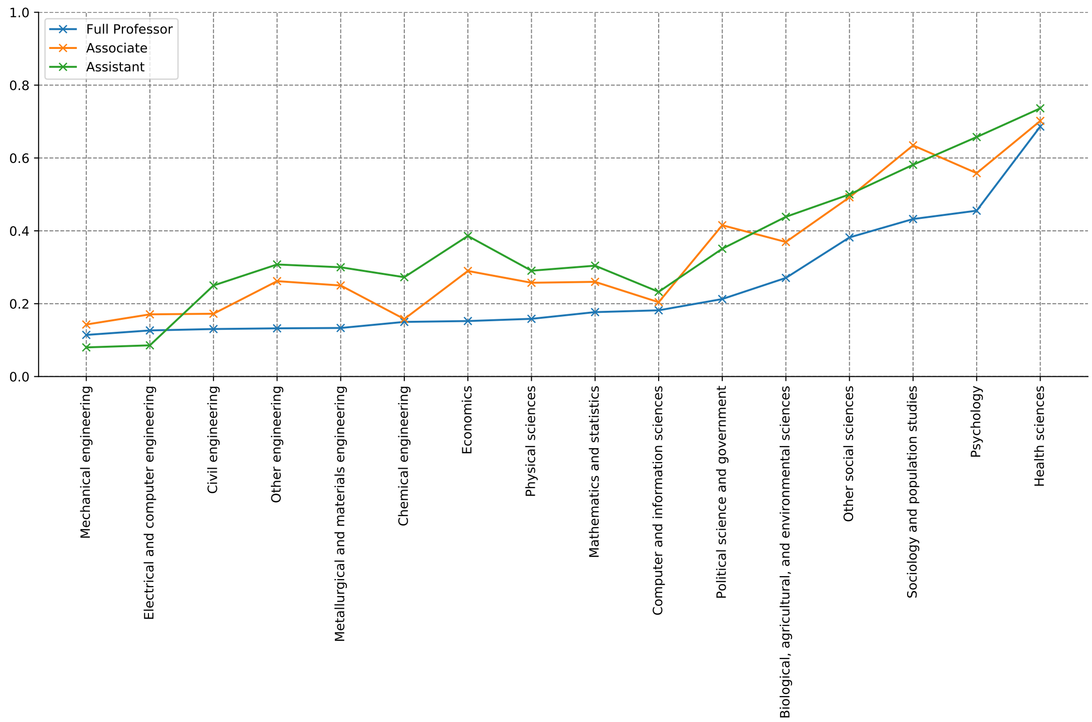

Figure 2.3. *The ratio of female professors by research fields and seniority in STEM (USA, 2017), Source: https://ncsesdata.nsf.gov/doctoratework/2017/index.html*

the productivity difference between men and women. Departmental characteristics and institutional prestige do not explain either why women become full professors in lower rates. However, if women succeed, they are more likely to get a position in lower-prestige departments [171]. It has been shown that female scientists interrupt their careers more often than their male colleagues, and having children influences only women's productivity negatively [178, 179, 180, 181, 177]. This put female scientists into a challenging position, since the productivity of a scientist rises rapidly at the beginning of a scientific career, then gradually declines [182].

Investigating factors associated with scientific success has became a popular research area over the last few years [183, 184, 185, 186, 182, 177]. Several studies have used large-scale publication data to examine the difference between male and female scientists' performance and achievements, measured by the number of publications and citations of their work [187, 55, 74]. Studies on scientific co-authorship networks revealed that male and female researchers develop different networks, which is a major factor why women are at a disadvantage. Various empirical analyses have pointed out that women have fewer co-authors and are less likely to develop long-lasting scientific collaborations [55, 74].

Unconscious cultural factors have also been associated with the shortage of female scientists: Lerchenmueller et al. found that articles published by research groups with first or last male authors were more likely to present research findings positively in the title and the abstract, which was positively correlated with higher citations [188]. Wenneras and Wold showed based on grant applications' peer-reviewer scores, that nepotism (personal connections to reviewers) and sexism influenced results [167].

In conclusion, one can say that women are disproportionally represented among STEM professionals worldwide, and face several barriers during their careers. Although there are important differences between the three fields discussed above (open source software development, the video game industry, academia) in terms of structural difficulties that women face, non-inclusive cultures and institutionalized sexism are generalizable phenomena. Playing video games can positively influence young girls' interest in the sciences. Creating gender-inclusive products that do not marginalize girls, and allow them to express themselves without being stigmatized might increase women's representation in technical fields in the long-term. Making sure that we have gender equality and an open culture in academia is crucial for training the next generation of female technical professionals. As technology is interwoven into our lives, and programming skills become a necessity in many professions, the gatekeeper role of platforms, where beginner programmers and early-stage professionals can ask questions and gain feedback, increases. GitHub serves as a portfolio site for early-stage professionals, therefore keeping women active in open source also has long-term positive impacts.

Since gender discrimination is closely related to the concept of gendered behaviour and gendered organization, I start my next chapter by discussing these key concepts. In the second part of the following chapter, I discuss the role of gender diversity in team performance. As the literature about the reasons behind the leaky pipeline indicates, (informal) networks can block women's access to crucial information to advance in their careers, therefore I give an overview on the role of networks in women's careers. As I outlined in the Introduction, gender equality is not only an important team asset which can create more successful and creative products, but it can also decrease bias. Since many aspects of our lives take place in online communities, which can serve as gatekeepers to jobs or career opportunities, understanding how the magnitude of gender bias online is crucial. Thus, I conclude the last introductory chapter with a short overview of recent literature about gender discrimination online.

CHAPTER 3

THEORETICAL FRAMING OF GENDERED BEHAVIOUR, GENDER DIVERSITY, AND ONLINE DISCRIMINATION

Studies discussed in the previous chapter provide evidence on the presence of long-lasting stubborn inequalities in STEM. This chapter conceptualizes a theoretical and methodological framework that can help to understand the root causes of these persisting inequalities. First, I describe related theories on gender and gendered behaviour. Second, I introduce key findings on the role of diversity in team performance. The third section explains the role of networks in female career advancement. Finally, I review the recent academic literature on gender differences and discrimination in online communities.

3.1 Gender and Gendered Behavior

Gender is a very modern term, coined by sexologist John Money in 1972. He distinguished between biological attributes of sexes and the socio-cultural context of how a person identifies themselves as male or female within society [189]. *Gendered behavior* is learned through socialization. Boys and girls learn while interacting with family, friends and peers what the expected behavior according to their gender is [190]. Men and women learn different roles, behavior, and forms of interactions in the course of their lives [191]. Windsor argued that young girls learn how to be a woman from the *scripts of femininity*, which are the norms and behaviors that reinforce the socially expected behavior of being a woman. On the other hand, boys learn how to be masculine, which is essentially the opposite of femininity [192].

In most Western societies hierarchical gender relationships are present, so men are usually more dominant in powerful institutions (science, religion, government) [21]. This subordinate position of women relies on the conventional values of femininity, such as vulnerability and the need to be protected. According to *Hegemonic Gender theory*, both genders are penalized by society if they do not follow their gender-specific scripts. Men are expected to be strong, powerful, independent and emotionally detached, otherwise they are labeled as weak and feminine. To keep the status quo, women should not have masculine characteristics, and they are also penalized if they behave in a way that is not written by the scripts of femininity. For example, women in powerful positions are often criticized for being too aggressive and not feminine enough [33, 34].

Contemporary feminist scholars emphasize that not only gender stratification, but the hierarchical structure of race, class and sexual identity influence the ideal script. The traditional script of femininity was written based on the most privileged women, who are white, middle- to upper-middle class, and heterosexual. Recently, new types of femininity have appeared in media which mix gender and race stereotypes. A study showed that advertisements in teen girls' fashion magazines reinforced gender-race stereotypes: connecting whiteness with beauty, blackness with hypersexuality and geekiness with East-Asians [193]. Indeed, race can play a significant role in gender inequalities, although recent studies focus only on the gendered aspects of inequalities due to the limitations of available methodologies and data [48, 49, 50, 51, 52, **?**, 53, 54, 55]. Since case studies presented in this work contain limited indication on ones race, I am not able to take into account the interaction of race and gender either.

3.1.1 Gendered technology

The modern meaning of *technology* was defined in the late nineteenth century by the influence of mechanical and civil engineering. Wajcman argues that the masculine culture of mechanical and civil engineering decreased the significance of women in technology and made it a traditionally masculine field, manliness turned into an important aspect of the ideal technical professional, and femininity became considered incompatible with it. As the importance and prestige of computing has been growing, women's access to it was denied [20]. The early years of computing illustrates how female marginalization takes place when the prestige of a field increases: as Hicks points out, computer programming was originally a feminine job, considered to be a low-level job, compared to typist, and paid accordingly. Nevertheless, women working in the early ages of computing (1950-1965) in the United Kingdom were trained programmers, operating complex military tasks. Since managers were not aware of the potential of the computing industry, they believed that this was an ideal career for women with no long-term opportunities. However, in the 1970s, as governments and the industry realized how powerful computing was, women were no longer welcomed in the field, and the already trained female workforce was replaced by men [194].

From the early era of *technofeminism* (1980s), when the research agenda focused on women's exclusion from science and technology, scientific interest shifted towards the gendered nature of technology and its consequences. Modern technofeminist scholars are interested in how gender is embedded into technology, and how it reinforces gender division and already existing inequalities [20]. Cockburn argues that since femininity is associated with being technologically incompetent, women need to adjust and give up a big part of their feminine identity if they want to build a successful career in technical fields [46]. As a historical analysis of female representation and wages indicates, if the ratio of women increases in an occupation, the prestige drops and salaries decrease [30]. Therefore, to keep the prestige of the field, the macho culture persists in most technical fields today as well.

With the rise of big data, machine learning and artificial intelligence, a *postmodern era of technofeminism* has arrived. Nowadays, not only feminists argue the negative impact of gendered technology, but also scholars from a wide spectrum of fields are concerned about gendered technology's unintended consequences (such as algorithmic bias and unconscious discrimination) built into it[1]. Recent years' scandals [195, 64] indicate that the gendered nature of technology might be an artefact of the non-diverse pool of workforce, non-inclusive working environment, and gendered organizational practices.

3.1.2 Gendered organizations

Most of the everyday organizational processes reinforce women's and other minorities' marginalization. All those organizational norms that are taken for granted, such as the 9 to 5 working day, might seem gender-neutral, but in reality they are based on masculine standards [47]. These policies are well-suited for men, especially white, heterosexual and middle class men. Thus, it has consequences on what the organizational culture values; more visible, task-oriented activities are usually rewarded more, and relationship-oriented tasks (such as solving conflicts) are less noticed [32]. The image of the ideal supervisor is also shaped by these norms; both men and women prefer leaders who are able to

[1]See Chapter 2: Related work Section: Gender discrimination and bias in online communities

work overtime, affirm control and are assertive, which are traditionally highly masculine attributes. Everyday social interactions are also influenced by gendered practices: at meetings men are often the actors (presenters) and women are supporters (taking minutes) [47].

These well-established organizational norms are even more present in fields where women are underrepresented, like the technological industry. It has been shown that non-inclusive cultures with bad gender balance cause worse performance in technical fields [196], and make women quit at higher rates than men [22]. As the technology industry has been criticized for not being equal and discriminating women, employees started to demand gender equality and more inclusive working environments [197, 198]. But this change is slow. Currently, different strategies are recommended for female professionals to overcome the difficulties that gendered organizational norms create. Meyerson et al. grouped the most common strategies and recommendations into four major categories [47].

The first type of "solutions" focuses on "equipping the woman", trying to teach them how to become more political and assertive, by enrolling them to leadership programs and making them attend workshops, to learn how to play by the scripts of masculinity. These methods can work for some women, but do not change systematic problems, and can provoke backlash [33].

The second group of solutions focuses on structural barriers while trying to create equal opportunities. This approach is legislative, policy-focused; all the shiny improvements that startups introduce and the media love belong here: alternative career, family benefits, flexible work arrangements. This approach is also criticized for reinforcing traditional gender roles. For example, introducing more and more women to flexible working has negative effects on their long-term career advancement.

The third type of solutions values differences, and fights for acknowledging feminine values more (e.g., behind-the-scenes peacemaking, listening, collaborating). However, these intentions also reinforce gender stereotypes and emphasize gender differences.

The fourth group's key statement is that organizations are gendered, and the goal is to re-think organizational processes from that perspective. The theory of gendered organizations means that gender is embedded in hierarchical structures, job descriptions, hiring processes, image of workers and managers, work/family connections and even individual identities. Changing gendered norms deeply rooted in every process is probably the hardest, and I think it is probably impossible without large-scale societal change.

Overall, these studies highlight the need for taking into account the role of gendered behaviour when one analyzes the structural factors of female marginalization in technology. Chapter 3, *Gendered Behaviour as a disadvantage in Open Source Software Development*, showcases a large-scale study on how gendered behaviour can be measured in online activities and manifests itself into disadvantage in open source software development. The studies presented thus far provide evidence that occupations with a higher ratio of women are more likely to be less prestigious, which can increase women's marginalization within these fields. In the section about gendered organizational norms it was shown that cultural factors and inclusive (non-segregated) environments can play a significant role in keeping women in technical roles. There is a limited number of empirical studies on quantifying inclusion, therefore one of the goals of Chapter 6. is to extend the methodological literature with our findings.

3.2 Structural and human components of team performance

As I outlined in the Introduction, there is evidence that gender diversity increases teams' overall intelligence [88], enhances creativity and quality in scientific research [37], and can reduce bias [38, 39]. However, in male-dominated fields gender diversity has been shown to impact teams' performance negatively [196, 199]. In everyday life and science we tend to celebrate individual success [200], nevertheless, most novel accomplishments were developed by teams or people who were embedded in a network of other artists, scientists or companies where they could share and develop ideas [201, 202, 203, 204, 205]. Therefore, understanding how the interaction of teams' network structure and diversity can effect performance and success is essential to develop the policies aimed at creating gender equality. In the following section, first I review the literature on the role of networks and diversity in team performance, then summarize the findings on how networks influence female career advancement.

3.2.1 The role of networks in team performance

Teams' performance and success have been explained by their intra- and intergroup structure (density, closure, network range) brokerage, tie strength and centrality [206]. Some have argued that high performance is the result of highly interconnected teams (high closure) [207, 208], a denser network promotes trust and decreases risk, and that is one of the reasons team members can work together [209]. Higher team density has been shown to increase performance [78, 210] and job satisfaction [211], but high density negative ties decrease performance [212]. In alignment with the positive effects of team cohesion, moderate centralization has also been shown to increase team efficiency and performance [213, 214].

Data from several studies suggest that team closure and density have an inverted U-shape relationship with creativity and group effectiveness. This view argues that high team cohesion is only beneficial until a certain point after which the lack of external influence can decrease creativity and group effectiveness [85, 215, 216]. Other views underline the importance of actors in broker or bridge positions, connecting otherwise segmented groups. Actors in broker positions have been shown to be important in value-adding or innovative processes. This view emphasizes that team members benefit from diversity because it generates links between people who access different sources, knowledge, and information [217, 218, 219].

When a new team is forming, members prefer to work with previous team mates, or with someone who is recommended by a trusted connection. In project-based industries, such as art and technology, shared team experience is a leading organizing factor in team formation [220, 202]. Similarly to the effects of high density, various studies have indicated that shared team experience has a non-linear (mainly inverted U-shaped) correlation with performance [202, 221, 206, 222]. Groups' external network range has also been positively associated with effectiveness and team performance [210, 223].

Recent studies have combined network structure with team diversity. De Vaan et al. found while analyzing video game teams, that teams with diverse skills, with limited shared working experience (*structural folds*) created hardly understandable, therefore less successful video games [85]. Troster et al. analyzed the interaction between network structure and the cultural composition of teams with their effects on performance and potency. They demonstrated that the positive effect of network density on team potency was higher if the team was culturally diverse, but it required higher centrality for better performance [224]. Reagans et al.'s research in teams in an R&D firm showed that high tenure diversity and high network density predict the highest productivity [78].

3.2.2 The effect of gender diversity on team performance

The relationship between gender diversity and teams' performance is still part of an ongoing debate. As the theory of brokerage emphasizes, teams can benefit from diversity [217, 218]; on the other hand, it can also cause less cohesion, and therefore, worse performance. Views against diversity argue that dense communication networks with homogeneous team members are less likely to have conflict, and do not suffer from the costs of harmonizing different backgrounds. Promoters emphasize the positive effects of connecting different opinions which can help to process information more carefully and reduce unconscious bias

[38, 39, 78, 86]. In an experimental setting, Woolley et al. found that teams with more women outperformed other non-diverse teams even with higher average IQ in innovative tasks. They argue that women increase teams' collective intelligence due to women's social sensitivity and ability to decode non-verbal communication clues about others' feelings and thoughts [36].

Recent research findings suggest that an equal ratio of men and women creates the best environments for team collaborations. For example, activity in teams meetings was the most equal between men and women when teams are gender-balanced. In addition, the same study found that when women were in minority they were less talkative than men being in the same situation [88, 225]. Several studies also support the finding that team performance is the best when they are more gender-balanced [226, 87, 88]. Hoogendoorn et al. found that sales teams with a gender-balance performed the best [227]. Fenwick and Neal also suggest, based on experiments with students, that teams where the ratio of women is higher or equal to men are the most effective to handle complex management activities [228]. Jehn and Bezrukova report, based on organizational data from a large Fortune 500 information-processing company, that gender diversity has significant positive effects on constructive group processes. In the case of missing group-process data, they found that business units with an inclusive environment (people-oriented climate, diversity-focused HR practices) and customer orientation, gender diversity was positively related to bonuses. However, if these cultural aspects were missing, gender diversity did not have any effect on group bonus outcomes [89].

Empirical research studies on teams in technical fields report various findings on the effect of gender diversity, highly depending on the context and how gender balanced the teams were. Campbell showed that gender-heterogeneous scientific groups produced more articles with more citations than gender-uniform authorship teams[37]. Analyzing software developer teams, Kang et al. found that a cognitive similarity influenced team effectiveness more than a demographic one [229]. This suggests that in male-dominated industries, which are more gender unbalanced, increased gender diversity is more likely to have negative effects. In traditionally male-dominated industries managing gender-diverse teams has been shown to be a challenging task [230], and due to negative stereotypes of women working in such industries, gender diversity has been shown to have negative impact on team performance [196, 199].

In traditionally non-diverse fields personal bias can influence one's perception of reality. Baugh and Graen found that gender and racial heterogeneous cross-functional project teams rated themselves less effective than non-diverse ones (all-male or all-white), however, the external evaluation showed no difference between diverse and non-diverse teams. White men in diverse teams were the most likely to perceive their team's performance the lowest if their team was diverse, indicating that stereotypes could form the perception of success [90].

In technical fields, a gender-balanced team can indicate that the organizational culture is gender-inclusive, which is a significant predictor of keeping women in the team [22]. As Joshi revealed, while analyzing academic research groups, gender diversity can interact with other factors, such as organizational culture, status, and expertise when it influences team performance. Only those teams benefited from a higher proportion of highly educated women, which had gender-inclusive environments [87]. The literature suggests that the positive effects of diversity can be utilized better if the organizational culture values diversity. The role of leadership has been associated with creating the appropriate culture and environments [91, 92, 93], but as long as the low ratio of women in the technical fields, and especially in leadership, persists, it is hard to see that organizations can change and benefit from gender diversity.

3.2.3 The role of networks in women's career advancement

The literature on social capital has highlighted several aspects of how networks influence one's career: networks can help to access information, maintain position and reputation, exchange resources and create trust [231, 232, 202, 221, 206, 207]. However, it is less studied how different types of network formations affect already existing gender inequalities, and whether women and men benefit from different structures [49]. Much of the gender studies literature since the mid-1980s has emphasized the role of homophily and segregation, tie strength portfolio, and network position in individual career advancement [233, 217, 218, 206].

A growing body of literature has investigated homophily in social networks. Network homophily means that similar people are more likely to create ties with each other than dissimilar ones [233]. Gender homophily has been shown in a wide range of studies: organizational networks, academic collaborations, online social networks, artists and many more [232, 234, 235, 236, 237, 79, 49].

McPherson and Smith-Lovin draw a distinction between choice and induced homophily. Induced homophily is the result of structural or institutional segregation which creates a lack of connections between men and women. Choice homophily, on the other hand, is something that the individual has control over, for example seeking advice from a female colleague [238]. The literature suggests that induced gender-homophilous ties can put women in more disadvantageous positions due to their (usually) lower status and fewer connections to important sponsors and decision-makers [239, 240, 49, 241]. By contrast, choice homophily can affect women's career advancement positively by channeling informal knowledge in a more trustworthy and safe environment (e.g., mentoring, role modeling). Choice homophily has been shown to be especially beneficial for women when they hold positions in male-dominated industries (e.g., upper management, technology, academia) [237, 234, 242].

The literature on organizational networks suggests that men and women develop different networks and benefit from different types of relationships. Ibarra found that men have stronger homophilous ties across different organizational networks and relations, while women receive social support form women and seek advice and influence from men. She explains gender differences in network centrality by background characteristics, departmental position and hierarchy of employees. Therefore, Ibarra suggests that the gender gap in centrality might be a result of women being considered as riskier investment than men [232]. McPherson and Smith-Lovin observed gender segregation in voluntary organizations but found that men had more gender-heterogeneous ties than women and created networks that provided access to power and better career possibilities [235].

Other findings suggest that women are more likely to create same-gender boundary-spanning relationships (strong ties across departments). Kleinbaum et al. analyzed the e-mail communication of a large information technology firm and found support for gender and unit homophily within the organization. They also revealed that women were more likely to create inter-unit connections with fellow female colleagues, while men stuck to their business unit [236]. Ibarra also found that women with high managerial potential relied more on close ties and relationships outside of their sub-units than men with high potential [234]. Van den Brink and Benschop showed that women in academic recruitment mobilize their same-gender strong ties more often than men to overcome institutionalized inequalities that favor men candidates [237].

Findings suggest that women benefit from similar network conditions as men but they often lack social capital to create them. Burt suggests that women and young professionals, who might not have developed the necessary level of social capital, need strong relations to sponsors who have entrepreneurial networks (access to structural holes). His study also revealed that sponsors embedded into highly cohesive cliques are not as beneficial for young professionals' career advancement [243]. Granovetter also suggests that weak ties are not as useful for people in "insecure positions" [231]. Similarly, Lutter found based on a large-scale study of actors that women can reduce the risk of failure if they do not close themselves into highly cohesive cliques, and create networks with open and diverse structures [49]. A recent empirical study by Jadid et al. also demonstrated that although men and women develop different networks over the course of their career, similar patterns help them to become successful [55]. They suggest that a core of trustful long-lasting collaborators can increase productivity, and innovation can come across structural holes. However, they found that women's networks were more closed, and they were less likely to be in brokerage positions and had less long-term collaboration partners which indeed made them less successful.

Network structure and experience have been associated in creative industries with creativity and novelty. Wachs et al. analyzed the community of designers on Dribbble and found that female and male designers both need to combine novelty and constraint to become successful: novel designs became more successful if the artists were embedded into cohesive local networks. They also found that users with longer activity history were less risk-averse and created less novel designs [54]. Askin et al. analyzed how network formation influences female and male musician's songs' novelty [244]. They found a U-shaped effect of artist tenure on song novelty: artists in the beginning and at the end of their careers are more likely to create novel songs. Similarly to Wachs et al.'s findings, more popular and famous artists are less risk-takers and less likely to create novel songs. Large collaboration networks were associated negatively with song novelty regardless one's gender. In addition, gender stereotypes influence male musicians negatively too: being associated with a female-majority genre is a negative predictor of novelty. Wachs et al. analyzed the effect of gender differences on design professionals' success and could only partly explain men's higher success with the gendered nature of skills and styles. Network structure turned out to be an important component of the success gap between men and women: women had more clustered and gender-homophilous social networks, which blocked them from reaching a wider audience [53].

These studies suggest that although men and women benefit from the same network structure, women are often lack of social capital to develop them. Women are more likely to develop less open, denser and clustered networks constrained by gender-homophilous ties. Since success and evaluation could be influenced by social norms and stereotypes, feminine network structures block women from becoming successful.

3.3 Gender differences and bias in online communities

The big data boom of the last decade developed a new scientific field: computational social science (CSS). CSS combines the computing power of computer science and the theoretical background of social sciences with the methods of network and data science. The availability of large-scale interaction data allows scientists to analyze and test hypotheses about such sensitive research topics as gender inequality, unconscious bias, and discrimination. Below I present recent findings of CSS on gender inequalities in online collaboration platforms [245].

Szell and Thurner examined a multiplex network of 300 thousand online gamers and found that many gendered roles were present in these online systems. They found that women were less risk-taking, which resulted in better economic performance. They found evidence that traditional gender roles also manifest online: men reciprocated female friendship requests faster than women, and engaged less in hostile actions against women. They also reported that women had more homophilous connections, and had more communication partners, while men had more competitive relationships with each other, and were less likely to create cooperative links with other men [246].

Investigating direct and indirect algorithmic bias is a growing research field [**?**, 247, 248, 249, 40, 41, 42, 43], and more and more studies analyze empirical data about how offline gender and racial bias influences the online job hunting opportunities of minorities. Hannak et al. presented evidence of gender and racial bias on online freelance marketplaces. They compared two major American job search sites, Fiverr and Taskrabbit and found that gender and race were significantly correlated with one's evaluation, which can harm long-term employment opportunities. Even though the sites have very different profiles (one is more blue-collar, the other is white-collar), users' reviews were consistent in that black men received the lowest rating, women received fewer ratings and Asian men were evaluated the best. Reviews of black women had significantly less positive adjectives, and black workers, in general, got more reviews with negative adjectives. The authors also noted algorithmic bias against women and black in search engine results at Taskrabbit, however, it is not clear whether this was the result of reviews, or the algorithm was designed in such a way that introduced bias [250]. Chen et al. examined three main career websites, Indeed, Monster, and Career Builder for direct and indirect gender discrimination. The authors presented results that support the claim that indirect discrimination (group unfairness) against women is present at all three websites: female candidates appeared lower in search results than male ones, even when they controlled for visible features. They did not detect any signs of direct discrimination, meaning that search engines did not use candidates' gender directly to rank them for job advertisers [251]. These studies suggest that racial and gender stereotypes harm individuals in the online sphere too, and career sites might introduce algorithmic bias, blocking the access of women and underrepresented minorities from important opportunities.

Horvat and Papamarkou analyzed gender-related differences in patterns of entrepreneurship in a UK-based equity crowdfunding platform. They found that 14.8% of investors and 13.7% of entrepreneurs were female, which is slightly higher female representation than in the offline capital markets. They tested whether female entrepreneurs asked for less money, but did not find any significant difference between men and women. In general, female entrepreneurs had a higher success rate in fundraising, but female investors chose campaigns with lower success rates. They also found that topics in female-majority industries attracted a higher percentage of female investors (e.g., Food & Drink, Health, Consumer Products), and male-majority ones (e.g., Finance, E-Commerce & Markets, IT & Telecom) interested a higher percentage of men [52]. This indicates that gendered patterns of choices online can put women at a disadvantage.

A number of studies has analyzed gender representation on Wikipedia. Wikipedia is among the top 20 most visited websites worldwide, with the goal to provide non-biased information about notable people and the achievement of humanity in various disciplines [252, 253]. Wikipedia is a crowd-funded effort, edited by volunteers. As Wagner et al. argue, the non-supervised, volunteering nature of the editors could introduce systematic gender bias into the content of Wikipedia, resulting in a lower representation of women in masculine fields [50]. Reagle et al. compared women's representation in Wikipedia biographies with the online Encyclopedia Britannica. They found that, in general, Wikipedia had better coverage of women than Britannica. They did not find a difference in article-length between men and women [254]. In another article, Wagner et al. analyzed gender bias on Wikipedia articles about notable people in 6 different languages. In terms of coverage and visibility, they did not find gender differences: men and women were equally represented by the number of articles and had the same probability to be featured on the front page of the site. However, they found that articles about women were more likely to be linked to men than vice versa. Traditional gender roles were also more likely to be discussed in articles about women, such as romantic relationships and family-related topics. In another study, Wagner et al. revealed that abstracts of men's biographies tended to describe positive achievements, while women's negative ones [50, 51]. Iosub et al. analyzed the emotions in the dialogues of Wikipedia editors from a gendered perspective. They found that female contributors promoted social affiliation and emotional connections more in debates than male editors. They also found that editors tended to interact with the editor with similar emotional style, which can lead to gender segregation within the community [255].

These studies clearly indicate that discrimination and gender bias also manifests online. As technology is becoming more important to operate different aspects of our lives, the presence of algorithmic bias is especially concerning. The lack of diversity has been associated with discriminating products, which makes it even more important to understand the reasons why women do succeed in STEM fields.

In the following three chapters I will showcase my three studies; each focuses on different aspects of the above explained reinforcing mechanisms of inequalities. The first study explores how gendered behaviour is displayed among open source software engineers online and how this contributes to increasing gender inequality. Then I explore the world of science to determine whether the online sphere can benefit female scientists to overcome well-documented inequalities. As the literature review indicates, the role of gender diversity and networks in team performance, a gender-inclusive culture is crucial to utilize the potential benefits of diversity. Therefore, the third case analyzes the role of diversity and inclusion in creativity and success in the video game industry.

CHAPTER 4

GENDERED BEHAVIOUR AS A DISADVANTAGE IN OPEN SOURCE SOFTWARE DEVELOPMENT

4.1 Introduction

Women suffer a considerable disadvantage in information technology: their proportion in the workforce is decreasing, and they are especially underrepresented in open source software development. The proportion of women in computing occupations has been steadily declining from 36% in 1991 to 25% today [9, 10, 11]. In open source software only about 5% of the developers are women [256] , and they exit their computing occupation careers with higher probability. Women suffer from a gender wage gap in STEM – and especially in computer programming – more so than in other fields [257]: that has not decreased over the past two decades [258]. Many women quit their computing occupation careers in the middle [259]. These developments are puzzling, especially in the face of a favorable shift in public consciousness, and considerable private and public policy efforts to counter gender discrimination. With accumulating evidence of the benefits of gender diversity in teams [260, 88, 261], it is clear that marginalization of women in software development leads to major societal costs.

In this article we analyze a large dataset of open source software developers to answer the question: are women at a disadvantage because of who they are, or because of what they do? Typically, gender discrimination is conceptualized as categorical discrimination against women [262] ; however, as much of the scholarship in gender studies had shown, to understand gender inequalities one needs to shift the focus to the gendered pattern of behavior [263, 264]: The more likely causes of discrimination are actions that are typical of men and women, rather than the gender category of the person [264, 265, 266]. Women in leadership roles often feel compelled to (or are expected to) follow male behavioral traits [267], just as men in feminine occupations take on female-like behavioral traits [268], and the choice of collaborators and mentors often follows gender homophily [49].

While categorical gender discrimination is an easy target for policies, discrimination based on behavioral expectations are more difficult to counter. Recently Google was sued by women for categorizing women as 'front-end' developers without reason, blocking their access to higher pay and faster promotion that 'back-end' developers enjoy, who are more likely to be male [269, 270]. This also underscores that when we analyze the gendered pattern of behavior, we should not assume that such behavior is a result of free choice. In fact, the history of computing occupations is also a history of marginalizing women from an increasing number of specializations [271]. Thus far there have been no analysis based on large data in a contemporary setting, to analyze behavioral traces, and to assess the relative weight of categorical and behavioral gender in gender inequality. Our data source is GitHub: the most popular online open source software project management system, which provides an opportunity to track the behavior of software developers directly, identify gender from user names, and observe success and survival [66, 272]. In open source software development the most important payoff to participants is reputation [76], hence we operationalize success as the number of users declaring interest in one's work by "starring" a repository. As a second dependent variable we analyze differences in the odds of sustaining open source development activity over a one year period subsequent to our data collection time window.

Using data about behavior in a large sample allows us to construct a measure of femaleness of observed behavioral choices over the entire career, as a measure of gender typicality. This approach has a long history, using survey data [273, 274, 263], and more recently with behavioral trace data in diverse settings [275, 276, 277]. In addition to the interval scale gendered behavioral dimension, we also identify multiple kinds of gendered behavioral patterns using a decision tree classification approach, and we assess the relative explanatory power of one behavioral dimension when controlling for multiple patterns of behavior.

We first compare men and women: users who display a recognizable gender on their profile, but we also analyze data of users with unidentifiable gender. The first question is whether gendered behavior makes any difference at all, or is it only the gender category, that relates to female disadvantage. If gendered behavior is related to outcomes, is that relationship the same for both women and men? Are there signs of change in patterns of gendered disadvantage?

It is also important to analyze gendered behavior of those who do not readily reveal their gender. Scholars have discussed the potential of online collaborations to mitigate gender inequalities, as it is easier to manipulate or hide gender identity online, compared to face-to-face settings [278, 279, 280]. Our first question here is whether we see evidence for surrounding users recognizing the gender from the behavior of focal users that are hiding their categorical gender. Our second question is whether success and survival for unknown-gender users are related to their gendered behavior as well.

4.2 Empirical Setting and Data

4.2.1 GitHub

Github (github.com) is a social coding platform that allows software engineers to develop and publish software together, recording their contributions to a collaborative activity. It is the most popular web-based 'git' software repository hosting and version tracking service, with 20 million users and over 57 million private and public repositories in May, 2018. Working in repositories collaboratively can lead to success through visibility and reputation, which helps developers to be noticed by potential employers [76, 281, 66]. We used coding and collaboration activity to conceptualize individual careers.

The empirical basis of this study is a data set acquired via githubarchive.org between 2009-02-19 and 2016-10-21 about the following: creation of a repository, push to a repository, opening, closing and merging a pull request. To collect information about users' names, e-mail addresses, number of followers, number of public repositories and the date they joined GitHub, we sent calls to the official Github users API.

4.2.2 Inferring Gender

Since users do not list their gender directly, we infer each person's gender using their first names. This is a commonly and successfully used method in Western societies [282, 275]. In this work, we rely on the 2016 US baby name dataset published by the US Social Security Administration annually. (SSA 2016). Users' first names for gender recognition come from a number of data points. Users can add their full names and e-mail addresses to their profiles, but only a nickname is required to use GitHub. We first check whether a user's full name is available and separate its first and last name(s). If not, we check the availability of the e-mail address and separate the part before the "@" by various punctu-

Probability	Inferred Gender	N in population	N after filtering
P<=0.1	female	194,010	56,731
0.1<P<0.9	unknown	6,163,370	977,389
P>=0.9	male	1,441,130	600,253

Table 4.1. *Inferring name for gender recognition Due to some names being used for both males and females, we assign a probability of being male to each candidate based on the fraction of times their first name was assigned to a male baby in the name dataset. We define gender probability cutoffs of 0.1 and 0.9 consistent with previous studies [3]. Our gender recognition yielded 11.87% females and 88.13% males out of all users with names. All in all we found 194,010 females, 1,441,130 males, and 6,163,370 unknowns.*

ation marks or capital letters, and save first and we then last name(s). Since in some countries such as Japan or Hungary the given name is the second or the third name, if our baby name database does not contain the inferred first name, we ran the algorithm on last name(s) as well. Baby names dataset mainly covers American and European names, and lacks Asian names. In Asia, it is a common tradition to choose Western given names and use them in real and online life [283, 284, 285] thus if no full name or e-mail data is available or not inferable we use the user's nickname as the name for gender recognition. *See Figure 4.1 for population size*

4.2.3 Accuracy of Gender Inference

We assess the accuracy of our gender inference by a comparison to a baseline (consensus of two manual coders), and by a comparison to two other methods. We took a sample of 600 users from our data set, and assessed their gender manually. We, the two authors independently hand-coded 600 user profiles (200 females, 200 males, 200 unknowns according to our original method), using information publicly accessible online, in approximately the same way a GitHub user would and could come to a conclusion about the gender of another user of interest.

There were 73 cases (12.2%), where the opinion of us, two manual coders differed. We re-checked these cases, and came to a consensus about each. To quantify our inter-rater reliability, we used Krippendorff's alpha [286], a commonly used statistic of agreement. Considering three gender categories - female, male, and unknown - the alpha was 0.80. Considering female and male users only, the alpha was 0.95. Both of these are conventionally considered to be good reliability.

40 users profiles had been deleted over the past two years, so our final tally is 300 males, 156 females and 104 unknowns. Using this consensus classification as our baseline, we compared our gender inference method, and two other well-known algorithms trained for inferring gender in online communities; Gender Computer by Valiescu [66] and Simple Gender by Ford [4]. Figure 4.1 shows the Precision, Recall and F Score of each algorithm by gender.

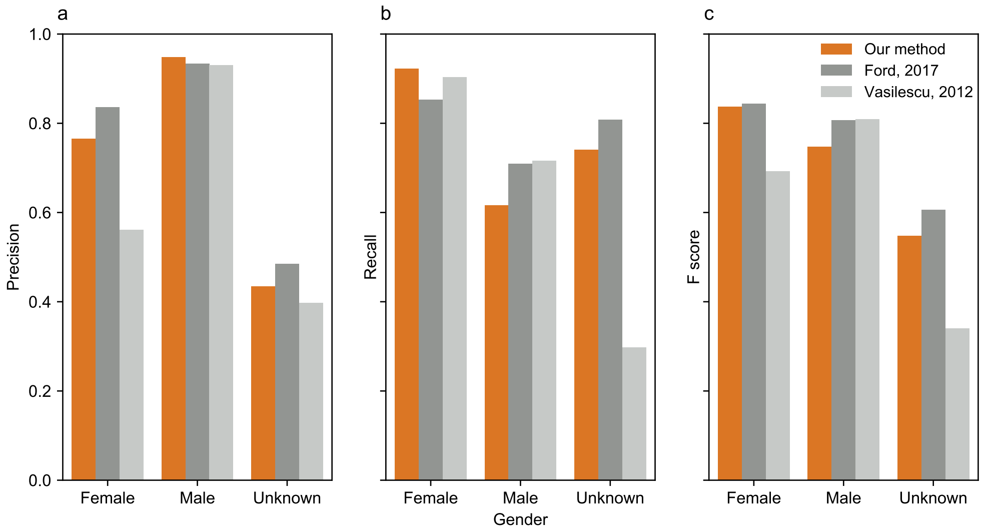

Figure 4.1. *Comparing Gender Inferring Algorithms Accuracy of our gender inference against a baseline and two alternative methods. Precision (a) measures for each category how many categorized items are relevant, and recall (b) captures how many relevant items are selected from all good ones, F score (c) takes the harmonic average of precision and recall, reaches 1 when both metrics are perfect.*

The three algorithms have very similar accuracy; all methods are optimized for high male-precision and female-recall. Valiescu's method minimizes the number of unknowns, which gives it's an overall worse precision in the case of women. Our method's weakness is the male-recall. Overall, we believe that our gender inferring method is robust and sufficiently accurate in comparison to other already published methods, while it has the advantage of being simple and easy to implement.

4.2.4 Data Cleaning

We decided to filter users by their level of activity, as there are many users who establish a GitHub account with hardly any subsequent developer engagement (but use GitHub, for example, as a web hosting platform). First we excluded organizational and company accounts, then selected those 1,634,373 users in our data set with at least 10 traces of activity over their careers. Then we deleted 1,604 users for evidence of being artificial agents (having a substring, like "bot", "test", "daemon", "svn2github", "gitter-badger" in their usernames). As we were interested in patterns of gendered behavior (for which we encountered resource and time intensive data crawling challenges regarding pages of connected users), we took a biased sample with 10,000 users of each gender groups (men, women, unknown gender). We repeated the sampling procedure five times, to test for robustness to sampling error. We crawled the profile pages of all sampled users, and collected who they follow, and whom they are followed by. Gender of followers and followed users were identifies with the same approach outlined above.

4.3 Measures

Identifying specializations

To capture the specialization of activity, we used principal component analysis of programming languages, where variables represented the number of times a given programming language was used by the individual. For each repository, GitHub auto-detects the main language. In total, we extracted 103 different programming languages, and kept those which appeared at least in 1000 projects within our samples, resulting in 22 most commonly used ones. *Figure 4.2* shows the language frequency. We used Scipy's PCA.decomposiation package with Varimax Rotation to identify independent factors. [287] We ran the PCA analysis on each sample, than used the least square criteria to extract the factors and compare them.

4.3.1 Femaleness

The main variables of interest in our article is the gendered pattern of behavior, which we operationalize as the probability of being female given behavior. Several studies had adopted a similar approach of using an empirical typicality measure as an explanatory variable, in a wide range of empirical problems, from the phonological typicality of words [288] to the typicality of music [289] , careers [290], businesses [291], or restaurants [292]. Typicality has been used to investigate gender as well [275, 293]. We selected variables that capture the most relevant aspects of behavior in open source software development. We use variables that represent choices reasonably under the control of the individual.

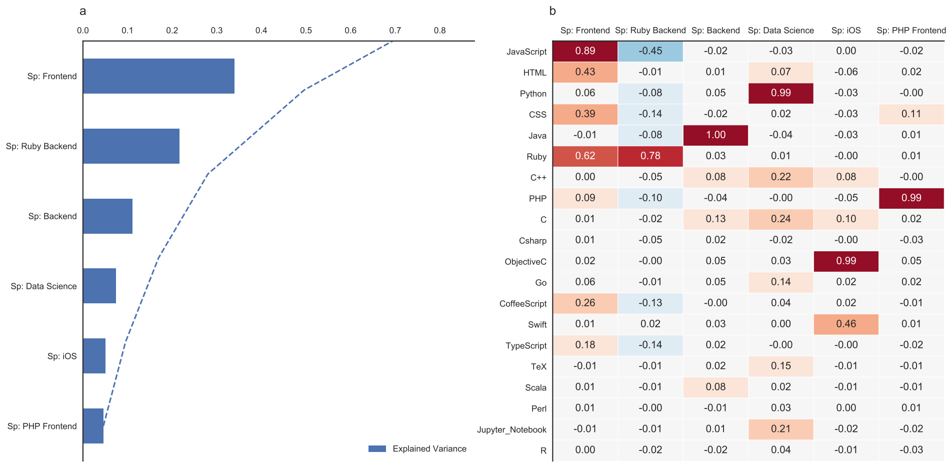

Figure 4.2. *Identifying Specializations Our method captured the same 6 factors in each sample. The correlation matrix shows the "importance" and the sign of the relationship of the language in the component. We identified 6 main specializations;* 1) *Frontend development (JavaScript, HTML, CSS, Ruby),* 2) *Developers using Ruby for backend development (strong positive Ruby and quite negative JavaScript),* 3) *Backend Development with high activity in Java,* 4) *Data Science (Python, Jupyter Notebook, R, C++),* 5) *iOS development (Objective C, Swift) and* 6) *PHP enthusiastic with Frontend focus (PHP,CSS).*

For measuring gendered behavior, we used a Random Forest model [287] to predict the gender identity conveyed by name choice of a user, using their collaboration history, activity, and specializations identified above by principal component analysis. We used the following variables: No of repositories, No of touched repositories, No of ′pushes, No of opened pull requests, No of followed females, No of followed people No of collaborator, Frontend, Ruby Backend, Backend, Data Science, iOS, PHP Frontend. We used a Random Forest classifier with 10-folds cross validation, to predict gender (a prediction of someone being female). The size of our dataset allows us to set k=10, which is a commonly used value in applied machine learning. [294, 295]

The Random Forest classification was moderately accurate – behavior in open source is not drastically different by gender. The area under the ROC curve was 0.71, which was consistent across five samples, and decreased to no less than 0.67 with 5% and 10% swapped gender. Variable importance scores were also robust to gender classification error. See S5 and S6. This is a moderate classification performance, which is weaker than classic instruments devised to measure gendered behavior [274] (AUC for inkblots test = 0.94, for combined test = 0.96), but similar to the performance of gender classifiers based on internet messaging [276] (AUC = 0.72), graphic design works (27)(AUC = 0.72), or biometric gender prediction based on screen swiping [277] (AUC = 0.71).

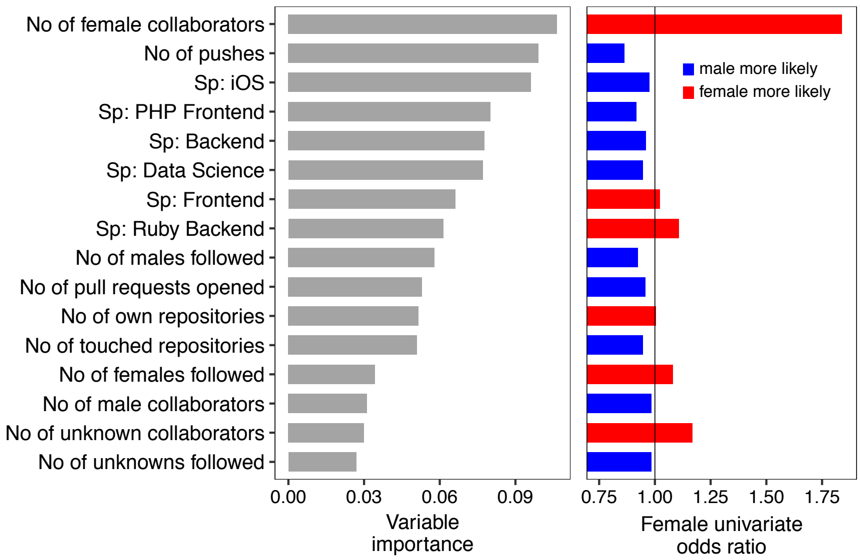

Figure 4.3. *Variable Importance Variable importance in gendered behavior prediction by the Random Forest Prediction and Female univariate Odds Ratios in predicting gender with logistic regression*

As Figure 4.3 shows, the most important behavioral aspect for femaleness prediction is gender homophily: the number of female collaborators (a collaborator is someone who contributed to the same repository with the user). This variable has both the highest variable importance and the highest odds ratio. With one standard deviation increase in the number of female collaborators, the odds of being female increases by 1.84 (p=0.000). Other gender-coded collaboration tie variables are far less important, corroborating findings of others that female homophily is a marked phenomenon in fields where women are underrepresented [49]. Specializations of programming languages are important components of gendered behavior, although contradicting stereotypical assumptions. Front-end specialization (work on the look of interfaces) is assumed to be feminine, while back-end (work on algorithms and data procedures under the hood) is considered to be more male. We identified two principal components of each specialization, and found that there is one pair of front-end and

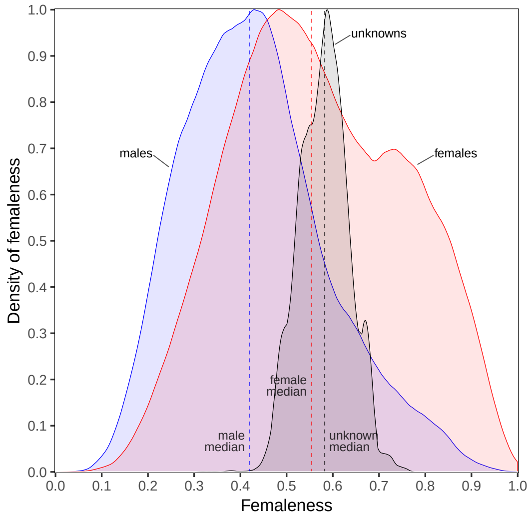

Figure 4.4. *The probability density of femaleness for males, females, and unknown gender Males have a median femaleness of 0.42, females 0.55, and the highest is unknown gender, with a median femaleness of 0.58. This indicates that users who do not reveal their gender are either females, or males with a decidedly female-like behavioral profile. Users with unknown gender also show the narrowest range of femaleness (0.32 to 0.76; compared to males: 0.07 to 0.96; and females: 0.06 to 0.99).*

one back-end specialty that is more male, while there is another pair of front-end and back end specialty that is more female. For the distribution of femaleness see Figure 4.4.

Robustness to mis-identification Gender prediction depends on inferred gender, which will have error. To test the sensitivity of our analyses to gender mis-identification, we re-ran the Random Forest prediction with datasets where 5% and 10% of the users had their gender swapped. This amount of error is in the range of mis-classification that we saw comparing our method to the baseline (7.5% of users with known gender was mis-identified by our method). We created 100 mis-classified datasets for each randomization type. Variable importance in the Random Forest prediction was robust to swaps of gender, figure 4.5 shows original variable importance (dashed grey line) compared with with the distribution of new variable importance calculated on gender-swapped datasets.

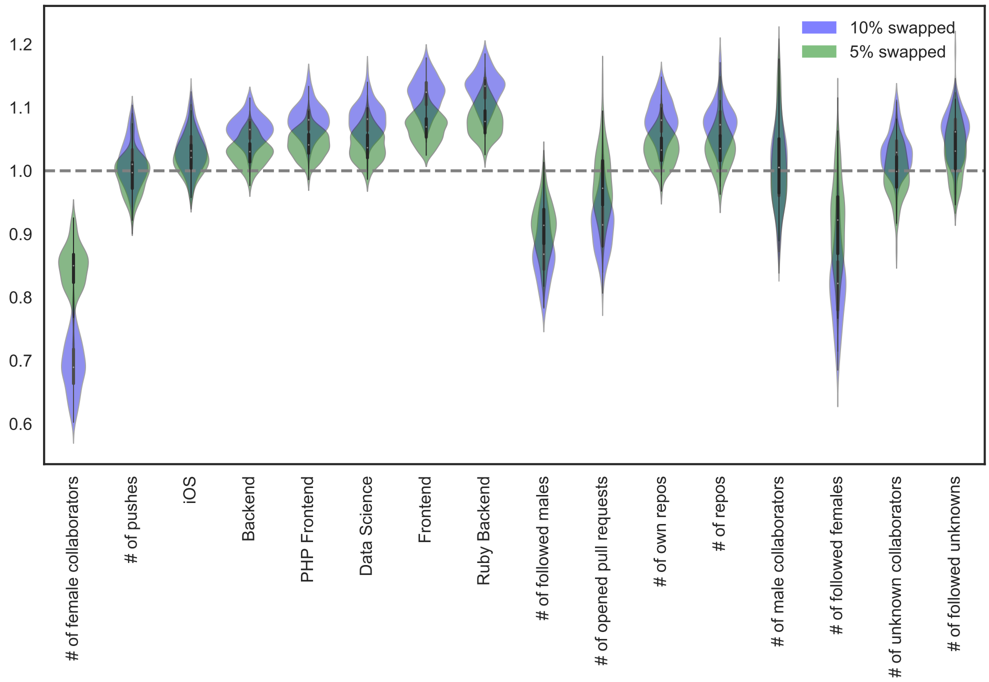

Figure 4.5. *Relative variable importance after randomization, normalized by original importance (n=100) Random Forest prediction with 100 datasets where 5% gender swapped AUC's mean is 0.672 (SE:0.002), and 10% mean: 0.651 (SE:0.003). Variables indicate female-gender homophily, number of female collaborators and the number of followed females and males are the most sensitive to gender swapping.*

4.3.2 Classes of gendered behavior

With our gender typicality measure we assume that the gendered nature of behavior varies along one continuous dimension. This assumption has been challenged before [296, 297], so we test whether multiple categories of gendered behavior is a more adequate approach. To accomplish this we identify multiple classes of femaleness with a decision tree prediction approach. We then include a set of binary indicator variables representing decision tree classes, with the most gender-balanced class being the reference category in our models for success and survival. We also identify a range of classes, from 5 to 100, to test the robustness of our findings to the resolution of the classification tree. *See section Models*

Our Decision Tree classifier is based on the same variables we calculated *femaleness*. Figure 4.6 shows the final tree with classes of typical gendered constellations of behavioral variables.

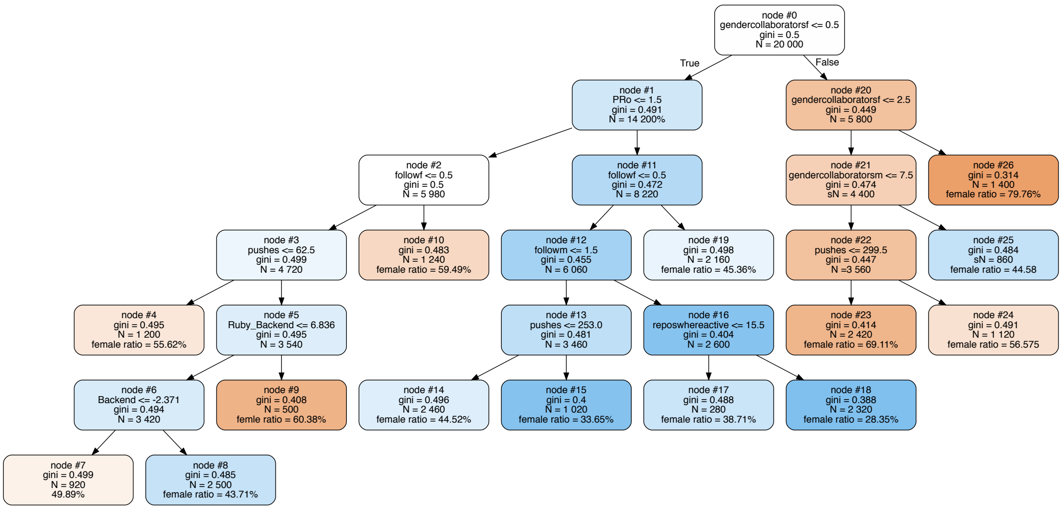

Figure 4.6. *Decision Tree model for gendered constellations of behavioral variables Our final tree (minimum samples split=1000,max depth=10, test size=0.6) resulted with a 0.6327 AUC and 14 classes.*

Optimization We optimized the decision tree classifier for maximum depth, running the algorithm with different fixed depth sizes, resulting with 5, 10, 20, 50 and a 100 categories. We use these categories for predicting success and survival for developers belonging to the same classes.

4.4 Models

Our dependent variables are success and survival. Our success measure is the total number of times other users have starred (bookmarked as useful) repositories owned by our focal user, during the entire career. A star is a statement of usefulness: interest from another user to easily locate and to utilize the given repository in the future. Since success and our behavioral variables co-evolve during the career, causal arguments can not be tested. We measured survival by re-visiting all users' pages exactly one year after the end of our data collection, and recording the number of actions taken by the user over this one year. If a user did not make any actions on the site for one year, we recorded exit for that user; otherwise we marked the user as survivor. Users seldomly close their accounts (0.3% of users), since keeping an account is free. In the case of survival we can test causal hypotheses, as behavior precedes cessation.

Our measure of success is an over-dispersed count variable, thus we use a negative binomial model specification. Moreover, we also know that many users of GitHub are not interested in accumulating stars for repositories, but use the platform for other purposes (e.g. as a personal archive); in other words users are a mixture of two latent classes: one interested in achieving success, and one without such interest. We therefore estimated a zero-inflated negative binomial model (ZINB), where we separately modeled excess zeros with a logit model, and the accumulation of stars with a negative binomial model. We also tested the robustness of our findings with an OLS model with the log of success as the dependent variable, and a specification identical to the count model of our zero inflated negative binomial models.

We estimate our ZINB mixture model with equation [1]: where γ_i is the number of stars accumulated by user i for own repositories, γ is the gamma distribution, k is a dispersion parameter, and n is a natural number > 0. We can model π_i and λ_i as functions of independent variables. For π_i - the model for the zero component - we specify a logistic regression with a logit link function at [2], and for the count model we use an identical specification [3], where x_g is the female gender category (for women $x_g = 1$, for men $x_g = 0$), and x_b is the femaleness of behavior from our random forest prediction.

$$\begin{cases} P(Y_i = 0) = \pi_i + (1 - \pi_i) \cdot (1 + k\lambda_i)^{-\frac{1}{k}} \\ P(Y_i = n) = \frac{(1-\pi_i)\cdot\Gamma(Y_i+\frac{1}{k})(k\lambda_i)^{Y_i}}{\Gamma\frac{1}{k}\Gamma(Y_i+1)\Gamma(1+k\lambda_i)^{Y_i+\frac{1}{k}}} \end{cases} \tag{4.1}$$

$$logit(\pi_i) = \gamma_0 + \gamma_g x_{gi} + \gamma_b x_{bi} + \gamma_{gb}(x_{gi}x_{bi}) + \gamma_n x_{ni} + \gamma_{gn}(x_{gi}x_{ni}) + \gamma_c x_{ci} \tag{4.2}$$

$$log(\lambda_i) = \beta_0 + \beta_g x_{gi} + \beta_b x_{bi} + \beta_{gb}(x_{gi}x_{bi}) + \beta_n x_{ni} + \beta_{gn}(x_{gi}x_{ni}) + \beta_c x_{ci} \tag{4.3}$$

As an auxiliary test for the presence of discrimination by categorical gender, we added a variable that records the relative frequency of the first name of the user (relative to the total number of users of the same gender) – an approach recently taken to measure discrimination in patenting [298]. If discrimination is by categorical gender, we expect women to be significantly disadvantaged in proportion to the frequency (easy recognizability) of their names. We expect that women with names like "Mary" (the most common female name) are more disadvantaged than women with names like "Maddie" (one of the least common female names). We thus include x_n as the normalized logged relative frequency of first name within gender: $x_{ngi} = \log \frac{f_i}{N_g} / max(x_n)$, where f_i is the overall frequency of the first name of user i , and N_g is the overall number of users of gender g.

Finally, x_{ci} stands for control variables. Our control variables represent alternative explanations connecting gender and outcomes: Tenure (number of years since joining) might favor men, as women tend to have shorter tenure (and drop out). The level of activity (number of own repositories and number of repositories where the user contributed) might also favor men, as women usually have less time to devote to professional activities. Social ties (number of followers and collaborators) might also favor men, as gender homophily is expected. Finally, we measure the total number of potential bookmarkers as the number of developers who worked with the same programming languages as our focal subject. A developer with a large potential audience might gather stars more easily for his or her repositories.

We estimate a logit model for survival with an identical specification to the success model [4], where $\gamma_i = 1$ for users with sustained activity over one year after data collection, and $\gamma_i = 0$ for cessation. The independent variables are defined in the same way as described above.

$$ln \frac{P(\gamma_i = 1|x)}{1 - P(\gamma_i = 1|x)} = \beta_0 + \beta_g x_{gi} + \beta_b x_{bi} + \beta_{gb}(x_{gi} x_{bi}) + \\ + \beta_n x_{ni} + \beta_{gn}(x_{gi} x_{ni}) + \beta_c x_{ci} \tag{4.4}$$

4.5 Results

4.5.1 Femaleness and outcomes

Considering gender as a category (females and males) for success, women on average received 8.76 stars, and men received 13.26, however, this difference is not statistically significant, neither by an F-test (F=2.208), nor by a bivariate ZINB model entering only an intercept and gender category (female=1, male=0) in both the zero inflation model (gender coefficient z= 0.488), and the count model (gender coefficient z= 0.835). Women, however, have a statistically significant disadvantage in the probability of survival: 92.8% men survived one year after our data collection, while only 88.2% of women (odds ratio=0.575, Chi-squared=126.1).

The femaleness of the pattern of behavior is significantly negatively related to success, using both a t-test (t=-5.337), and a ZINB model (zero inflation model z=23.947; count model z=-12.365). Femaleness is also negatively related to survival (bivariate logit model z=-9.875)

Turning to multivariate models, Figure 4.7 shows point estimates of expected success and expected probability of survival for gender-related variables from five model specifications. All variables are measured on the 0-1 scale, making estimates comparable. In our full models – ZINB models for success *(Table 8.1 in Appendix)* and logit models for survival *(Table 8.3.)* – the coefficient for being female shows no consistent relationship with outcomes. In our main models of success and survival (model 1 with variables shown on Figure 4.7 and additional control variables), females are not significantly disadvantaged compared to males. In fact, our success model shows a weak positive coefficient (0.62, p=0.049). We tested the robustness of this finding by adding binary indicator variables for decision tree classes representing typical gendered behavioral patterns (model 2), or adding all programming language use frequencies (model 3). We also re-estimated model 1 (both for success and survival) with randomly swapped genders. We estimate model 4 by using the same variables as in model 1, but randomly swapping the gender for 5% of developers in the sample with known gender, and in model 5 swapping 10%. Both model 4 and model 5 report 95% confidence intervals from 100 trials. Of the five models, only models 4 and 5 (with 5% and 10% randomly swapped gender) show significant disadvantage for females in survival. Our findings for success were robust with an OLS specification predicting log(success+1) as well *(Table 8.2.)*.

While categorical gender is not a consistently significant predictor of outcomes, the femaleness of behavior is in all models for both success and survival. Femaleness of behavior is a strong negative predictor of both success and survival, and it is the only coefficient related to gender that is consistently and significantly different from zero. Figure 4.8 shows predictions for success and survival along the range of femaleness, keeping all other variables constant at their means. The difference between females (red line) and males (blue line) is small compared to the difference along the range of femaleness.

First, consider success at the median for both males and females (Figure 4.7 panel a). Taking the predicted success of males at the median is 2.53 (stars for their repositories), for females the prediction at their median femaleness is 1.07. Taking the male prediction as 100%, the expected success of females is

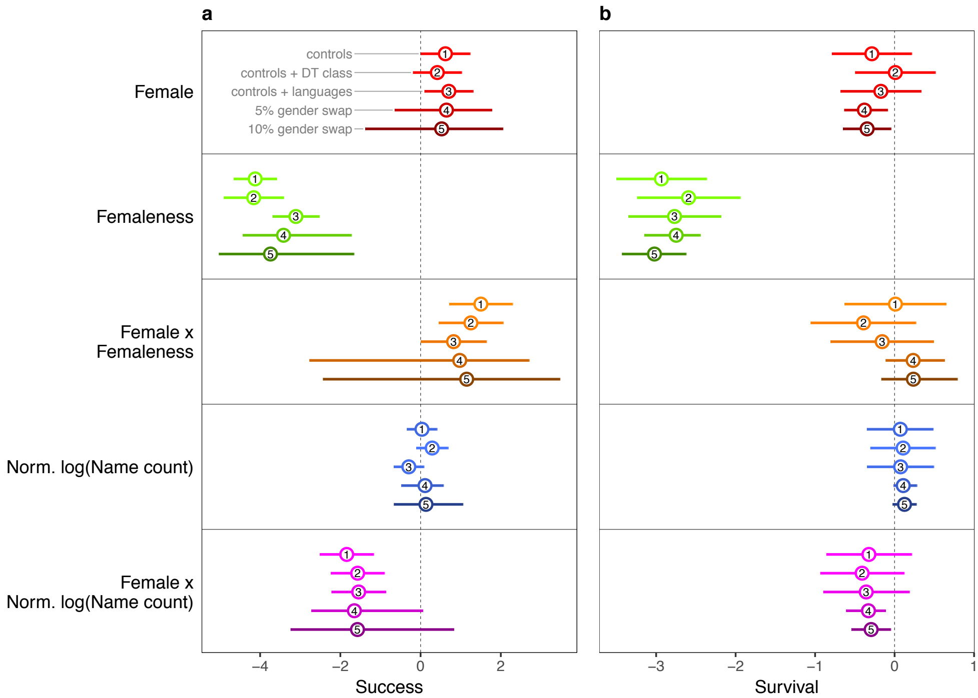

Figure 4.7. *Point estimates, with 95 percent CIs, for variables related to gender (variables are listed on the vertical axis). Panel a. shows coefficients from count models of zero-inflated negative binomial models predicting success (the number of stars received), while panel b. shows log odds ratios from logit models predicting survival over a one year period following our data collection. Labels of five specifications (identical for success and survival models) are shown in the legend. The first model enters gender variables and controls, the second enters controls and categorical gender behavior classes from the decision tree analysis, the third enters controls and 23 variables recording programming language use. The fourth is identical to the first, but with data with 5 percent gender swaps, and the fifth is with 10 percent gender swaps. For the fourth and fifth models confidence intervals show the 2.5 – 97.5 inter-quantile range from 100 simulated datasets.*

42.3% of that. The disadvantage is 57.7% points, of which 8.9% points are due to categorical gender, and 48.8% points are due to difference in femaleness. In other words, only 15.4% of the expected female disadvantage in success is due to categorical gender, and 84.5% is due to femaleness of behavior. Considering the same decomposition for probability of survival (Figure 4.7 panel c), we see a smaller disadvantage for women: 6.1% points, of which 4.0% points is doe to categorical gender, and 2.1% due to differences in femaleness (34.8% of the expected disadvantage in survival).

Males are also disadvantaged by their gendered behavior. Considering the interquartile range of femaleness, the expected success of males at the first quartile of femaleness (0.32) is 4.16 stars, while the same expectation at the third quartile (0.52) is only 1.51 stars, which is 63.7% less. For females the predicted success at the first quartile of femaleness (0.43) is 1.84 stars, while at the third quartile (0.72) it is only 0.51 stars – a difference of 72.2%. For survival the same inter-quartile disadvantage for males is 2.7%, for females it is 8.8%.

The coefficient of the interaction between female gender and femaleness is positive for success, but not significantly different from zero for survival (considering model 1). This indicates that the penalty for femaleness is higher for males overall than for females. (The female disadvantage over the interquartile range is nevertheless higher than males because of the wider spread of femaleness for females.)

Using the frequency of first name shows some evidence of discrimination in success, but not in survival. The interaction of being female and having a frequent name is negative, while the coefficient for name frequency itself is not significant, indicating that it is only women, who suffer a disadvantage if their name is more common, and thus their gender is easier to recognize. The prediction for a woman with the rarest name is 2.74 stars, while the prediction for a woman with the commonest name is only 0.95 stars – a 65.5% lower success.

Figure 4.8 also shows predicted outcomes for users with unknown gender. To predict outcomes for unknowns, we use a specification identical to model 1, without variables for categorical gender and name frequency *(see Table 8.4.)*. Again, our findings about success were robust with an OLS specification predicting log(success+1) *(see Table 8.2.)*. As apparent on Figure 4.7 panel b and d, the femaleness disadvantage is also demonstrable for those who do not reveal their gender. At the first quartile of femaleness (0.54) the expected number of stars is 1.99, while at the third quartile (0.62) it is only 1.03 stars – a 48.0% drop. The disadvantage for survival is even more severe: a reduction of 10.4% across the interquartile range (compared to 2.7% for males, and 8.8% for females). These results are robust if we restrict our analysis to those users who do

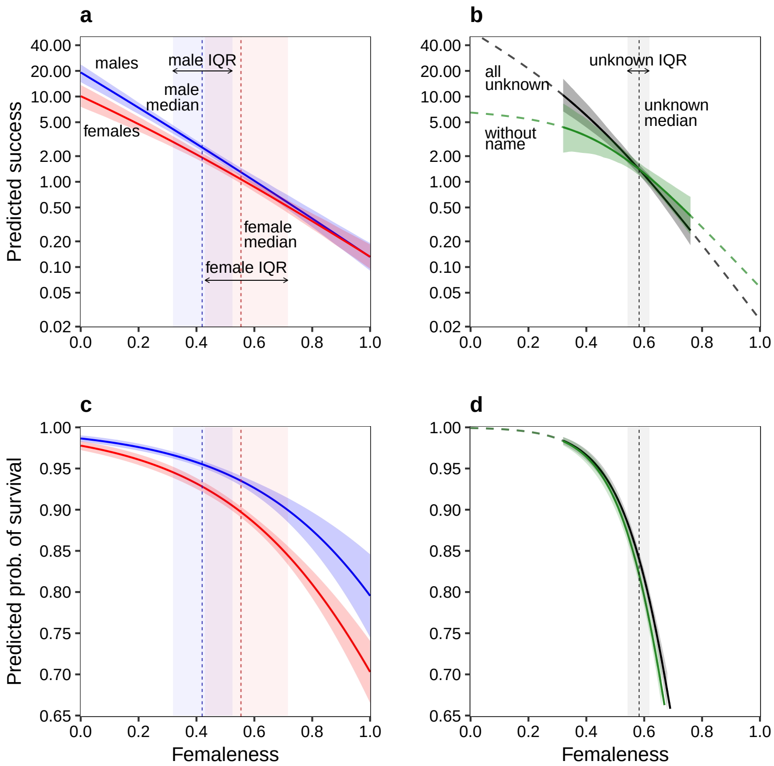

Figure 4.8. *Marginal predictions for femaleness by gender category from model 1 from Figure 4.7 of success and survival, with fixing all other variables at their means. Panels a. and c. uses data for males and females, panels b. and d. uses data of users with unknown gender. Prediction is only shown for the observed range of femaleness. Vertical dashed lines indicate medians of femaleness, and shaded vertical bars show the interquartile range (IQR).*

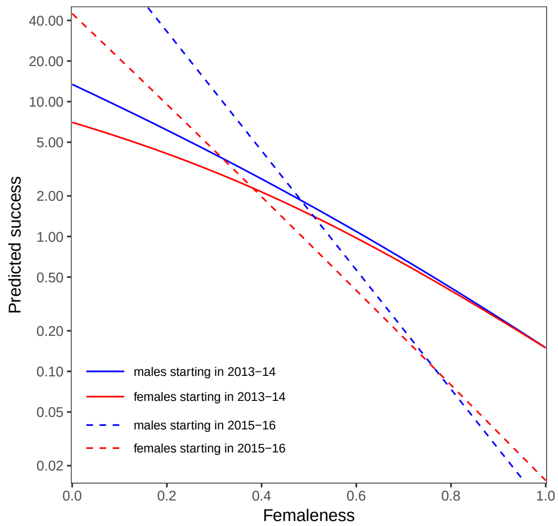

Figure 4.9. *Marginal predictions from zero-inflated negative binomial model (model1) of success, for femaleness by gender category, separately for those who started in 2013-14, and those who started in 2015-16. As a simple analysis of a time trend, we introduced a variable capturing those who started in the years of 2015 and 2016 (as opposed to starting in 2013 or 2014), and entered interactions for this time variable with categorical and behavioral gender into our model of success (Table 8.9.). We do not see evidence for a mitigating trend in the effect of behavioral gender, in fact, it seems that inequalities in success along the behavioral gender dimension have become more severe.*

not reveal any name, and omit those who do reveal a name that was not listed in the US baby name dataset.

4.5.2 Classes of gendered behavior and outcomes

Thus far we focused on relating one continuous dimension of gendered behavior, femaleness, with outcomes. We now turn to estimating how classes of gendered behavior relate to outcomes. In our models of success and survival presented in the previous section (specifically model 2 on Figure 4.7) we entered 14 decision tree classes of gendered behavior alongside the continuous dimension (omitting the most gender balanced as reference category), and found that the coefficient of the continuous dimension remains unchanged. This indicates that classes of gendered behavior do not add qualitatively different insights into how behavioral disadvantage operates. Now we test this idea further, by estimating models of success and survival by substituting the continuous dimension of femaleness by the classes of gendered behavior.

Figure 4.10 shows the marginal predictions for decision tree classes for success and survival, aligned by the female proportion in the class. In this analysis we use an OLS model with log(success+1) as the dependent variable, as the zero inflated negative binomial models did not converge for the robustness checks with a range of classes from 5 to 100. For both the success and survival models we use an identical specification to model 1 on Figure 4.7, the only difference being the replacement of the continuous femaleness variable by 13 binary indicators for classes (the 14th class being the omitted reference category). The trends on these figures show a negative relationship between female proportion in the class and outcomes: Regardless of the content of the behavior class, the proportion of women in the class is strongly negatively related with outcomes. This is true both for men and women.

To test the significance of this downward trend, we ran multilevel models, where we entered the class level female proportion instead of the dummies of behavioral class. We specified these models otherwise the same way as model 1 on Figure 4.7. We found that the female proportion in the decision tree class is a significant negative predictor for both success and survival, and that the difference between the intercepts and slopes of males and females is not significant. This finding holds with a range of decision tree class resolutions, from 5 to 100. *(Table 8.8. Table 8.9.)* This suggests that gender segregation operates along emergent types of activities, regardless of the level of detail. It is chiefly the female quality of these classes of activities that relates with outcomes, and one dimension of femaleness is adequate to capture that.

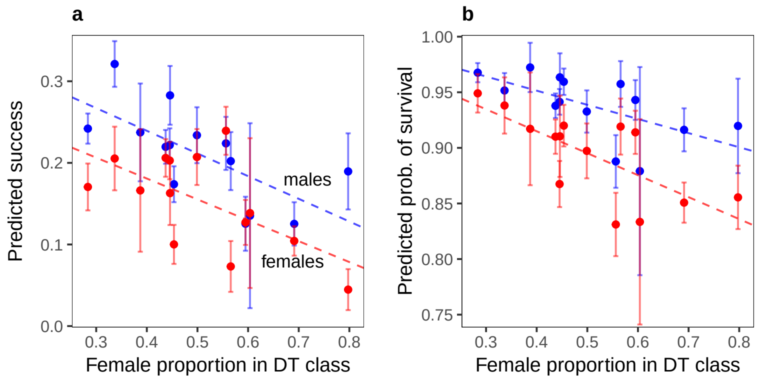

Figure 4.10. *Marginal predictions of success and survival in classes of gendered behavior. Predicted means and 95 percent CI for 14 classes of gendered behavior are marked separately for males (blue) and females (red). Classes are aligned by the female proportion in the decision tree class. Dashed lines show OLS predictions for the predicted class means by the female proportion of the class, separately for males (blue line) and females (red line). Panel a shows OLS predictions of log(success+1) as the dependent variable. Panel b shows predicted probabilities from a logit model.*

4.6 Discussion

We found that gendered behavior is a significant source of disadvantage in open source software development: our models show negative coefficients for femaleness, and only weak support for categorical discrimination. Femaleness of behavior is not only a disadvantage for women: men and users with unidentifiable gender are just as disadvantaged along this dimension. Even of we consider classes of gendered behavior with as many as 100 different decision tree classes, outcomes are chiefly related to the female proportion in those classes, both for men and women. This is an important finding, as thus far the relative importance of categorical and behavioral gender have not been studied in the context of software development, and gender segregation was only studied at the level of professions.

Our findings have important consequences for policy and interventions in gender inequalities in software development, and possibly other creative fields. In the short term, attempts to set quotas for women in software companies will not address the component of inequality that is related to gendered behavior. Increased proportion of women eventually might lead to the flattening of the slope of the relationship between behavioral femaleness and outcomes. A higher proportion of women can lead to questioning stereotypes, more visible female success stories in conventionally male types of behavior, and decisions to re-classify types of work that are now packaged in masculine-feminine stereotyped specialties.

In the longer term, as the use of AI systems in human resources management advances, the importance of gendered behavior in disadvantage means an increased risk of algorithmic discrimination. Algorithms can be policed to exclude manifest gender information from their decision making, but they can perpetuate discrimination based on behavioral typicality, as a recent case at Amazon's AI-aided hiring have shown [195]. It will be difficult to hold such algorithms accountable, as the particular behavioral specializations figuring in gendered behavior can be shifting constantly. Today activist target the front end - back end dichotomy at Google [269, 270], but tomorrow they might need to target D3 and Hadoop.

We should re-think the place of coding schools for women that are becoming widespread. These schools are typically training women in specialties that already have a number of women working in them (such as Ruby), and thus might perpetuate the disadvantage of women by their femaleness of behavior [299]. Another unintended consequence of these schools is that they contribute to gender homophily by creating more women-to-women ties among the participants.

Users, and especially women, should re-think the potential benefits of hiding their gender online. It seems that the inequalities stemming from gendered behavior impact those just as much who hide their gender. A hidden gender identity can prevent discrimination by categorical gender, but it might also lead to a lack of trust and exclusion from projects, that might be behind the higher exit rate of such users. Comparing our calculation of the marginal effects of behavioral gender for users with unknown gender and women with known (manifest) gender shows that there is no advantage for gender hiding, the effect of categorical discrimination can not be escaped from by hiding.

While we were discussing gendered behavior, it is important to distinguish gendered behavior from gendered free choice. We were composing our measure of gendered behavior out of variables that could be controlled by the individual, but we don't want to leave the impression that these traits are fully under the control of the individual. It is likely that the reasons behind the high (and increasing) negative slope of femaleness of behavior is due to constrained choice and deep-rooted stereotypes, rather than free choice. Women are being boxed into specializations even despite their manifest protest against it, as the legal case against the front end - back end distinction have shown. What is hopeful though, is that there is already a recognition that action needs to be targeted at discrimination by specializations.

CHAPTER 5

GENDER DIVERSITY IN COLLABORATION NETWORKS AND THE ONLINE POPULARITY OF SCIENTISTS

5.1 Introduction

Even with the remarkable progress of women entering higher education in the past century, female professors are still under-represented. In 2018, 49.7% of assistant professors and only 39.3% of tenured professors were women in the US [300]. Research has shown that due to the lack of female role models and non-welcoming organizational cultures, women are less likely to pursue academic careers and are more likely to drop out from graduate schools [301, 23]. Even when they opt for an academic career path, female scientists earn less [72], have access to less funding [164], are less likely to be promoted [170], have fewer co-authors [55], are less likely to develop long-lasting scientific collaborations [74, 55], benefit less from co-authorship [126], publish less [302, 303], publish in less prestigious venues [304], and their work receives fewer citations [303]. These disparities persist, notwithstanding evidence that female members increase the overall intelligence of teams [305] and gender-diverse scientific teams are more creative and produce higher quality science [37]. The societal costs of lacking gender diversity in academia range from not developing proper medical diagnosis and intervention for women to not ensuring that technological innovations profit women and men equally [40, 41].

Women in academic fields dominated by men are facing a paradoxical visibility problem: they are evident as women, but many times overlooked as experts [35]. This problem could be alleviated by effective science dissemination, which is the crucial first step in exposing scientists' work to their research communities. Therefore, it underpins subsequent academic success and reputation. Science dissemination has undergone dramatic changes over the past decade. According to large-scale surveys, 75 to 80% of researchers use online platforms such as social media sites, electronic news outlets, blogs, and knowledge repositories for the dissemination or promotion of their work [306, 307, 308, 309]. Scholarly tweets and blog posts have been shown to often contain direct or indirect links to recent journal articles [310, 311, 312]. Most scientists use their full name and identify themselves online [313, 314] and engage routinely in public discussions among scholars about the latest advances [315]. In this context, traditional metrics for quantifying academic performance, such as the impact factor and the h-index, have been increasingly contested [316, 317, 318]. Social media-based bibliometrics have been heralded as metrics which could lead to a more democratic science by quantifying the broad influence of new scientific results online [319]. It is unclear, however, whether the online sharing of scientific articles mitigates, perpetuates, or reinforces inequalities that exist offline between male and female scholars.

The literature on how science is disseminated online and how the lay public interacts with such content is mostly nascent [320, 321, 322, 323]. Essential work is based on surveys with scientists publishing in prime venues and describing their findings to non-scientists who then rate the likelihood of sharing them [324]. This research has revealed the effect of content and linguistic style on shareability and showed that women select research topics that are more likely to be shared because non-scientists find these topics more comprehensible, useful, and interesting. It is unclear, however, whether the online coverage of female scholars' work reflects this potential advantage based on topic selection. There are reasons for skepticism. First, in the world of social media, self-promotion is a crucial factor to success but typically avoided by women due to double standards in society [325]. Second, there is initial evidence that scientific communication on social media is male-dominated [326, 327], which makes women less likely to participate and benefit from it [328]. Aside from topic selection, several aspects of scientific production, both at the level of individual scholars and their co-author networks, might determine the extent of online coverage for male vs. female scholars' work. Indicators of a scientist's productivity and impact are hypothetically related to the dissemination of their scholarship [329, 330]. Their present and past co-author networks can also be assumed to contribute to the visibility and promotion of their work [331, 55, 81, 83, 84, 332, 333, 187, 74]. Specifically, the dissemination of a certain article will be determined, on the one hand, by who its co-authors are, and on the other hand, by the broader social capital of the authors, i.e., their prior collaborators who could endorse their work by way of sharing it online. Finally, we expect that these factors will differ based on the gender ratio in different scientific areas, which calls for a study that spans a wide range of research areas, instead of just one or a couple, as it has been done so far [334, 55, 335, 336].

To study the effect on article dissemination of factors spanning attributes of co-author networks and individual characteristics, we studied 537,486 scientists who had at least one article shared online in 2012. We collected meta-data about these scientists and their scholarship. In particular, we gathered their publication history and collaboration network for the five preceding years from the Open Academic Graph [337]. We also used Web of Science (WOS) data to determine scientific fields based on the references within publications [2] and to generate topics using article titles [2]. We inferred the authors' gender with a method based on their first names [4]. The used gender inference algorithm handles international names well and yielded 52% men, 29% women, and 19% unknowns among the considered scientists (see *Materials and Methods* for details). Using this unique data mash-up, we first investigated gender's connection with the online coverage of different research areas and topics to tackle open questions about the link between gendered topic selection and shareability across broad domains with widely different levels of gender imbalance. Then, to expand on research that has shown how the structure of co-authorship networks influences scientific success, we established network characteristics that are associated with differences in online coverage. Finally, we carried out a systematic investigation of the importance of topic and network-related attributes for determining online coverage with models that account for a wide range of further factors traditionally linked with scientific success, such as individual productivity and impact [183, 186, 338, 184]. Our analyses and machine learning models provide the first comprehensive view on gender-related characteristics in scientific production both at the level of individual scholars and co-author networks. Importantly, our study covers all broad research domains and points to critical variables associated with inequities in scholars' online coverage.

5.2 Materials and Methods

5.2.1 Data

Our data combine three sources connected by the unique document object identifier (DOI) of each research article, which are the following. (1) Data from *Altmetric.com* containing 757,527 articles published in 2012 with their mentions in public social media posts, e.g., on Twitter, Facebook, and Reddit, their coverage in online news, citations on Wikipedia, in policy documents, and research blogs. (2) Publication history data from the *Open Academic Graph* (OAG) for the period 2008-2012 were used to build the co-authorship network. After excluding research articles with more than 10 authors, our data contained 241,386 articles. Beyond information on collaborations, we used this source to quantify scholars' previous productivity and success, such as the number of articles they wrote in the preceding 5 years and their h-index in 2012. (3) We took a stratified sample of the size of our Altmetric data from the articles published in 2012 according to the *Web of Science* (WOS). These data contained the references of each publication and were used to determine the scientific fields of articles [2]. Our random selection ensured that in the matching sample from WOS, each research field's representation was proportional to their occurrence in Altmetric data. Finally, we identified 244 unique scientific sub-fields for the articles in the Altmetric and matched WOS samples, such as X, Y, and Z. We aggregated our combined Altmetric-OAG-WOS data to the author level by assigning article attributes to all authors of the article. See Table 8.2, in the Appendices for basic descriptive statistics of the resulting data set.

5.2.2 Gender imputation

To identify authors' gender we adopted a commonly used method based on their first names [1, 54, 339, 53, 4]. We ran the algorithm developed by Ford et al. [4] on the three data sources. The algorithm used a conservative heuristic to establish gender, leaving unlabeled 20%, 38%, and 22% of the scholars on Altmetric, WOS, and OAG, respectively. The high fraction of individuals with unknown genders is a limitation of this study that impacts the relevance of absolute numbers and percentages. Altmetric and OAG yielded very similar gender ratios, even though OAG contains co-authors' names too. To test the accuracy of gender imputation, we took a random sample of 100 scientists from our Altmetric data and manually checked their gender based on information available about them online. This sample contained 66% males, 28% females, and 6% scholars of unknown gender, which might indicate that most unknowns in our large sample are men. To explore this possibility, we validated the gender imputation algorithm using the manually confirmed genders as the baseline. The accuracy of the algorithm on the baseline set was above 0.8 when quantified using the F-score, which is the harmonic average of precision and recall, reaching 1 when both metrics are perfect. (See Appendix, 8.10 for more details.)

5.2.3 Femaleness

We quantified the extant of femaleness by calculating the odds ratios of women publishing articles in a given topic. We generated the contingency table for each topic by gender by research fields. Odds ratios are quantified the following:

$$OR = \frac{T_{Nfemale}/T_{Nmale}}{NT_{Nfemale}/NT_{Nmale}}$$

T_N: number of articles published in the topic

NT_N: number of articles published NOT in the topic

We use Fisher's exact test [340] to calculate the probability whether the observed proportions in the contingency table can be caused by random chance, given the marginal totals. The test assumes that the margins are fixed, and use combinations to determine the probability of every possible tables. Fisher's exact test uses the hypergeometric probability of the given table configuration (See Table 5.1 for a toy example), assuming the given margins on the null hypothesis of independence.

	Topic	Not in topic	*Margin*
Female	a	c	*a+c*
Male	b	d	*b+d*
Margin	*a+b*	*c+d*	N=*a+b+c+d*

Table 5.1. *Toy contingency table to illustrate how Fisher's exact test calculates hypergeometric probability.*

$$p = \frac{\binom{a+b}{a}\binom{c+d}{c}}{\binom{N}{a+c}}$$

Table 5.2 shows three contingency tables of an example topic with the same gender ratio in our Altmetrics dataset. The first columns show a topic with significant femaleness, where women are 5 times more likely to publish in the given topic ($OR = 5$, $p = 0.00$). The middle columns show an example of non-significant genderedness, where women and men publish at the same rates ($OR = 1$, $p = 1.00$). The last columns show a topic with significant femaleness, where women are less likely to publish in the given topic than men ($OR = 0.2$, $p = 0.00$).

	Sign. female		NO genderdness		Sign. male	
	Yes	No	Yes	No	Yes	No
Female	25	11	18	18	10	26
Male	20	44	32	32	42	22
Odds Ratio	5.00		1.00		0.20	
Fisher Exact test	0.00		1.00		0.00	

Table 5.2. *Different genderedness scenarios based on toy contingency tables with similar gender ratio in population.*

5.3 Results

We measured the online coverage of scholars' work based on the mentions of their research articles. Our data tracks the number of times articles were shared on social media sites, in online news, blogs, and other websites (see *Materials and Methods*). Despite the wide variety of online sources covered, 77% of article shares come from Twitter, 10% from public Facebook posts, and 4.4% from news outlets (Appendix, Table 8.3). The distribution of the number of shares is similar on all platforms and there is no single platform that drives gender differences in coverage (Appendix, Table 8.3). Therefore, henceforth we quantify individual scholars' online coverage with the total number shares of their articles published in 2012 across all platforms. As with most success metrics, the distribution of the total number of shares is highly skewed: although the median number of shares is 2 both for men and women, the 99th percentile represents 93 shares for men and 78 shares for women. Recent empirical evidence suggests that female and male scientists publish annually on average 1.33 articles [177, 55]. We found a small but significant difference between the average number of articles shared online for the two groups ($\mu = 1.95$ and $\mu = 1.66$, $p = 0.0$). These averages are slightly higher than previously found, which indicates that scientists whose work is featured online might be more productive than the average.

5.3.1 Gender inequalities across broad research areas and topics

There is a lower proportion of female than male scientists whose articles are shared online. Women represented 28.6% of scholars with articles mentioned in 2012. Our gender imputation algorithm could not determine unambiguously the gender of 19.8% of the scholars. The percentage of women varies

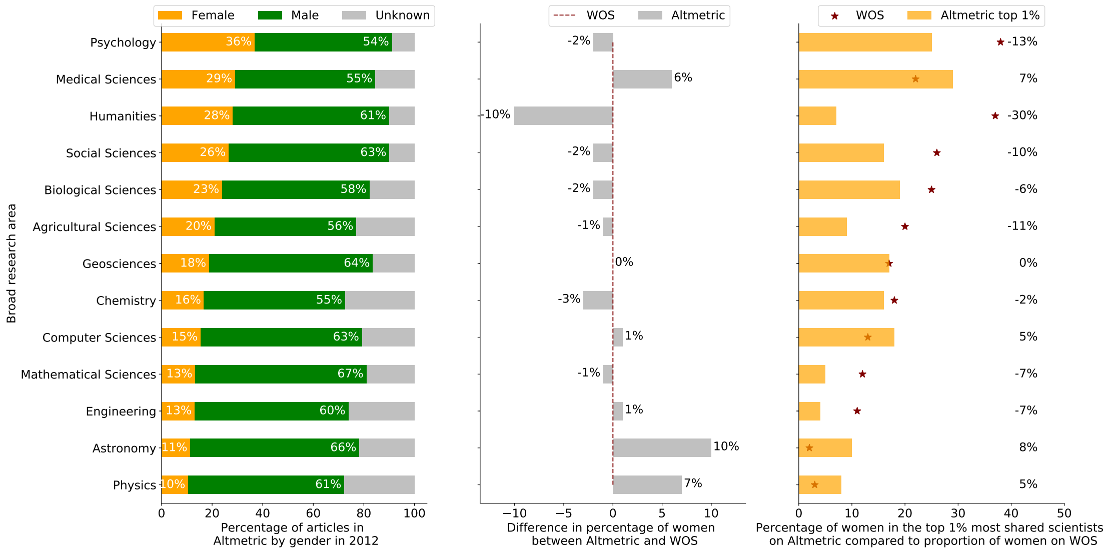

Figure 5.1. *Online coverage of female scholars' articles by broad research areas. Left: Percentage of women among scholars who had articles mentioned online in 2012. Middle: Online representation of female scholars based on Altmetric in comparison with women who published research papers according to the Web of Science. Right: Proportion of women among the top 1% of the most highly covered scientists compared with the percentage of women among scholars who published in each field. (See Table 8.4 for detailed descriptive statistics.)*

considerably by broad research area, ranging from 10-13% in Physics, Mathematics, and Engineering to 36% in Psychology (Figure 5.1, left). We compared these percentages with a simple baseline computed as the proportion of women who have had an article recorded in the Web of Science in these broad research areas. We found that the online representation of women is higher than expected in Medical Sciences, Computer Science, Engineering, Astronomy, and Physics (Figure 5.1, middle). In Medical Sciences and Computer Science, the over-representation of female scientists persists in increasingly selective success categories (i.e., top 25%, 5%, and 1% scholars based on online coverage). However, in 8 out of 13 fields women are under-represented in the top 1%. This trend is especially salient in the Humanities, Psychology, Agricultural Sciences, and the Social Sciences (Figure 5.1, right). In addition to inequities in the online coverage of different research areas with varying gender ratios (See Appendix, Figure 8.11 for details), we expect stark differences in the mentions of individual research topics, which might be linked with gender-based differences in the coverage of scholars' work online.

To test whether the observed gender differences in online coverage are due to the different research interests and specializations of men and women [341, 53] and a potential difference in the size of audiences, we systematically compared the topic choices of female and male scientists, and investigate their online coverage. We quantified the "femaleness" of a given topic as how much more likely it is that a female scientist publishes in the topic as opposed to a male scientist. Specifically, we calculated an odds ratio and test for significance by applying Fisher's exact test with a 5% significance level (see *Materials and Methods*). High femaleness means that it is more likely for women to publish articles about the topic, which does not imply that only women research this topic. Figure 5.2 shows the total number of shares received by articles written on topics of varying levels of femaleness in Social Sciences, Physics, and Medical Sciences. (See Appendix, Table 8.6 and Table 8.7 for more details about the coverage of topics associated with men and women.) Overall, only 1% of the identified topics showed significant genderedness, which indicates that the importance of gendered topic selection for online dissemination affects merely 628 topics. However, we found that in each field, except for Medical Sciences and Psychology, topics significantly associated with male scholars have a higher number of total shares than feminine and non-gendered topics. As depicted in the inset of Figure 5.2, in the Social Sciences, significantly masculine topics receive on average over five times more shares than significantly feminine topics (82 vs 14.55 shares). In Physics, significant masculine topics are shared on average 51 times, while significant feminine topics 4.15 times, this difference being an order of magnitude. On the contrary, in Medical Sciences masculine topics have a lower average number of shares (154.3) than significant feminine topics (182.43). This suggests that in research areas with higher ratios of women a gendered choice of research interests is not penalized.

In all fields but Medical Sciences, gendered patterns of topic selection are less articulated among the most popular topics. However, in agreement with the literature on gendered career choices suggesting that women are more likely to work on research topics that are stereotypically considered more feminine, such as family, children, and gender [341], we found that in areas like Social Sciences and Psychology, traditionally feminine topics are significantly more common among female than male scientists. Importantly, these same topics receive systematically less coverage online. In the Social Sciences, women are significantly more likely to publish articles related to diversity ($OR = 27.61$), language ($OR = 19.29$), or gender difference ($OR = 12.4$); while men publish on economics ($OR = 0.21$), trade ($OR = 0.09$), or greenhouse gas emissions ($OR = 0.0$). One of the reasons behind this clear separation could be that Social Sciences cover a wide variety of subjects with very different gender ratios. For example, the ratio of female tenured professors in the US was 42% in Sociology and only 15% in Economics [300]. So far, unmapped patterns emerge in Physics. High-femaleness topics are, for example, optical excitation ($OR = 18.51$) and spin hall ($OR = 9.26$), while the only significantly more male topic is communication ($OR = 0$). These topic selection patterns, and the fact that there are very few significant associations with either gender, indicate that in Physics, a field with a strong gender imbalance, female scholars chose non-stereotypically female topics which are still associated with low levels of coverage. Interestingly, in Medical Sciences, the most highly shared topics have either a significant low-femaleness (patient $OR = 0.75$, meta $OR = 0.84$) or, conversely, a significant high-femaleness (risk $OR = 1.13$, children $OR = 8.94$). Medical Sciences have a relatively high female representation of scholars (22% according to WOS) and their scholarship enjoys a larger than expected online coverage (Figure 5.1, middle). Our topic analysis across various broad research areas indicates that there is an intricate link between gendered topic selection and online coverage that our comprehensive models will take into consideration.

5.3.2 The role of collaboration networks

To investigate social capital as another crucial factor in determining the online dissemination of scholarship, we constructed authors' collaboration networks based on their publication history. Specifically, the network ties of scientists who co-authored a research article published in 2012 and recorded in the WOS. The strength of each tie is equal to the number of times the scientists published together between 2007 and 2012. We conceptualized network-embeddedness and cohesion around a scholar based on this collaboration network. First, we calculate the density of their ego network, i.e., a sub-network that contains them, their direct co-authors, and all collaborations among those co-authors. Then, we captured gendered tie formation: gender homophily is measured by the scholars' average tie strength to female/male authors and the ratio of female-female and male-male ties between co-authors.

We compared scientists' ego networks by gender and online coverage. We found significant differences between men's and women's ego network structure: in general, men have more connections, therefore a higher degree, but women have denser ego networks. We also found that gender homophily is a key driver of collaborations. Due to the unbalanced structure of academia, male homophily in ego networks is present for both genders, but female homophily is more common among women. Similarly, both genders have a higher ratio of male co-authors, but women have a higher ratio of female co-authors than men (Figure 8.12, Table **??**.) As Figure 5.3 indicates, popular scientists have more and stronger connections and less dense ego networks than non-popular ones, regardless of gender. The role of homophily is even more significant among pop-

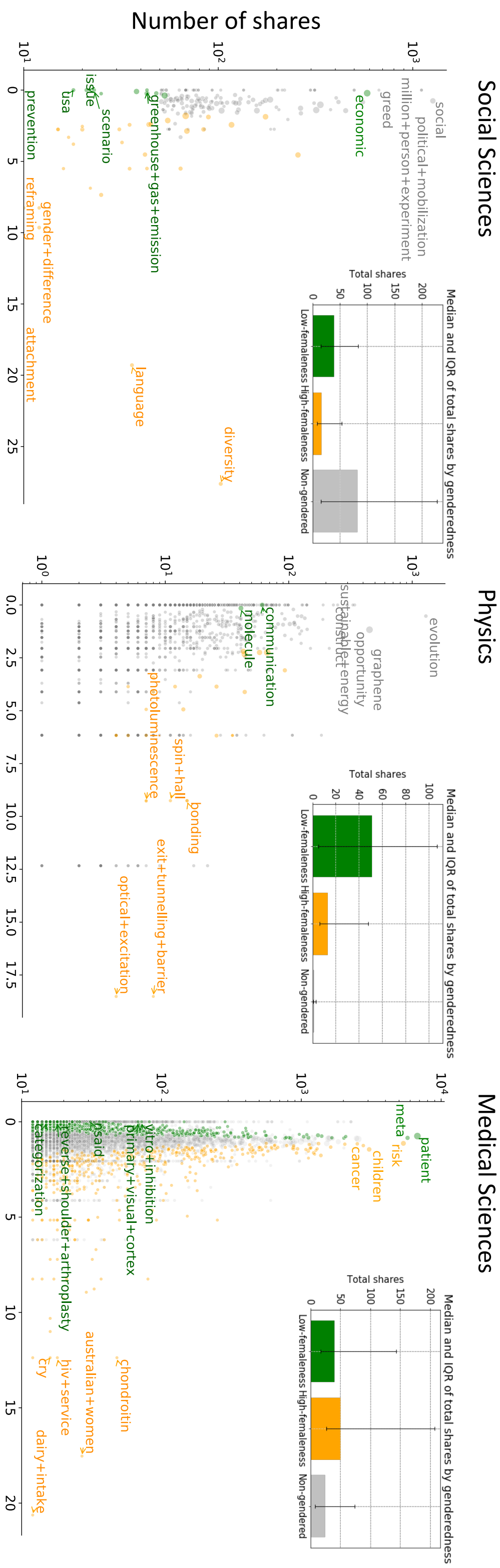

Figure 5.2. *Gendered topic selection and obtained coverage on log-scale in Social Sciences, Physics, and Medical Sciences. The femaleness of a given topic is measured as the odds ratio of women publishing at least one article in the topic as opposed to men. Significance of associations is established with Fisher's exact test, 5% significance level. Colours indicate topics with the highest (orange) and lowest (green) femaleness values; topics with non-significant femaleness are coloured gray. Circle size indicates the number of papers published in the topic, according to WOS. Data points for Medical Sciences are based on a sample that covers topics with a higher than average number of shares (mean = 11.29, N = 8,000). Inset shows the median number and the IQR (Interquartile Range) of total shares by genderedness (SI Table 8.8.)*

ular scientists: popular male scientists have lower female-homophilous ego networks than non-popular male scientists, but much more male-homophile ones. On the other hand, popular female scientists have more female-homophilous ego networks than non-popular female scientists, but the difference in the case of male homophily is negligible. We also found that the ratio of female scientists influences the typical network structure of fields: Computer Science and Mathematics have the highest male homophily (0.39, 0.36), and Chemistry the highest female homophily (0.05) (See Table 8.10).

We quantified *team gendered diversity* as the number of articles written in teams with different gender composition in 2012. The ratio of women depends on the academic field under consideration, thus for each field we calculate a *field-dependent gender majority*: a paper has a certain gender majority if the ratio of the given gender is higher than the average ratio in the particular scientific field (at WOS in 2012), plus a standard deviation. Therefore, we have female majority, male majority and diverse teams. We calculated for each author the number of articles published in the given team composition in 2012 (SI Table 8.12). Since most fields have lower female representation and since men's number of shares is significantly higher than women's (Figure 5.1), we hypothesized that women who publish in male-majority teams are more likely to be successful. However, we found that female scientists are less likely to publish articles in male-majority teams, and this trend is even more salient among the top 25% most shared authors (See Table 8.13). Our findings indicate that homophily is a key driver of team formation: both female and male scientists are more likely to have at least one article in same gender-majority teams, especially among the top 25% most successful ones (See Table 8.14). Gender homophily is especially dominant in male-dominant fields for both genders: male scientists in the Humanities are 45.07, in Computer Science 37,88, and in Mathematical sciences 28.3 times more likely to publish at least one article in male-majority teams. Female scientists in the Humanities are 15.38, in Computer Science 19.07, and in Mathematical sciences 19.34 times more likely to publish at least one article in male-majority teams.

5.3.3 Predicting online coverage

To understand how different aspects of a scientific career influence science dissemination online, we computed several variables that can be grouped into five categories. Author attributes are included to take into account the Matthew effect in science [200]. They control for the impact on online coverage of the scholar's previous productivity (the number of articles they wrote in the preceding 5 years), scientific success (indicated by their h-index in 2012), and social capital (the average size of co-author teams they were part of in the previous 5

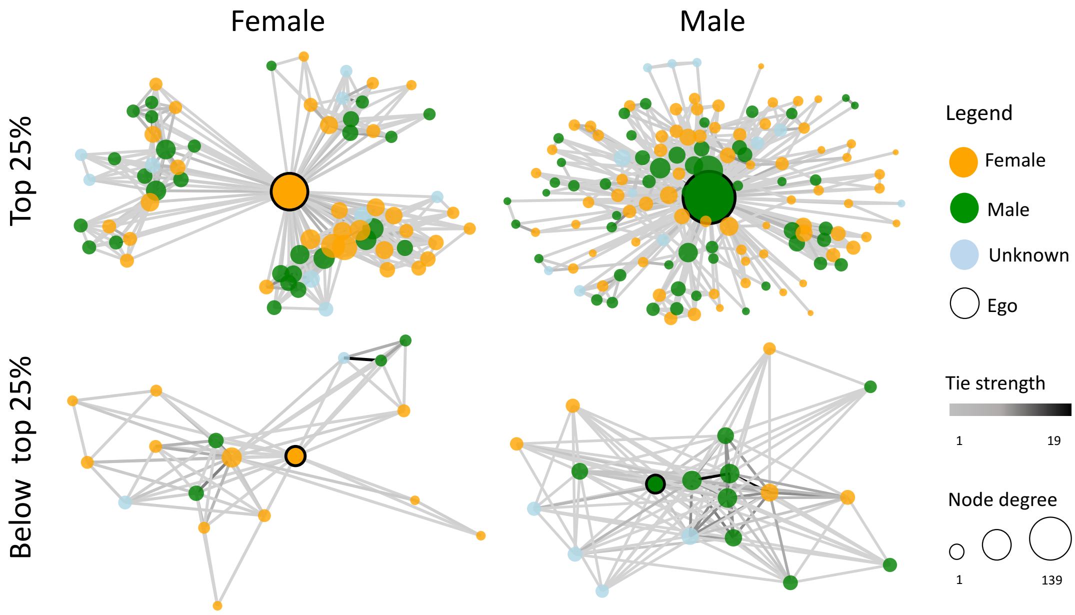

Figure 5.3. *Example networks of popular and non-popular Medical scientists by gender. (See Table 8.11 in SI for statistical comparison) The popular female scientist in the top left corner published 4 papers in 2012, which were shared 519 times, her h-index was 4 in 2012. The female scientist on the bottom left published one paper in 2012, which was shared only 3 times, her h-index was 3 in 2012. The popular male scientist in the top right corner published 6 papers in 2012, which were shared 4626 times, his h-index was 27 in 2012. The male scientist in the bottom right corner published 1 paper in 2012, which was shared 3 times, his h-index was 4 in 2012. Similarly to our overall findings (Table 8.10 in SI), non-popular scientists have denser networks than popular scientists. Popular male scientists have a median of 0 female homophily in their ego networks, and a high male homophily, while popular female scientists have both a high male and female homophily.*

	Female			Male		
	Top 25%	Below Top 25%	Cliff	Top 25%	Below Top 25%	Cliff
Ego network density	0.32	0.46	-0.18	0.18	0.29	-0.23
Tie strength to women	1.50	1.33	0.14	1.56	1.35	0.15
Tie strength to men	1.64	1.46	0.13	1.83	1.67	0.12
Female homophily	0.18	0.15	0.11	0.05	0.03	0.15
Male homophily	0.15	0.14	0.03	0.35	0.35	0.01

	Top 25%			Below Top 25%		
	Male	Female	Cliff	Male	Female	Cliff
Ego network density	0.18	0.32	-0.26	0.29	0.46	-0.22
Tie strength to women	1.56	1.50	0.04	1.35	1.33	0.03
Tie strength to men	1.83	1.64	0.13	1.67	1.46	0.14
Female homophily	0.05	0.18	-0.62	0.03	0.15	-0.58
Male homophily	0.35	0.15	0.65	0.35	0.14	0.59

Table 5.3. *Averages of ego network statistics of Medical Scientists compared by gender and popularity. All compared distributions are significantly different. (See Table 8.10 in SI for the results of the Mann-Whitney U test for 5 scientific fields)*

years). Our last author attribute quantifies self-promotion through the number of times a scientist shared their own article online. Self-promotion is interesting in this context because it is a key factor of success in the world of social media, but typically avoided by women due to double standards in society [325]. Article attributes account for the gate-keeping role of publishers in science communication [342, 343]. As a proxy for the prestige of the publication venue we included the impact factor of the journal where the article was published and explicitly flag articles published in high impact journals that have an advanced science communication machinery, like PNAS, Nature and Science. Drawing on our previous topic analysis and prior work establishing links between article topic and received citations [344, 345], we also established whether the article is on a "sticky topic", i.e., one that is among the topics that cover 80% of all article shares online. As main variables of interest, we included descriptors of the gender composition of co-author teams in 2012 through team gender diversity attributes. The ratio of women depends on the academic field under consideration, thus for each field we calculate a field-dependent gender majority. A co-author team has a certain gender majority if the ratio of the given gender is higher than the average ratio in the particular scientific field (WOS in 2012) plus a standard deviation. Accordingly, we differentiated between female-majority, male-majority, and diverse teams. For each scholar, we included variables that quantify the number of articles they published in 2012 in each type of teams, in addition to the number of their solo-authored articles. Five additional variables—ego network density, tie strength with women/men, and ratio of female-female/male-male ties in ego network—measure different attributes of a scholar's collaboration network based on a five-year co-authorship history (2007 to 2012). Including these longer-term indicators of collaboration patterns is essential since individual success in science is the product of previous research involvement. Finally, in our last attribute category we added variables capturing the number of articles published in individual sub research fields. See *Materials and Methods* for data sources.

Given field-dependent differences in coverage patterns, we ran prediction models separately for each major field. Our data are also heterogeneous with respect to gender. Therefore, we built separate models for male and female scholars. Even though our outcome measures the number of shares a scientist's publications receive, is a continuous variable, we tackle the binary problem of whether the scientist is popular or not. Our indicator of broad coverage is presence among the top 25% scholars in a ranking based on the number of shares. We used random forests because they can capture non-linear relationships between variables and enable intuitive ways to quantify variable importance [346, 347, 348]. In particular, we adopted a drop-feature importance method that re-runs the prediction without the "dropped" variable. Then, the importance of the variable is the difference between the overall accuracy of the model and the accuracy of the model built after dropping the variable. An important advantage of this method is that it allows us to calculate variable group importance using the same idea. Our final model's overall accuracy varies between 0.76 (Social Sciences) and 0.80 (Computer Sciences) for women, and 0.76 (Social Sciences) and 0.80 (Computer Sciences) for men. See Table 8.15 for detailed model accuracy, and Figure 8.13 for threshold selection.

Figure 5.4 shows the grouped variable importances for Social Sciences, Physics and Medical Sciences for the top top 25% most successful scientists by gender. Similar variable groups are the most important factors to belong to the top 25% of most successful scientists: ego network structure and team diversity. Interestingly, author (such as productivity, h-index and the number of articles at last 5 years) and paper attributes (venue prestige, impact factor) matter the least in all fields, regardless of gender. In most cases, we did not find significant difference between the variable group importances of models by gender. One of the few exceptions is the relative importance of author attributes in Social and Medical Sciences, which turned out to be more important for female scientists than men. There is also notable difference in subfields and ego network structures' importance in Physics: subfields are more important for men

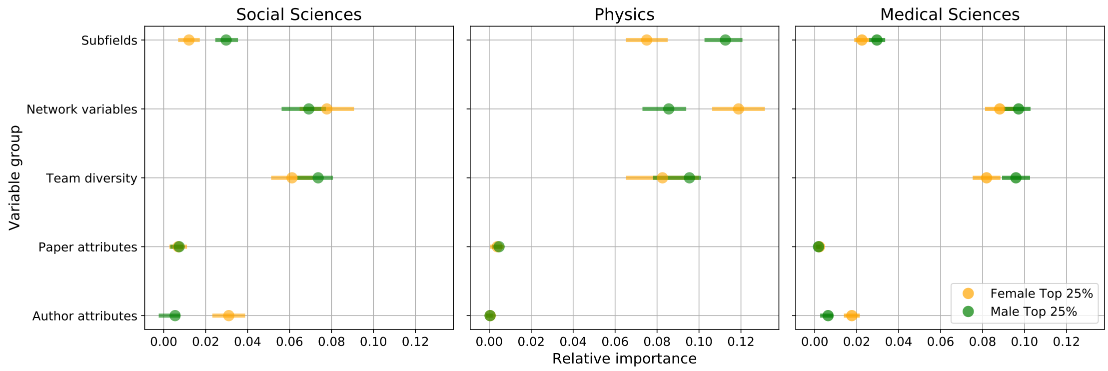

Figure 5.4. *Group variable importances of 100 Random Forest Models. The importance of a variable group is the difference between the baseline overall accuracy, and the accuracy of re-ran model without the given feature set. Points indicate the average variable importance, lines the standard deviation of 100 runs.*

and networks for women (see Supplementary Information for group variable importance plots for all research fields 8.14).

We measure relative variable importances within each group using the above mentioned method: removing one variable at the time, while keeping all the others in the model and comparing the change in accuracy to the baseline model. Figure 5.5 left) presents details within group relative variable importance for Medical Sciences. Since variable importance does not indicate the sign of a relationship between variables and success, we explore the relationship using partial dependency plots. Partial Dependency plots show how the average prediction changes when a given feature is changed (average marginal effects). Figure 5.5, right shows the partial dependency plots for the strongest predictor of each variable group in Medical Sciences. See Figure 8.15 for within group variable importance across fields, and Figure 8.16 8.17, 8.18, 8.19 for partial dependency plots for multiple fields in Supplementary Information.

Variables capturing network structure were the most important predictors of success in all fields. Detailed results show that ego network density has the highest relative variable importance, and tie strength has the lowest among variables capturing ego network structure (Figure 5.5, A, left). In Medical and Social Sciences, female homophily in ego networks was the second important variable, in Physics, male homophily. Even though we did not see striking differences between gender groups in relative importances of network features (Figure 5.5, A, left), partial dependency plots show significant differences between gender groups in sign (5.5, A, right) and (See 8.16) in SI): ego network density has a positive relationship with success for both genders in each field. Female homophily in ego networks predicts higher success for women at all fields, however; it has a steep negative relationship with success. This, corroborated with previous studies, indicates that working on a subfield which has a higher female ratio puts both genders at a disadvantage [1, 349, 335].

The relationship between male homophily and success is more field-specific: in Computer, Medical and Social Sciences the U-shape-like relationship indicates that a very low male homophily and higher male homophily both predict success for women. In Physics and Psychology the relationship is negative for women. For men in Computer and Social Sciences male homophily is beneficial, in Physics it predicts higher success; however, the relationship is negative, and in Psychology it is completely negative.

Gendered tie strength varies by fields, too: in Medical Sciences, both genders benefit from weak ties and very strong ties, but men have a higher predicted success. In Psychology, weak ties are more beneficial for both genders, however, in this field women have higher predicted success, regardless of the gender of the ties. Similarly to Jadidi et al.'s findings in Computer Science and Physics we found that men benefit more from weaker ties to women, and women to stronger ties to women, but it is beneficial for both genders to have stronger relationships with men [55]. In Social Sciences, both genders benefit from very strong ties to men, but women are better off if they have no male co-authors.

We found the biggest differences in relative variable importance between men and women in team diversity (Figure 5.5, 2). Similarly to others' findings [1], gender homophily has a latent effect on prediction results: in all fields, for men it is an important factor to publish in male-, and for women in female-majority teams. Diverse teams are more beneficial for men in Computer Science and Social Sciences. Publishing alone has zero predictive power in all fields, except for Social Sciences where men benefit from it (Figure 8.17). Women have a higher predicted success than men if they publish in female-majority teams, and men have a higher predicted success if they publish in male-majority teams. Publishing in male-majority teams punishes women less than publishing in female-majority teams punishes men.

Our analysis shows that the most important factor among author attributes for each field was the average team size (last 5 years) (Figure 5.5, 3). This indicates that social capital is an important asset for becoming successful online. The h-index is relevant up to a certain level in each field, which indicates a younger/less experienced science population online. Being more traditionally recognized helps men relatively the most in Psychology, and matters the most for men in Computer Science. Productivity helps men in Computer and Social Sciences and women in every other field (See Figure 8.18).

The relative importances of paper attributes (Figure 5.5, 4) are field-dependent: choosing topics which are popular online (sticky topics) is more important for men, and matters the most in Physics and Psychology, and the least in Computer Science. Traditional scientific merit, the Impact factor of the 2012 papers is a stronger predictor of women's success, especially for women working in fields associated with lower-impact journals in the Social Sciences, Psychology and Computer Science. The higher impact factor of the paper and publishing in prestigious journals predict lower online success in each field, however, it benefits women more in each field, except for Computer Science (See Figure 8.19).

5.4 Discussion

Scientific literature supports that science dissemination is a crucial first step in exposing scholars' work to other scientists and the public, therefore it might be an important channel for female scientists to overcome gender-related inequalities in academia. It is unclear, however, whether the online sharing of scientific articles mitigates, perpetuates, or reinforces known gender-related inequalities.

Our analysis provides the first comprehensive view on gender-related characteristics in scientific production both at the level of individual scholars and co-author networks, and points to critical variables associated with inequities in scholars' online coverage.

We analyzed patterns of gender inequity in the dissemination of research articles of 537,486 scientists across all scientific areas. Our study uses a unique data mash-up that combines detailed traces of the online sharing of scholars' articles, their publication histories, collaboration networks, scientific fields, and research topics.

There is no consensus on which research fields bring the most popularity on social media [350]. In some fields, social media usage is more common among scholars, such as biomedical sciences [351], computer science and mathematics [313, 352, 327], but others have found that doctoral students in the Arts, Humanities and Social Sciences are heavy users of social media platforms to promote their research. [350]. We presented evidence that life sciences (Medical Sciences, Biology, Chemistry, Psychology) are the most popular research fields online.

We found that there is a lower proportion of women than men among scientists whose articles are shared online. Women represented 29% of scholars with articles mentioned in 2012. This percentage varies considerably by broad research area, ranging from 10-13% in Physics, Mathematics, and Engineering to 36% in Psychology. Our findings indicate that scientists whose work is featured online might be more productive than the average.

Prior survey-based experimental work indicates that female scientists should be more likely to produce shareable content that is interesting for wider audiences [324]. We found that this presumed advantage due to language use was not enough to ensure broad coverage and that, in fact, women across various fields published about topics that were shared less frequently than topics associated with men.

We used machine learning models to systematically study how the building blocks of an academic career influences scholars popularity online in five distinct research fields (Medical, Computer and Social Sciences, Physics and Psychology). We found robust evidence that factors related to social capital are the most important to predict success: team diversity and gendered network formation, which makes it harder to overcome gender inequalities that exist offline among scholars. Interestingly, factors measuring traditional scientific merit (such as productivity, the h-index and the number of articles in the previous 5 years) and prestige (venue prestige, impact factor) matter the least in all fields predicting online popularity, regardless of one's gender.

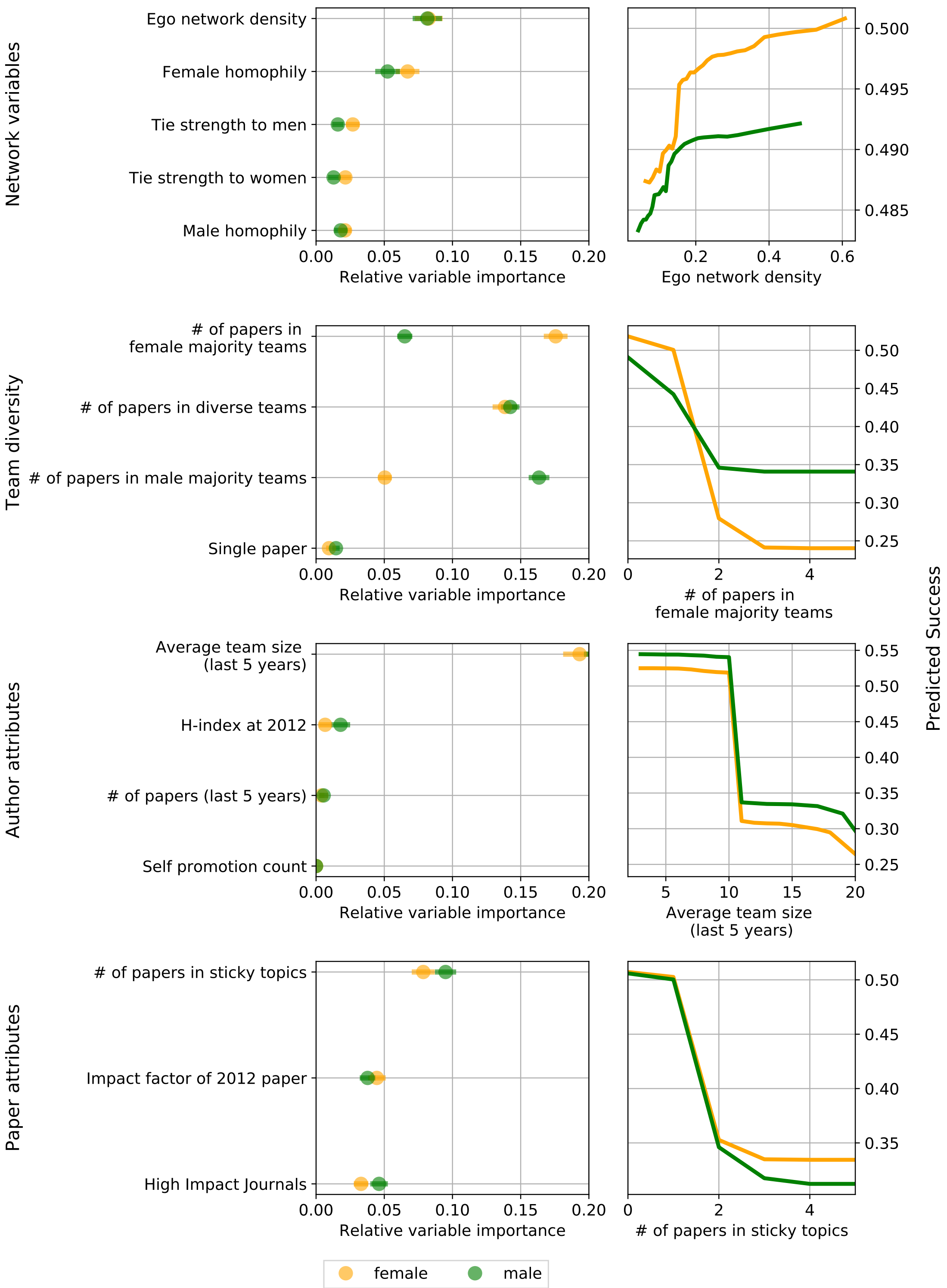

Figure 5.5. *Left: Relative variable importances of features for predicting top 25 % of most successful scientists in Medical Sciences. Right: Partial Dependency Plots of selected variables for predicting top 25% of most successful scientists in Medical Science.*

CHAPTER 6

THE ROLE OF GENDER DIVERSITY AND INCLUSION IN SUCCESS AND CREATIVITY IN THE VIDEO GAME INDUSTRY

6.1 Introduction

Due to the harsh criticism of the tech industry's white male-dominated workforce [16, 15, 17, 95], and research suggesting diversity can improve teams' success and creativity [36], companies are trying to hire women and minorities to reflect the demographics of their customers [353]. 47% of the 500 largest companies worldwide have hired Chief Diversity Officers in the last 3 years in order to increase the diversity of their workforce. Unfortunately, badly managed diversity advocacy might be counterproductive and reinforce the culture of marginalization and victimization [354, 355].

In July 2017, Google engineer James Damore started to circulate a document among Google employees called *"Google's Ideological Echo Chamber"*, which was a critical essay on Google's diversity policies. In his memo Damore argues that Google's positive discrimination towards women is harmful, and the company is not aware of how women and men are biologically differ in their interest towards technology [96]. The memo was leaked on August 7, 2017, and attracted huge media attention. In August, Damore got fired for violating Google's Code of Conduct, as well as policies and anti-discrimination laws. As a response Damore and another ex-Google employee submitted a class action lawsuit accusing Google of discriminating conservatives, white people, and men. Later they dismissed their claims, but kept being outspoken against Google's hiring policies.

As the example of the Google case shows, this urgent need to bring more diversity to technology is not fully welcomed, and might result in backlash. Furthermore, there is an ongoing debate on whether gender diversity is beneficial for teamwork or not [36, 38, 39, 78, 86, 87, 88, 89, 90, 91, 92, 93, 226, 94]. Views against diversity argue that teams with culturally more similar members are less likely to have conflict, and do not suffer from the costs of harmonizing different backgrounds. Promoters emphasize the positive effects of connecting different opinions which can help to process information more carefully and reduce unconscious bias [38, 39, 78, 86].

Recent research findings suggest that an equal ratio of men and women creates the best environments for teamwork: it can equalize influence on meetings [88, 225] and increase performance [226, 87, 88, 227, 228]. In technical fields, where the ratio of female employees is around 30% worldwide [25], managing gender-diverse teams is a challenging task [230], and due to negative stereotypes of women working in such industries, gender diversity has been shown to have a negative impact on team performance [196, 199]. Among software development teams, it has been shown that a cognitive similarity influenced team effectiveness more than a demographic one [229], and personal bias can influence one's perception of reality, rating one's team performance lower if the team is diverse [90].

In technical fields, a gender-balanced team can indicate that the organizational culture is gender-inclusive, which is a significant predictor of keeping women in their technical jobs [22]. Organizational culture and gender diversity are not independent factors from one another, and a gender-inclusive environment is needed to make gender diversity flourish [87, 354, 97, 91, 92, 93, 89]. However, most of the foundational studies reflecting on the effects of gender diversity on success and creativity focus on gender diversity itself, without taking into account other important aspects of teamwork [36, 88, 356, 357]. Team cohesion and network structure have been also shown to influence the creative performance of teams [49, 202, 358], but very few studies combined gender diversity and team cohesion – inclusion or integration – to understand what type of team formation can utilize the positive effects of diversity [224, 85]. The few empirical studies focusing on inclusion and integration use surveys and interviews to capture the scale of belonging and acceptance of individuals, which restricts scholars from testing their hypothesis on larger sample sizes [359, 360, 361]. We propose a data-driven approach to operationalize inclusion on a larger scale, relying on the structural properties of team-collaboration networks.

Without investing into integrating women, the hiring effort to attract them will not pay off. Very often when companies hire “diverse talent”, what happens is that the new employees with different backgrounds try to avoid marginalization, so they avoid conflicts while adapting to company culture [362]. Thus, the “diversity benefit” that they are supposed to bring is the first thing they give up. Research also indicates that individuals with different backgrounds are often excluded from informal social networks, decision-making and opportunities in organizations [363]. To tackle this, companies are providing various trainings on valuing diversity (gender, race, ethnicity, religion, disability), handling sexual harassment, and diversity management (mentoring, coaching, family friendly policies, flexible working hours)[47]. However, most of these functional and structural interventions do not help to integrate and utilize the potential of the diverse workforce for company goals [364]. Without real integration and inclusion, all the hiring efforts and projects targeted to attract and retain diverse talents are useless: if the company culture as a whole is not coherent in promoting inclusion, the newly hired people will not feel included and it can easily turn into a strong motivation for leaving [361].

The term ”inclusion” conceptualizes the perception of how individuals feel a part of organizational processes [362]. These processes include the access to information and resources, embeddedness into organizational networks, ownership and decision-making opportunities [363]. Social identity theory suggests that belonging to a group is a source of self-esteem and helps to increase the sense of fitting in [365]. Intergroup theory argues that our social reality and interactions are highly influenced by our group memberships, race, gender and ethnicity [366]. Individual identity and group belonging form organizational networks together. These networks’ meso- (e.g., segregation) and micro-level (e.g., centrality) structures can quantify one’s perceived belonging and integration level [367].

In this article, we present evidence based on 15 years of video game development data, that diversity and team cohesion are both significant drivers of creativity. First, we briefly introduce the challenges that women face in the video game industry, then define diversity and team cohesion in our context. Then we form two hypotheses about how different types of team cohesion with diversity predict success and creativity in the video game industry. Finally, we test our hypothesis with two hierarchical linear regression models, and conclude our findings in the context of the video game industry and technology.

6.2 Gender imbalance and marginalization in the video game industry

Women being a minority in software engineering and its consequences is a widely discussed topic in the media [137, 138, 139, 140, 141]. However, it is less discussed how particularly low female representation is in one of the most financially successful sectors of the decade: the video game industry. Less than 30% of women who work in the video game industry have creative roles, where they can influence the games' content [155], and they often encounter unbreakable glass-ceilings while trying to rise within the hierarchy [69]. Recent studies indicate that almost 50% of gamers are women [154, 155], even though old stereotypes such as "gaming is for boys" persist, and female representation among playable characters is not getting better: in 2018, five times more video games centered male characters than female ones [156].

Research suggests that playing video games increases the interest of children in STEM fields, therefore making games attractive for young girls can be an important step towards a better female representation in technical fields [75]. In 2010, Greenberg et al. argued that women were not as engaged as men with games because video games had been designed by males for males. They suggested that the industry should focus on developing more gender-inclusive games to expand the market size [144]. One of the firs qualitative studies in 1998 by Dietz et al. found that 41% of video games did not have female characters, and among those which had female characters in 28% women were portrayed as sex objects [145]. In the 2000s, multiple other studies using bigger datasets found that women were under-represented [146, 69] and portrayed in a hypersexual way [147], for example exposing more skin than male characters [148]. However, it has been shown that the sexist attitudes of the online video game community drive women away more than games' sexist content [149] Furthermore, the industry culture does not value inclusivity: in 2013 Near found that video games with a central female character were negatively correlated with sales, indicating that the expectation of the main user base is still male-focused [70].

Meanwhile, the video game industry has become the most popular entertainment sector, and is predicted to generate US $ 152.1 billion revenue in 2019 from 2.5 billion games around the world [143]. Creating epic video games sounds like a dream job for many, but as the industry has become more lucrative and competitive, more and more employees started to reveal its dark side: 100-hours working weeks, obligatory overwork, mental illness and discrimination [161]. According to a survey taken by the International Game Developers Association, 48.5% of industry employees believe that there is no equal treatment and opportunity for all people [162]. Women also reported that sexism is highly accepted and part of the everyday culture of the industry [150]. Female game designers organized a couple of online campaigns ("1ReasonWhy", "womenaretoohardtoanimate") to draw attention to the lack of diversity, harassment and discrimination against women in the game industry [150]. Unfortunately, these pursuits generated backlash and resulted in harassing female game developers publicly [163].

6.3 Hypotheses

The positive impact of gender diversity has been shown in creativity, problem solving, and innovation [88, 356, 357, 36, 224, 85]. Some scholars argue that good diversity management and an inclusive climate with a collaborative environment is necessary to harvest the benefit of diversity [368, 369, 370]. Other views underline the importance of actors in broker or bridge positions between otherwise segmented groups, therefore brokerage is key in value adding or innovative processes [31, 217, 218, 371, 85]. This view emphasizes that team members benefit from diversity, because it generates links between people who access different sources, knowledge and information.

Hypothesis 1.1.: Gender diversity is a positive predictor of how creative a product is in the video game industry.

Hypothesis 1.2.: Integration has a positive relationship with creativity in the video game industry.

Hypothesis 1.3.: The positive effect of gender diversity on creativity is especially strong when teams are more inclusive.

In a male-dominated sector, such as the video game industry, managing gender-diverse teams is not easy [230]. Findings about the effect of gender diversity on teams' success have been mixed: some studies have argued the positive effect of gender diversity on performance [230]. In contrast, others have found that demographic diversity had no or only a weak negative impact on team performance [226], but when the team was gender-balanced this weak negative effect turned into positive [196, 87]. Gender-diverse teams with high inclusion are more likely to ensure that women's opinions matter in product development. Since success is a collective measure that captures a community's reaction on performance [56], and the meaning of success is actively formed by opinion leaders and members of the community, it is very unlikely that in the video game industry highly inclusive gender diverse teams will not be successful. However, integration without gender diversity can be beneficial in this setting, because high performance was associated with highly interconnected teams, a denser network promotes trust and decreases risk, which is one of the reasons a team can work together [207, 209].

Hypothesis 2.1.: Gender diversity has a negative relationship with success in the video game industry.

Hypothesis 2.2.: Integration has a positive relationship with success in the video game industry.

Hypothesis 2.2.: The negative effect of gender diversity on success is especially strong when teams are more inclusive.

6.4 Data, Measures, and Methodology

6.4.1 Data Collection

We collected data from the video game industry, relying on MobyGames.com[1] Our dataset contains 8,617 unique video games, with a list of each game's developer teams, critic's reviews, and stylistic elements such as genres, perspective (e.g., first-person shooter, role-playing) and the platforms it can be played on (e.g., PlayStation, Nintendo Switch, etc.). We also record each game's developer studio, publishing house, and the year of the first release.

The video game industry has gone through a major change, with the rising popularity of mobile games in the early 2010s [143]. As the industry became more competitive, and labour shortages hit the tech industry, companies stopped publishing the entire credit list of their project teams, probably to avoid offers sent to their employees from competitors. Therefore our analysis covers games published between the 1980s to 2010.

In project-based industries it has been shown that shared team experience is a leading organizing factor in team formation [220]. Previous collaborations result in highly clustered small world networks where common memberships create credibility and trust [202, 221, 230]. Since our database goes back to the very beginnings of the video game industry, we are able to infer each individual's full career path; connecting unique user accounts with the games they had worked on in a consecutive order. It allows us to create team-level weighted

[1] https://www.mobygames.com/, MobyGames is a website which catalogs video games via crowdsourcing. It covers 300 gaming platforms and over 230,000 games [372].

Number of games	8,617
Years	1993-2009
Number of developers	630,420
Women	119,826 (19%)
Men	397,520 (63%)
Unknown	113,074 (18%)
Number of teams in analysis	5,042

Table 6.1. *Descriptive Statistics*

networks for each video game: two team members are connected based on how many times they had worked on the same game.

Similarly to film credits, Moby Games lists each team member's full name and task in the production (imaging, scripting, design, music, etc.). To infer team members' gender we relied on developers' full names, and adopt a commonly used first-name based gender inferring method [4]. Our gender inferring yielded 19% female, 63% male and 18% unknowns. (See Appendix for gender detection robustness and more details about the accuracy of our gender inferring method.)

For our analysis we only considered games which were published between 1993 and 2009, and had at least one female team member, and a network with 5 nodes. We excluded all re-released and mobile games. Since gender diversity is a key interest of our study, we had to exclude all those video games from our analysis which did not list team members' full name, and used only initials instead of first names.

6.4.2 Quantitative Measures

Dependent Variables

We measured *success* by the evaluation of critics' review scores published on the Moby Games platform. We took the average of listed scores (a number between 0 and 100) and normalized it.

We measured *creativity* by adopting De Vann et al.'s distinctiveness metric, which compares the combination of each game's stylistic elements to all games released in the preceding five years and compute a distance (1- cosine similarity) between them [85].

Independent Variables - Gender Diversity & Team cohesion

Our core interest is how teams' gender diversity and inclusion predict creativity and success in the video game industry.

Gender Diversity is measured as the ratio of women in the production team. Technology companies have been criticized for not separating the ratio of technical and non-technical female employees in their diversity reports, thus we also recorded the ratio female developers separately.

We measured *Inclusion* as $1 - SI$, where SI is the Segregation Index developed by Freeman [373]. Higher inclusion means less segregation, meaning that men and women are more likely to create ties with each other. Inclusion was also calculated for developers only.

$$SI = (Exp(e) - e)/Exp(e)$$

where $Exp(e)$ is the expected value of the cross-calls occurrence of a certain attribute(gender), and e is the observed measurement. $Exp(e)$ is calculated, as the following:

$$Exp(e) = L * 2_n(Nn)/(N(N1))$$

N : number of nodes
n: number of a gender categories
L: number of links

Integration is operationalized as an individuals' perception of belonging and fitting in, so it is measured on member level, and aggregated for each team. We quantified integration by the average closeness centrality of each team. Closeness centrality is defined as the reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the graph []. Higher average inclusion indicates that the team is well connected and the actors are more "close" to one another.

Controls

We controlled for multiple attributes of a team, such as size, tenure, previous experience and group formation effect of shared working experience.

Team size is measured as the number of team members involved in the game production. Bigger teams indicate more established companies, therefore more likely to have bigger networks, and higher budget, which can easily influence games' success.

Community size Team members who have worked on previous project(s) together, can collaborate easier due to shared culture and increased trust. We quantified the presence of previously shared work experience with he mean size of groups (based on shared working experience) within the team.

Number of Newbies, measures the number of team members with no experience in game development (based on our database). We also counted for the *number of star developers*, those who have been awarded a Game Developers Choice Award.

Game tenure captures the experience level of a team, measured as the average number of games team members have produced prior to the year of production of the given game.

Single-Firm Production Is a dummy variable, which is 1 if the publisher and the developer company is the same entity, otherwise 0.

Firm Age accounts for experience and reputation in the industry, measured as the average number of years of the publisher and developer firm had been active in the video game industry.

We also controlled for the stylistic and genre elements of each game. We measured *game complexity* by the number of elements used in a video game. We controlled for 8 different *genre dummies*, and the *platforms* the game was developed for, because certain genres and platforms can be more popular than others. We also controlled for temporal trends, with the *year of release*.

6.5 Models

We tested our hypotheses with running multiple OLS regression models. The first group of models analyse how the role of gender diversity and inclusion relates to the level of creativity of a video game. The second group of models explores how gender diversity and inclusion are associated with the level of success of a video game. Our main interest is how the interaction between gender diversity and inclusion predicts creativity and success. Our baseline models' predictors are only Diversity and Inclusion (Model 1.), then we added to our models' integration (Model 2.), and finally we included controls with fixed effects for year, and games platforms as well (Model 3.).

Predicting Creativity

Our baseline model (Table 6.2. Model 1) contains Diversity, Inclusion and their interaction as predictors, explaining 2.7% of the variance of how creative produced video games are. Adding integration to the model increases the explained variance to 6.4% (Table 6.2. Model 2). Our final model contains all control variables (See Quantitative methods section for details), and has fixed

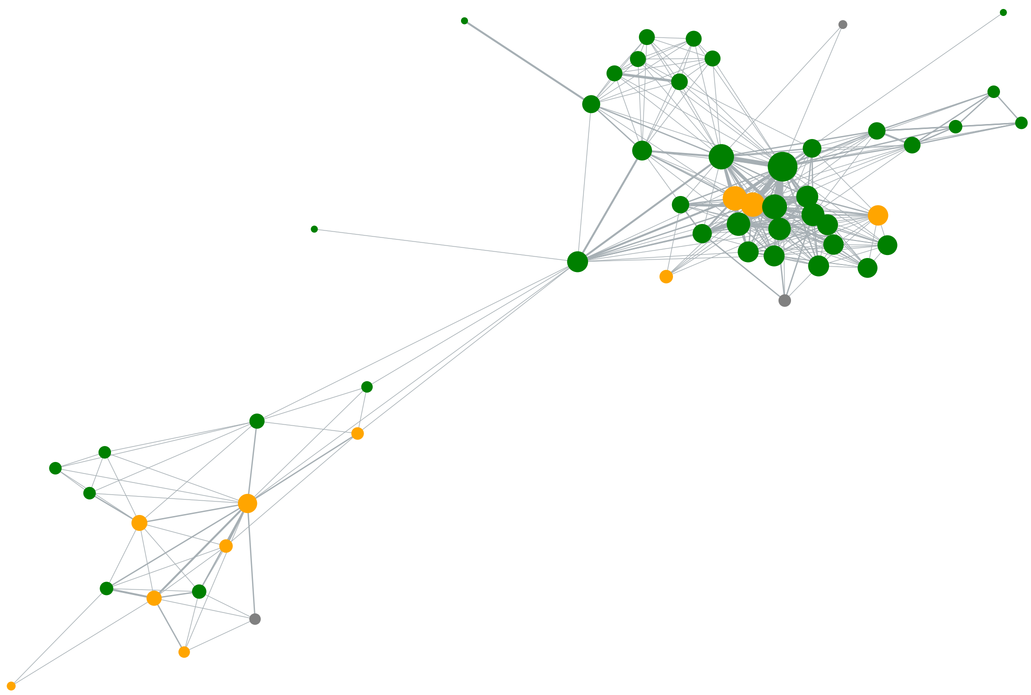

Figure 6.1. *Collaboration network of a focal game. This is the collaboration network of Silent Hunter II, a World War II combat simulator, the sequel of the critically acclaimed Silent Hunter. Green dots represent men, orange dots women, two developers are connected if they had worked on the same team before. This game had 19% women in the team (belonging to the top 25% most diverse teams), and 16.7% developer women. It was ranked in the top 5% of most creative games, but based on critics' reviews its success was worse than average, with an average of 72 out of a 100.*

effects for main console platforms and the year of production. This model explains 22.7% of the variance of creativity (Table 6.2. Model 3, for the full table see SI.8.16). Gender diversity and Inclusion are significant positive predictors of our final model. Although Inclusion is not a significant predictor of creativity by itself, its interaction with diversity is a significant positive predictor of teams' creativity. Integration of team members is the strongest positive predictor of teams' creativity; however, the interaction with gender diversity is not significant.

Figure 6.3 shows the interaction between Diversity and Inclusion. It indicates that a high level of diversity with a low level of inclusion predicts the lowest level of creativity. To create creative video games, teams need both high inclusion and high diversity. Figure 6.4 shows the interaction between Diversity

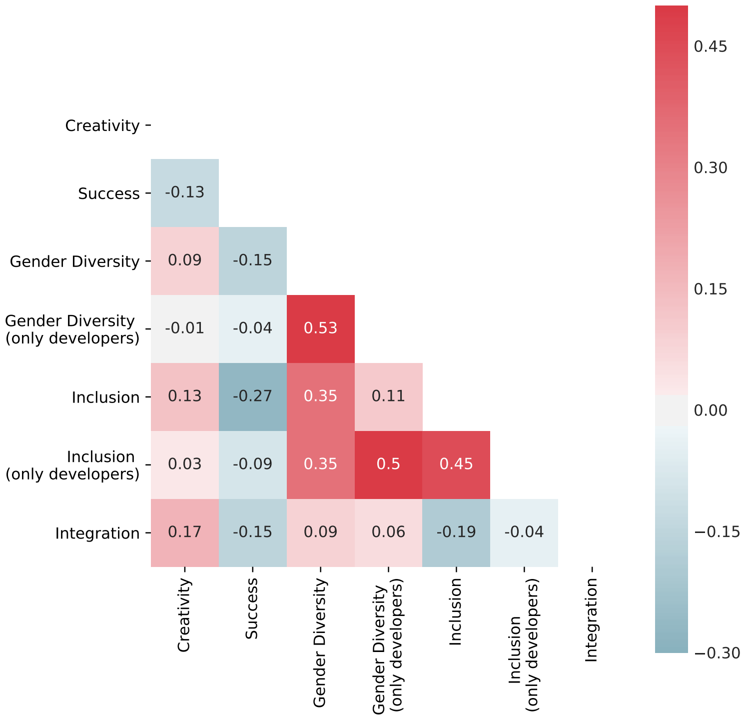

Figure 6.2. *Pearson correlation between key variables. Our dependent variables, Success and Creativity have a negative correlation with each other. Creativity has a positive correlation with integration, inclusion and the ratio of women (Diversity) in the team. Success correlates negatively with all predictors, but especially with Inclusion, Ratio of women and Integration.*

and Integration. This interaction was not significant in our final model, which explains the linear relationship between Integration and Diversity: teams with high level of Diversity and Integration are predicted to create the most creative video games on average.

Predicting Success

Creativity has been shown to be an important predictor of success in the video game industry [85], therefore our baseline success model contains, beyond Diversity and Inclusion and their interaction, the creativity of the focal game as well (Table 6.3. Model 1). The baseline model explains 3.3% of the variance of how successful the produced video game is, although the only positive significant variable is Creativity. Inclusion has a significant, but negative relationship

	Model Creativity		
	Model 1 *D.& I.*	**Model 2** *+ Integration*	**Model 3** *+ Controls*
Diversity	.009	−.037	.050*
	(.020)	(.020)	(.019)
Inclusion	.127***	.183***	.022
	(.017)	(.017)	(.019)
Integration		.205***	.092***
		(.017)	(.017)
Diversity:Inclusion	.112***	.112***	.065***
	(.019)	(.019)	(.016)
Diversity:Integration		.033	.016
		(.017)	(.016)
Intercept	−.091***	−.073***	.428
	(.015)	(.015)	(.080)
Observations	5042	5042	5042
R^2	.027	.064	.227
Signif. codes: *:p<.05 **: p<.01 ***: p<.01			

Table 6.2. *Key predictors of creativity, based on nested linear regression models.*

with success, but Diversity and their interaction is not significant. Adding integration to our model does not improve much the predicting power ($R^2 = 0.034$), because neither Integration, nor its interaction with Diversity are significant (Table 6.3. Model 2.). Our final model including controls can capture 10.6% of the variance of success (Table 6.3. Model 3., see full table at Appendix Table 8.17). Creativity is still the strongest predictor. A closer inspection of the table shows that neither Diversity, nor Integration is a significant predictor of success, and Inclusion has a strong negative relationship with Success. Figure 6.5 shows the predicted success based on the negative (but not significant) interaction between Diversity and Inclusion: the model predicts highest Success for those teams which have low Diversity and Inclusion (probably 100% male teams). Figure 6.6 shows the Success predictions based on the non-significant interaction between Integration and Diversity. The model predicts the highest success for teams with high Integration and low Gender Diversity, and lowest for teams with high Integration and high Gender Diversity. Meaning that all-male teams, who have highly cohesive team networks are the most successful ones. These results further support the idea that male-dominated fields do not benefit from gender diversity.

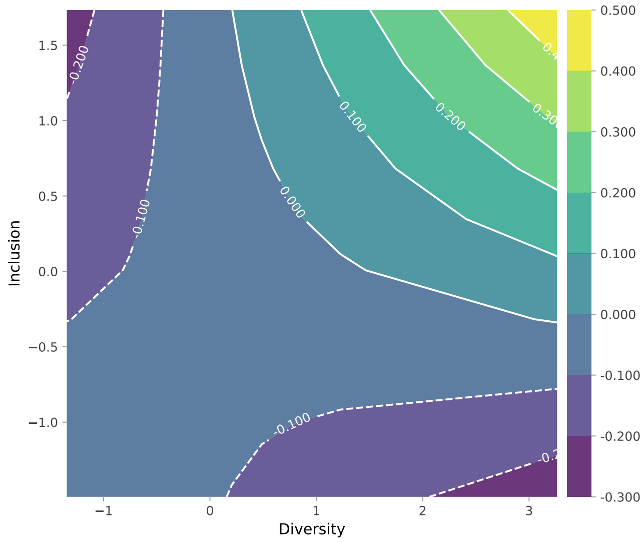

Figure 6.3. *Partial dependence plots of creativity predictions based on the interaction of diversity and inclusion from Table 6.2. Model 3. All other variables are fixed at their mean.*

6.6 Discussion – Beyond Diversity

The video game industry has been criticized for being sexist, and having the least diverse workforce in the technology sector, even though the ratio of male and female gamers is almost equal [162, 149, 70, 154, 155]. Based on 15 years of video game development data we tested five hypotheses about how a team's gender diversity, inclusion and integration predict creativity and success in the video game industry. Our findings indicate that companies should invest in recruiting and retaining more gender diverse workforce, if they want to produce more creative video games. Although creativity is a significant predictor of the success level of a video game, inclusion is negatively associated with success.

Our hypotheses are built on the literature on the effects of gender diversity on teams' creativity and success. Two main views have been developed by scholars: promoters emphasize that diversity brings together people with different knowledge and backgrounds. Opponents argue that diversity can create more conflict, which leads to worse performance and efficiency [38, 39, 78, 86].

The first group of hypotheses tests whether Gender Diversity and Inclusion relate to teams' creativity positively. Our first hypothesis, *"Gender diversity is a positive predictor of how creative a product in the video game industry."*, turned out to be verified. Our second hypothesis, *Integration has a positive relationship*

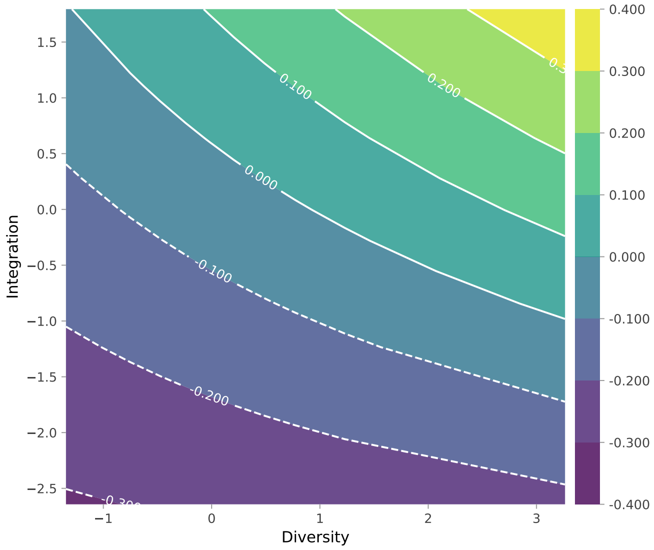

Figure 6.4. *Partial dependence plots of creativity predictions based on the interaction of diversity and integration from Table 6.2. Model 3. All other variables are fixed at their mean.*

with creativity in the video game industry. was also supported, indicating that higher team cohesion indeed helps teams to be more creative. We also found supporting evidence for the third hypothesis, *"The positive effect of gender diversity on creativity is especially strong when teams are more inclusive."*: the interaction between Inclusion and Diversity are significant predictors of creativity in the video game industry. Our findings also indicate that investing only into Diversity without Inclusion is less beneficial: a high level of Diversity with a low level of Inclusion predicts the lowest level of creativity. These results corroborate the findings of a great deal of the previous work in creativity and diversity [85, 215, 216, 88, 225, 226, 87, 88]: teams need both high Inclusion and high Diversity to create an environment where creativity can flourish.

The second group of hypotheses builds on the cultural aspects of success. The literature suggests that gender diversity has a negative influence on success in male-dominated sectors, but gender-balanced teams with an inclusive working culture can benefit from diversity [37, 196, 199, 219, 230]. Since success is a collective measure that captures a community's reaction on performance, and the meaning of success is actively formed by opinion leaders and members of the community, (unconscious) gender bias can impact reputation [56]. Therefore, we hypothesized that highly inclusive gender-diverse teams are especially unsuccessful. Teams' cohesion has been shown to impact performance and success positively, therefore we assumed that higher Integration could pre-

	Success		
	Model 1 *D.& I.*	**Model 2** *+ Integration*	**Model 3** *+ Controls*
Creativity	.097 * **	.094 * **	.099 * **
	(.012)	(.012)	(.013)
Diversity	.012	.010	−.021
	(.017)	(.017)	(.017)
Inclusion	−.151 * **	−.145 * **	−.084 * **
	(.014)	(.015)	(.000)
Integration		.023	.027
		(.014)	(.016)
Diversity:Inclusion	−.010	−.048	−.002
	(.016)	(.016)	(.016)
Diversity:Integration		−.020	−.013
		(.015)	(.014)
Intercept	.046 * **	.049 * **	−.474 * **
	(.013)	(.013)	(.000)
Observations	5042	5042	5042
R^2	.033	.034	.106
Signif. codes: *:p<.05 **: p<.01 ***: p<.01			

Table 6.3. *Key predictors of success, based on nested linear regression models.*

dict higher success. Our first hypothesis about success, *"Gender diversity has a negative relationship with success in the video game industry."* was not verified, since gender diversity was not a significant predictor of success. We did not find supporting evidence for the second hypothesis, *Integration has a positive relationship with success in the video game industry.*, either. And last but not least, our third hypothesis, *The negative effect of gender diversity on success is especially strong when teams are more inclusive.* was not supported completely either, since the Interaction between gender Diversity and Inclusion was not significant. However, we found a significant negative relationship between Inclusion and the level of success of video games.

The video games industry's recent scandals about toxic masculinity, sexism and online harassment of female game reviewers indicate that video game reviewers are probably gender biased [150, 163]. Unfortunately, no structured database is available about reviewers, so we checked manually the top ten most popular online video game reviewer sites, and found that 24% of listed staff

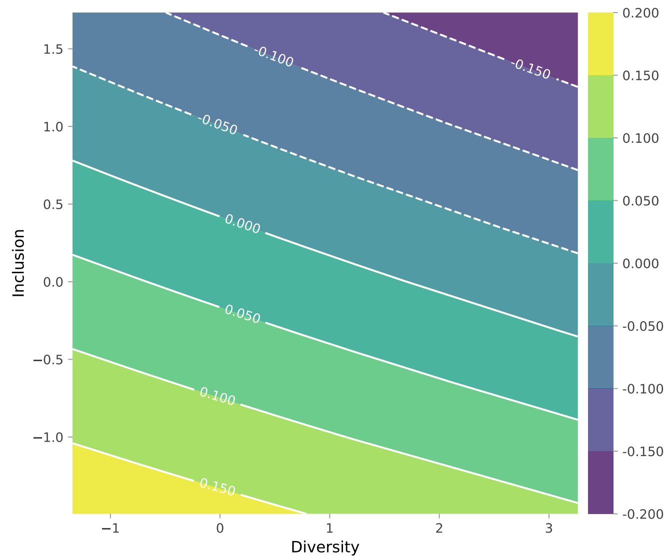

Figure 6.5. *Partial dependence plots of success predictions based on the interaction of diversity and inclusion from Table 6.3. Model 3. All other variables are fixed at their mean.*

was female in average, although none of them was a reviewer[2] It is possible, therefore, that as long as a cultural shift does not happen, gender diversity of production teams itself will not be a valuable asset of a game's success [70]. However, if companies manage to keep working with women, diversity can become valuable. Moreover, we found that diversity and inclusion together are positive predictors' of creativity, which is the most important predictor of success.

Moving beyond the descriptive practices of diversity management (e.g. reports) towards investing into team cohesion amd creating inclusive environments is important for successful diversity management. Companies with integrated employees who can trust each other, will create more creative, reliable and therefor successful products. Our analysis found quantitative evidence on a large-scale dataset that investing into diversity without inclusion is less ben-

[2]We checked manually the *About us* page of the ten most popular video game reviewing websites: Game Informer, N4G, Gamespot, Eurogamer, Polygon , GameZone, Giant Bomb, Metacritic, Kotaku and IGN. Out of these ten only Kotaku, Gaminformer and Eurogamers had staff listed. Kotaku had 24% female employees out of 29 people working there. Out of 7 women, 3 worked in illustration and one was a contributor. At Game Informer, out of 24 listed team members only 8 were women, but only one of them had a position which can influence content as an editor. The rest of the female employees worked as marketers, office assistants and web designers. In EuroGamers, 11% of the employees were women, which means two women out of 15 people. See Table 8.18, 8.19, 8.20, for position, name and gender.

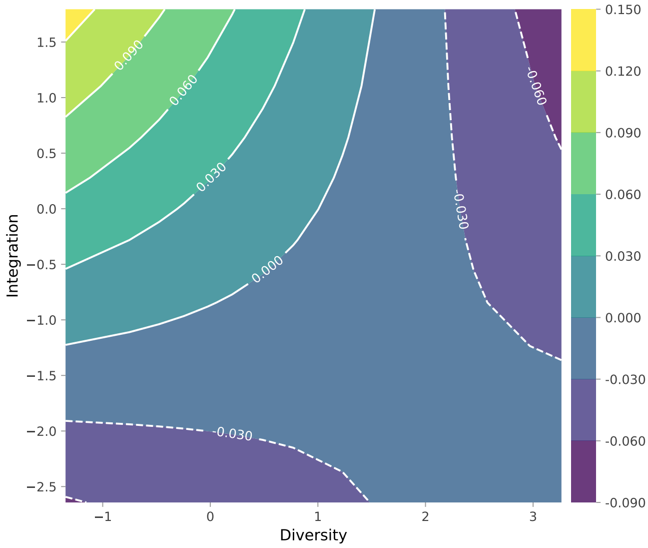

Figure 6.6. *Partial dependence plots of success predictions based on the interaction of diversity and integration from Table 6.3. Model 3. All other variables are fixed at their mean.*

eficial, and can result in less distinct products. However, investing into both inclusion and diversity is not just the right thing to do, but can also be profitable, since creativity is the number one predictor of success.

CHAPTER 7

CONCLUSIONS

7.1 Summary

This dissertation demonstrated that computational methods can be used to investigate how gender inequalities are embedded into social networks. I presented findings on how gendered behaviour, and gendered network formation influence women's success in three male-dominated STEM fields: Open Source Software Development, Academia and the Video Game Industry. The problems that women face in these fields are typical among STEM professionals: low female representation, especially in higher positions [63, 64, 65, 66, 67, 68], a highly masculine culture which defines who is successful [64, 69, 70, 71, 72, 73] and a project-based environment which increases the significance of interpersonal networks [66, 55, 74]. In addition, these fields serve as gatekeepers for future STEM careers. Therefore, understanding those relational and behavioural inequalities that discourage women from pursuing careers in STEM could help to create more actionable policies leading to better female representation in STEM fields.

This work has three major contributions. First, the main contribution of my dissertation is applying data and network science methods on large datasets to uncover the relational complexity of hidden gender inequalities. Second, my research moves beyond a typical gender inequality research, which conceptualizes gender discrimination as a categorical discrimination with quantifying gendered behaviour based on users' online activity. The third key contribution is introducing a new approach with relevant findings to the ongoing debate on positive and negative effects of team diversity.

First, I applied data and network science methods on large datasets to uncover the relational complexity of hidden gender inequalities. By focusing on the relational perspective of career building, the path-dependency of structural and cultural inequalities become visible. In the first case study (Open Source Software development in Chapter 4) we analyzed 7 million users' entire career data at the most popular Open Source Software development platform, GitHub. We investigated why women are less successful, and drop out at higher rates than men in Open Source Software development. Our findings suggest that gender segregation is manifested in collaboration patterns: we found that the most important behavioural predictor for *female-like behavior* is the number of female collaborators. With one standard deviation increase in the number of female collaborators, the odds of being female increases by 1.84 (p=0.000). Other gender-coded collaboration tie variables were less important, although collaboration with unknowns (who are more likely to be women), and following female and unknown-gendered developers were also associated with higher odds of being female (higher than 1). This is an especially surprising result considering the fact that only 11.87% of analyzed users were identified as women, although other scholars also found that minorities are more likely to create homophilous networks [335, 336].

In the second case study (Academic research in Chapter 5) we explored gender differences in the dissemination of articles of 537,486 scientists who had at least one article shared online in 2012. This chapter used a unique data mashup that combines detailed traces of the online sharing of scholars' articles, their publication histories, collaboration networks, scientific fields, and research topics. Results provide evidence that variables associated with social capital are the most important predictors of online popularity across research fields. The gender diversity of coauthor teams (articles written in male majority, female majority or diverse scientific teams) and gendered patterns in the authors' previous collaborations (ego network density, female and male homophily, tie strength to men and women) had the highest relative variable importance[1] in predicting the top 25% most successful scientists. Similarly to our findings in the Open Source Software community, gender homophily was an important predictor of success and a higher ratio of female homophily in ego networks predicted lower success for both genders. We found minor differences between successful and unsuccessful scientists' network compositions between the genders in each field. However, our analysis revealed significant differences between successful male and female scientists' ego network structures: male scientists had more

[1]The relative importance of a variable group is the difference between the baseline overall accuracy, and the accuracy of re-ran model without the given feature set. Both ego network structure's and team diversity's average variable importance is around 10-10 %. The models' overall accuracy varies between 0.76 (Social Sciences) and 0.80 (Computer Sciences) for women and 0.76 (Social Sciences) and 0.80 (Computer Sciences) for men. See Table **??** for detailed results.

connections and less dense networks, low female, but high male homophily, and stronger ties to other men. On the contrary, successful female scientists' ego networks had high female homophily in ego networks constructed by strong connections to other female scientists. These results corroborate the findings of other studies that female homophily is a marked phenomenon in fields where women are underrepresented [49, 55, 335, 336].

Second, we operationalized gendered behaviour in an online setting. In the case of Open Source Software Development we predicted with a machine learning model whether a user's inferred gender is female. Our model took into account variables covering behavioral choices in the level of activity, specialization in programming languages, and the gender choice of collaborators. An important methodological consideration was that variables that capture one's behaviour are theoretically under the control of the individual. The Random Forest classification was moderately accurate – indicating that behavior in open source development is not drastically different between the genders ($AUC = 0.71$, which was consistent across five samples, and decreased to no less than 0.67 with 5% and 10% swapped gender). We called the resulting prediction score *femaleness*, which quantifies on a scale between 0 to 1 how female-like one's behaviour is. As mentioned above, variables capturing gender tie formation, such as the number of female collaborators, were the most important predictors of being female. We also found that specializations in programming languages were significant components of gendered behavior as well.

We tested with two models whether women are at a disadvantage (less successful and drop out at higher rates) because of categorical gender discrimination, or due to the gendered nature of their behaviour (femaleness). Our dependent variables were success and survival. Success is measured as the total number of times other users have starred repositories owned by the focal user, during their entire career. We used zero-inflated negative binomial models to predict success for two reasons. First, our success measure is an over-dispersed count variable. Second, many users of GitHub are not interested in accumulating stars for repositories. Thus, users represent a mixture of two latent classes: one interested in achieving success, and one without such interest. We operationalized survivor by re-visiting all users' pages exactly one year after the end of our data collection and recorded whether a user took any action on the site. Users with action(s) were marked as survived. This method allowed us to test our causal hypothesis. Results show that women's disadvantage in success and survival is mainly due to the gendered nature of their online behaviour. Categorical gender was not a consistently significant predictor of outcomes. The femaleness of behavior is a strong negative predictor of both success and survival, and it is the only coefficient related to gender that is consistently and significantly different from zero.

We found evidence that the gendered choice of interest is present among academics as well, and the femaleness of research topic selection can have negative consequences. We quantified the *femaleness of a given topic* as the likelihood of a female scientist publishing in a topic as opposed to a male scientist. Specifically, we calculated an odds ratio and tested for significance by applying Fisher's exact test with a 5% significance level. High femaleness of a topic means that it is more likely that women publish articles in it, but does not mean that exclusively women publish in it. Overall, only a small fraction (1%) of topics were significantly gendered, and the gendered patterns of topic selection are less articulated among the most popular topics. In fields with a higher female ratio (Social Sciences, Psychology, Medical Sciences), traditionally feminine topics were significantly more common among female than male scientists, and received systematically less coverage online. In male-dominated fields (Physics, Computer Sciences) we found fewer topics associated with gender, indicating that in male-dominated fields the successful strategy for women is to follow less female-like behaviour. We found that significantly feminine topics have lower coverage. Similarly to Open Source Software Development, female-like behaviour, such as publishing in feminine topics, put both genders at a disadvantage.

Third, we introduced a new approach to the ongoing debate on positive and negative effects of team diversity. In the third case study (Chapter 6) we analyzed the collaborative careers of 8,617 video game production teams consisting of 630,420 unique developers. This case moved from individual careers to the meso-level, and analyzed how gender diversity and inclusion predict teams' creativity and success. In this chapter a new *inclusion* metric was operationalized, defined as the as $1 - SI$, where SI is the Segregation Index developed by Freeman[373]. Higher inclusion means less segregation, meaning that men and women are more likely to create ties with each other. Furthermore, we added to our analysis *integration* which is an individual's perception of belonging and fitting in. Therefore, integration is measured on an individual level, and aggregated for each team. We quantified integration by the average closeness centrality [2] of each team. Higher average integration indicates that the team is well-connected and the actors are more "close" to one another.

We tested two groups of hypotheses on how teams' gender diversity and network structure (inclusion and integration) predicts teams' creativity and the level of success, using linear regression models with fixed effects for production year and game platform. The first group of hypotheses is built on the

[2] Closeness centrality is defined as the reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the graph.

literature on the effects of gender diversity on teams' creativity. Two main views have been developed by scholars: promoters emphasize that diversity brings together people with different knowledge and backgrounds. Opponents argue that diversity can create more conflict, which leads to worse performance and efficiency. [38, 39, 78, 86] The second group of hypotheses is built on the cultural aspects of success. The literature suggests that gender diversity has a negative influence on success in male-dominated sectors, but gender-balanced teams with inclusive working cultures can benefit from diversity [37, 196, 199, 219, 230]. Since success is a collective measure that captures a community's reaction to performance, and the meaning of success is actively formed by opinion leaders and members of the community, (unconscious) gender bias can impact success [56]. Therefore, we hypothesized that highly inclusive gender-diverse teams are especially unsuccessful. Teams' cohesion was shown to impact performance and success positively, therefore we assumed that higher integration could predict higher success.

Our findings indicate that teams' network structure and gender diversity are both significant predictors of creativity. We found that integration has a positive relationship with creativity in the video game industry, indicating that higher team cohesion indeed helps teams to develop more creative products. Inclusion in itself was not a significant predictor of creativity: teams need both inclusion and diversity to create an environment where creativity can flourish. In the case of success we did not find a significant relationship between success and gender diversity, although inclusion turned out to be a strong negative predictor of success. Surprisingly, integration was not a significant predictor of the level of success of a video game.

7.1.1 Discussion

The first two case studies (Open Source Software development in Chapter 4, and Academic research in Chapter 5) analyzed the role of gendered behaviour and gendered network formation in *individual success*. While one's career success is analyzed, it is important to keep in mind that all careers are linked and influence one another. The study about scientists' popularity online shows that the offline gender inequalities in scientists networks' perpetuate, or even reinforce women's offline disadvantage. Both studies deal with individual careers that are embedded into collaboration networks, and present that gender homophily is a key driver of collaborations. Due to the subordinate role of women, lower ranking positions and prestige in technical fields [13, 14], the marginalization of women is especially harmful and slows down the progress towards gender equality [31].

While analyzing the online forms of gendered behavior in Open Source

Software Development, we found that women are being boxed into specializations which are associated with lower success and survival rates. Similarly to Open Source Software Development, we found evidence that the negative consequences of gendered choice of interest is present among scientists as well. Results suggest that sub-field marginalization reinforces gender inequality. We found that in male-dominated research fields the successful strategy for women was to follow less female-like behaviour in terms of topic selection and specialization. In addition, both in Academia and Open Source Software Development men who followed female-like behavior were less successful than those who followed highly masculine career paths. However, men were still more successful than women with the same extent of female-like career traits. This indicates that gendered behaviour is a key driver of online inequalities, although the negative consequences of categorical gender stereotypes might still be present as well.

Findings of Open Source Software Development and Academia indicate that segregation of women is the product of the masculine culture in STEM fields. Most diversity advocates agree that developing gender-inclusive environments has significant positive impact on gender equality [97]. The term of inclusion conceptualizes the perception of whether and to what extent individuals feel part of organizational processes [362]. These processes include access to information and resources, embeddedness into organizational networks, ownership and decision-making opportunities [363]. Therefore, we operationalized inclusion and integration from a network science perspective: inclusion quantifies the lack of segregation, and integration is measured by the average closeness centrality of team members within the collaboration network of the focal game.

Our findings indicate that investing only in diversity without inclusion is not beneficial: a high level of diversity with a low level of inclusion predicts the lowest level of creativity. Teams need both high inclusion and diversity to develop creative products. Moreover we found that teams with a higher ratio of women but low inclusion created the least creative products. This suggest that hiring more women without creating an inclusive team culture can result in backlashes. In addition, we found supporting evidence that inclusion is negatively related to success in the video game industry, indicating that until a cultural shift happens, the gender diversity of a production team itself will not be a valuable predictor of a game's success. This case demonstrates that even though well-integrated gender-diverse teams can create more creative products, if the cultural norms and values are defined by a non-diverse pool of stakeholders, the positive effects of diversity cannot manifest itself in success. Thus, I argue that we cannot overcome gender inequalities as long as a cultural shift does not happen.

7.2 Policy Recommendations

Our findings indicate potential implications in policy and interventions to improve gender equality in software development, academia and possibly other male-dominated STEM fields. First, setting quotas will not debug the gender gap in these fields, since inequalities are embedded into gendered tie formation and behaviour. Moreover, our findings indicate that hiring women without an inclusive team culture could lead to worse team performance. However, an increased ratio of women might eventually change cultural stereotypes and lead to more visible female success stories that can encourage more girls and young women to consider STEM careers. Nevertheless, our findings indicate that this future is still far away. Without changing the definition of success to be more inclusive, women need to adopt and develop behavioural strategies that reinforce the current status quo.

We found that female marginalization is present in science and software development as well, resulting in more female-dominated specializations and research fields associated with lower prestige. This indicates that initiatives that are aimed to empower women with women-only events, conferences and courses might have unintended negative consequences. For example, coding schools for women, which are typically training women in specialties that already have higher female representation, such as Frontend development, might perpetuate the disadvantage of women by their femaleness of behavior [299]. Moreover, these endeavours contribute to creating more women-to-women ties among the participants. Unfortunately, gendered specializations have consequences: as the ratio of women grows in an occupation, the occupation's prestige, and therefore the salary, drops [30].

However, we found that successful female scientists had a larger ratio of strong connections to other women, and they could turn this into an advantage. In male-dominated sectors women often develop *impostor syndrome*, and receive less credit for their work [126]. Due to unconscious gender bias, group-achievements are more likely to be credited to male team members, making women less successful and invisible. The lack of visibility has been associated with reasons why women are less likely to choose STEM careers [22, 58, 112]. Women in male-dominated fields face a paradoxical visibility problem: they are highly visible as being female, but often overlooked as experts, as they do not fit the stereotype [35]. Therefore, creating platforms where women share their expertise can be beneficial. The Women in Data Science (WiDS) Initiative is a great example of how a feminist conference can support women while being gender-inclusive. [3] At WiDS conferences exceptional female data scientists talk about

[3] WiDS started at Stanford University in 2015 as a protest by Prof. Margot Gerritsen. She was

their work. It helps speakers to gain visibility and they also pose as role-models for the future generation of data scientists.

Since male universality is widespread and society takes men's perspectives and experiences as default, therefore, half of the population is discriminated against. Male universality causes a gender data gap: the majority of human knowledge is based on men's achievement and histories [375]. As technology, and especially AI systems advances, the gender data gap, and stereotypes rooted in social networks and behavior have long-lasting consequences. For example, in algorithm-driven human resource management, gendered behaviour has been shown to discriminate against women, without knowing applicants' gender [195, 250]. Although diversity has been shown to enforce objectivity and reducing unconscious bias, most widely adopted algorithms are developed in mainly white, male-dominated teams [38, 39, 8, 9]. Furthermore, gender bias can manifest itself in what is considered to be successful [376], which indeed reinforces female marginalization. Reconsidering what type of behaviour is valued by an organization and how it relates to gender stereotypes could result in more successful female employees.

As a result of the harsh criticism of the technology industry, companies are trying to hire women and minorities to reflect the demographics of their customers [353]. Unfortunately, poorly managed diversity advocacy might be counterproductive, and reinforce the culture of marginalization and victimization [354, 355, 96]. Moving beyond the descriptive practices of diversity management (e.g., diversity reports) towards exploring inclusion with network science metrics is highly suggested for HR professionals and people analytics experts, to see a more granular picture of unconscious bias within their organizations.

7.3 Limitations

This dissertation relies on large-scale open datasets where individuals do not self-report their gender. This indicates important limitations of our findings: first, gender is inferred based on individuals' names. In scientific research and video game development, where professional activity was analyzed, gender

invited to talk at a local data science conference at Stanford in 2014, but she could not make it, and cancelled her talk. After the event she saw that there was no female speaker at all. When she asked the organizer how is it possible, they said they did not find any female data scientist. In the middle of the Silicon Valley. She got very upset, and decided to organize a protest event where the best female data scientists would talk about their work, so nobody can say they could not find female speakers. WiDS has 150+ regional events worldwide; a datathon and a podcast, featuring female data scientists talking about their work, their journeys, and lessons learned [374].

inferring was much more reliable than in Open Source Development, where individuals can pick any username. Second, name-based gender inferring algorithms can be culturally biased towards Western names [282], therefore our findings cannot be generalized to every culture. Third, our data is collected from public data sources, therefore we cannot be sure that it does not have some systematic bias. Considering that the gender data gap is a persistent phenomenon, our datasets are more likely to underestimate the presence of women [375].

The presented studies do not take into account the hierarchical structure of race, class and sexual identity, since we do not have information about it. Since the script of femininity was written based on the most privileged women, who are white, middle- to upper-middle class, and heterosexual [193], conceptualizing gender behaviour for the intersections of race, class and sexual identity would be a significant extension.

Since none of the datasets are analyzed from a time-dependent perspective, our findings are rather descriptive and do not explain time-dependent casual effects of increased/decreased gender ratios. These limitations serve as an opportunity for further research. Since gender segregation is present in all analyzed sectors, analyzing macro-level collaborations from a historical point of view would be a significant next step to extend our findings. It could help to understand the process of how female marginalization emerges. Furthermore, a deeper understanding of gendered topic selection among scientists in newly emerged scientific fields, such as computational social sciences, linguistics and biology, could help to understand whether women create fields where they feel more comfortable, or if they are pushed to less prestigious fields.

7.4 Future of computational social science of gender inequalities

The Federal Court of the United States ruled on 28 March 2020 that discrimination studies do not violate federal anti-hacking laws [377]. This major breakthrough can open up more research on the intersection of algorithmic fairness [**?**], explainable AI and gender bias. Hopefully this will increase interdisciplinary research in the field of computational social science, bringing together computer, data, natural and social scientists, including fields which are traditionally less quantitative, such as gender studies and philosophy. Increased computer–human interactions have raised many research questions about gender and status in voice user interfaces and chat bots already [247, 248, 249]. Furthermore, as automatized video user interfaces are becoming widespread, stereotypes at the intersection of gender, race and age might manifest in products. Therefore, analyzing gender inequalities in a wider context will be a significant research direction.

Studies indicate that professional visibility matters for women more than for men. However, it is not quantified what the value of certain visibility efforts is: do female scientists benefit from their online visibility as much as men in terms of citations? What is the impact of being a keynote speaker at an international conference? How do only-women endeavours impact women's careers? Quantifying with large-scale quantitative studies how different visibility efforts improve one's career outcomes can help to develop targeted policies that can really help women to become more successful.

Team science still needs to develop a deeper understanding of the effects of diversity and inclusion. It is well-documented that the lack of gender diversity could result in discriminating products [40, 41, 42, 43], however, what type of team setting leads to the least biased decision making is less studied [38, 39]. Research on *collective objectivity* among development teams could be an important engine of developing more *ethical algorithms*. Developing further the methodological framework of data-driven inclusion research is another exciting research direction that can lead to better organizational climate and benefit many. Moreover, studying the impact of inclusion on team performance in different sectors and gender settings could help to convince everybody that inclusion is a "must" and not a "nice to have".

Many aspects of our work have started to migrate online, and due to the the global COVID-19 pandemic this process accelerated. This fast-track shift in human collaborations has unknown effects on team cohesion and segregation. Feminists argue that the current situation has deepened gender inequalities and the pandemic will result in higher female drop-out in many fields [378, 379]. Understanding how inclusion and integration form in fully online environments and interact with gender diversity is a crucial question that should be answered as soon as possible.

BIBLIOGRAPHY

[1] Vedres, B., Vasarhelyi, O.: Gendered behavior as a disadvantage in open source software development. EPJ Data Science **8**(1), 25 (2019)

[2] Milojević, S.: Practical method to reclassify web of science articles into unique subject categories and broad disciplines. Quantitative Science Studies, 1–24 (2020)

[3] Vasilescu, B., Serebrenik, A., Filkov, V.: A Data Set for Social Diversity Studies of GitHub Teams. 2015 IEEE/ACM 12th Working Conference on Mining Software Repositories, 514–517 (2015)

[4] Ford, D., Harkins, A., Parnin, C.: Someone Like Me: How does peer parity influence participation of women on stack overflow? In: Proceedings of the IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC). VL/HCC '17, pp. 239–243 (2017). doi:10.1109/VLHCC.2017.8103473

[5] Wossen, T., Abdoulaye, T., Alene, A., Haile, M.G., Feleke, S., Olanrewaju, A., Manyong, V.: Impacts of extension access and cooperative membership on technology adoption and household welfare. Journal of rural studies **54**, 223–233 (2017)

[6] Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N.: Technological innovation, resource allocation, and growth. The Quarterly Journal of Economics **132**(2), 665–712 (2017)

[7] Fagerberg, J.: A technology gap approach to why growth rates differ. Research policy **16**(2-4), 87–99 (1987)

[8] National Science Board, "Chapter 2: Higher Education in Science and Engineering," Science Engineering Indicators 2018 = `https://nsf.gov/statistics/2018/nsb20181/report/`

sections/higher-education-in-science-and-engineering/undergraduate-education-enrollment-and-degrees-in-the-united-states , note = Accessed: 2020-02-01

[9] Bureau, U.C.: Women's Employment in Science, Tech, Engineering and Math Jobs Slowing. Available at: https://www.census.gov/newsroom/press-releases/2013/cb13-162.html. Accessed: 2018-09-04 (2011)

[10] United States Department of Labor: Women's Bureau (WB) - Computer and Information Technology Occupations. Available at: https://www.dol.gov/wb/stats/Computer_information_technology_2014.htm. Accessed: 2018-09-04 (2015)

[11] Beckhusen, J.: Occupations in Information Technology. Available at: https://www.census.gov/content/dam/Census/library/publications/2016/acs/acs-35.pdf. Accessed: 2018-09-04 (2016)

[12] When women stopped coding = https://www.npr.org/sections/money/2014/10/21/357629765/when-women-stopped-coding' , year=2019, note = Accessed: 2020-02-01

[13] Adams, R.B., Kirchmaier, T.: Women on boards in finance and stem industries. American Economic Review **106**(5), 277–81 (2016)

[14] Eastman, M.T.: Women on Boards: Progress Report 2017 (MSCI, December 2017) = https://www.msci.com/www/research-paper/women-on-boards-progress-report/0806530251 , note = Accessed: 2020-02-01

[15] Jacobs, J.: Google gender pay gap: women advance suit that could affect 8,300 workers = https://www.theguardian.com/technology/2018/oct/26/google-gender-pay-gap-women-class-action-lawsuit , year=2018, note = Accessed: 2020-03-18

[16] Levin, S.: Macho 'brogrammer' culture still nudging women out of tech = https://www.ft.com/content/5dd12c50-dd41-11e8-b173-ebef6ab1374a , year=2018, note = Accessed: 2020-03-18

[17] Houser, K.: The Tech Industry's Gender Problem Isnt Just Hurting Women "Women in leadership positions serve as a significant deterrent against a permissive culture towards sexual harassment." = https://futurism.com/tech-industrys-gender-problem-hurting-women , year=2017, note = Accessed: 2020-03-18

[18] Kolhatkar, S.: The Tech Industry's Gender-Discrimination Problem = https://www.newyorker.com/magazine/2017/11/20/the-tech-industrys-gender-discrimination-problem , year=2017, note = Accessed: 2020-03-18

[19] Tarr, T.: By The Numbers: What Pay Inequality Looks Like For Women In Tech = https://www.forbes.com/sites/tanyatarr/2018/04/04/by-the-numbers-what-pay-inequality-looks-like-for-women-in-tech/#64175eaf60b1. Accessed: 2020-03-18 (2018)

[20] Wajcman, J.: Feminist theories of technology. Cambridge journal of economics **34**(1), 143–152 (2010)

[21] Windsor, E.J.: Femininities (2015)

[22] Ahuja, M.K.: Women in the information technology profession: a literature review, synthesis and research agenda. European Journal of Information Systems **11**(1), 20–34 (2002). doi:10.1057/palgrave.ejis.3000417

[23] Kulis, S., Sicotte, D., Collins, S.: More than a pipeline problem: Labor supply constraints and gender stratification across academic science disciplines. Research in Higher Education **43**(6), 657–691 (2002)

[24] Kahn, S., Ginther, D.: Women and stem. Technical report, National Bureau of Economic Research (2017)

[25] Women in science: quarterly thematic publication, issue I. March 2015 = https://unesdoc.unesco.org/ark:/48223/pf0000235155 , note = Accessed: 2020-02-01

[26] Occupational Employment Statistics = https://www.bls.gov/oes/2018/may/oes150000.htm , note = Accessed: 2020-03-04

[27] Bureau of Labor Statistics, "Table 11: Employed Persons by Detailed Occupation, Sex, Race, and Hispanic or Latino Ethnicity," Current Population Survey, Household Data Annual Averages 2017 (2018). = https://www.bls.gov/cps/cpsaat11.htm , note = Accessed: 2020-02-01

[28] Tarr, T.: Cyberstates 2019 The definitive guide to the U.S. tech industry and tech workforce = https://www.cyberstates.org/pdf/CompTIA_Cyberstates_2019.pdf. Accessed: 2020-03-18 (2019)

[29] Tarr, T.: A woman would have to be born in the year 2255 to get equal pay at work = https://www.weforum.org/agenda/2019/12/

global-economic-gender-gap-equality-women-parity-pay/. Accessed: 2020-03-18 (2019)

[30] Levanon, A., England, P., Allison, P.: Occupational feminization and pay: Assessing causal dynamics using 1950–2000 us census data. Social Forces **88**(2), 865–891 (2009)

[31] Burt, R.S.: The gender of social capital. Rationality and society **10**(1), 5–46 (1998)

[32] Acker, J.: Hierarchies, jobs, bodies: A theory of gendered organizations. Gender & society **4**(2), 139–158 (1990)

[33] Farmer, A.: The political pillorying of pantsuits-the media's gender bias in the 2008 presidential campaign. Perspectives **17**, 4 (2008)

[34] Sullivan, D.A.: Cosmetic Surgery: The Cutting Edge of Commercial Medicine in America. Rutgers University Press, ??? (2001)

[35] Fernando, D., Prasad, A.: Sex-based harassment and organizational silencing: How women are led to reluctant acquiescence in academia. human relations **72**(10), 1565–1594 (2019)

[36] Wooley-Williams, A., Chabris, C..F., Pentland, A., Hashmi, N., Malone, T.M.: Evidence for a Collective Intelligence Factor in the Performance of Human Groups. Science (80-.). **330** (2010)

[37] Campbell, L.G., Mehtani, S., Dozier, M.E., Rinehart, J.: Gender-heterogeneous working groups produce higher quality science. PloS one **8**(10) (2013)

[38] Rock, D., Grant, H.: Why diverse teams are smarter. Harvard Business Review **4**(4), 2–5 (2016)

[39] Levine, S.S., Apfelbaum, E.P., Bernard, M., Bartelt, V.L., Zajac, E.J., Stark, D.: Ethnic diversity deflates price bubbles. Proceedings of the National Academy of Sciences **111**(52), 18524–18529 (2014)

[40] Westerman, S., Wenger, N.K.: Women and heart disease, the underrecognized burden: sex differences, biases, and unmet clinical and research challenges. Clinical Science **130**(8), 551–563 (2016)

[41] Bolukbasi, T., Chang, K.-W., Zou, J.Y., Saligrama, V., Kalai, A.T.: Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In: Advances in Neural Information Processing Systems, pp. 4349–4357 (2016)

[42] Raymond, J.: Most of us are biased. Nature **495**(7439), 33–34 (2013)

[43] Bajorek, J.P.: Voice Recognition Still Has Significant Race and Gender Biases (2019). `https://hbr.org/2019/05/voice-recognition-still-has-significant-race-and-gender-biases`

[44] Fisher, A., Margolis, J.: Unlocking the clubhouse: the carnegie mellon experience. ACM SIGCSE Bulletin **34**(2), 79–83 (2002)

[45] Vitores, A., Gil-Juarez, A.: The trouble with 'women in computing': a critical examination of the deployment of research on the gender gap in computer science. Journal of Gender Studies **25**(6), 666–680 (2016)

[46] Cockburn, C.: 1983 brothers: Male dominance and technological change, london, pluto press (1983)

[47] Meyerson, D.E., Kolb, D.M.: Moving out of thearmchair′: Developing a framework to bridge the gap between feminist theory and practice. Organization **7**(4), 553–571 (2000)

[48] Vasilescu, B., Capiluppi, A., Serebrenik, A.: Gender, representation and online participation: A quantitative study. Interacting with Computers **26**(5), 488–511 (2014)

[49] Lutter, M.: Do Women Suffer from Network Closure? The Moderating Effect of Social Capital on Gender Inequality in a Project-Based Labor Market, 1929 of 2010. American Sociological Review **80**(2), 329–358 (2015). doi:10.1177/0003122414568788

[50] Wagner, C., Garcia, D., Jadidi, M., Strohmaier, M.: It's a man's wikipedia? assessing gender inequality in an online encyclopedia. In: Ninth International AAAI Conference on Web and Social Media (2015)

[51] Wagner, C., Graells-Garrido, E., Garcia, D., Menczer, F.: Women through the glass ceiling: gender asymmetries in wikipedia. EPJ Data Science **5**(1), 5 (2016)

[52] Horvat, E.-A., Papamarkou, T.: Gender differences in equity crowdfunding. In: Fifth AAAI Conference on Human Computation and Crowdsourcing (2017)

[53] Wachs, J., Hannak, A., Voros, A., Daroczy, B.: Why do men get more attention? exploring factors behind success in an online design community.

In: Eleventh International AAAI Conference on Web and Social Media (2017)

[54] Wachs, J., Daróczy, B., Hannák, A., Páll, K., Riedl, C.: And now for something completely different: Visual novelty in an online network of designers. In: Proceedings of the 10th ACM Conference on Web Science, pp. 163–172 (2018)

[55] Jadidi, M., Karimi, F., Lietz, H., Wagner, C.: Gender disparities in science? dropout, productivity, collaborations and success of male and female computer scientists. Advances in Complex Systems **21**(03n04), 1750011 (2018)

[56] Yucesoy, B., Barabási, A.-L.: Untangling performance from success. EPJ Data Science **5**(1), 17 (2016)

[57] Griffith, A.L.: Persistence of women and minorities in stem field majors: Is it the school that matters? Economics of Education Review **29**(6), 911–922 (2010)

[58] Qian, Y., Zafar, B., Xie, H.: Do female faculty influence female students' choice of college major, and why? Technical report, Northwestern University Working Paper (2010)

[59] Canes, B.J., Rosen, H.S.: Following in her footsteps? faculty gender composition and women's choices of college majors. ILR Review **48**(3), 486–504 (1995)

[60] Rask, K.N., Bailey, E.M.: Are faculty role models? evidence from major choice in an undergraduate institution. The Journal of Economic Education **33**(2), 99–124 (2002)

[61] Hoffmann, F., Oreopoulos, P.: A professor like me the influence of instructor gender on college achievement. Journal of human resources **44**(2), 479–494 (2009)

[62] Carrell, S.E., Page, M.E., West, J.E.: Sex and science: How professor gender perpetuates the gender gap. The Quarterly Journal of Economics **125**(3), 1101–1144 (2010)

[63] 2018 Women in Tech Index= `https://https://www.honeypot.io/women-in-tech-2018/eur/#table-content` , note = Accessed: 2020-02-20

[64] Chang, E.: Brotopia: Breaking Up the Boys' Club of Silicon Valley. Portfolio, ??? (2019)

[65] Sohan Murthy: Women in Software Engineering: The Sobering Stats= `https://business.linkedin.com/talent-solutions/blog/2014/03/women-in-engineering-the-sobering-stats` , note = Accessed: 2020-02-20

[66] Vasilescu, B., Serebrenik, A., Filkov, V.: A Data Set for Social Diversity Studies of GitHub Teams. MSR '15 Proc. 12th Work. Conf. Min. Softw. Repos., 514–517 (2015). doi:10.1109/MSR.2015.77

[67] National Center for Education Statistics, IPEDS Data Center, "Full-Time Instructional Staff, by Faculty and Tenure Status, Academic Rank, Race/Ethnicity, and Gender (Degree-Granting Institutions): Fall 2018," Fall Staff 2018 Survey (2018). Available at: `hhttps://nces.ed.gov/ipeds/use-the-data`. Accessed: 2020-02-04 (2018)

[68] Commission, E.: She figures 2018 (2019)

[69] Bailey, E.N., Miyata, K., Yoshida, T.: Gender composition of teams and studios in video game development. Games and Culture, 1555412019868381 (2019)

[70] Near, C.E.: Selling gender: Associations of box art representation of female characters with sales for teen-and mature-rated video games. Sex roles **68**(3-4), 252–269 (2013)

[71] May, A., Wachs, J., Hannak, A.: Gender differences in participation and reward on stack overflow. Empirical Software Engineering **24**(4), 1997–2019 (2019)

[72] Shen, H.: Inequality quantified: Mind the gender gap. Nature **495** (2013). doi:10.1038/495022a

[73] Ceci, S.J., Ginther, D.K., Kahn, S., Williams, W.M.: Women in academic science: A changing landscape. Psychological Science in the Public Interest **15**(3), 75–141 (2014)

[74] Zeng, X.H.T., Duch, J., Sales-Pardo, M., Moreira, J.A., Radicchi, F., Ribeiro, H.V., Woodruff, T.K., Amaral, L.A.N.: Differences in collaboration patterns across discipline, career stage, and gender. PLoS biology **14**(11) (2016)

[75] Hayes, E.: Girls, gaming and trajectories of it expertise. Beyond Barbie and Mortal Kombat: New perspectives on gender and computer games, 138–194 (2008)

[76] Bonaccorsi, A., Rossi, C.: Why Open Source software can succeed. Research Policy **32**, 1243–1258 (2003). doi:10.1016/S0048-7333(03)00051-9

[77] Dabbish, L., Stuart, C., Tsay, J., Herbsleb, J.: Social Coding in GitHub: Transparency and Collaboration in an Open Software Repository. In: Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work, pp. 1277–1286. ACM Press, New York, New York, USA (2012). doi:10.1145/2145204.2145396

[78] Reagans, R., Zuckerman, E.W.: Networks, diversity, and productivity: The social capital of corporate r&d teams. Organization science **12**(4), 502–517 (2001)

[79] Thelwall, M.: Homophily in myspace. Journal of the American Society for Information Science and Technology **60**(2), 219–231 (2009)

[80] Abramo, G., D'Angelo, C., Caprasecca, A.: Gender differences in research productivity: A bibliometric analysis of the italian academic system. Scientometrics **79**(3), 517–539 (2009)

[81] Badar, K., Hite, J.M., Badira, Y.F.: Examining the relationship of co-authorship network centrality and gender on academic research performance: the case of chemistry researchers in pakistan. Scientometrics **94**(2) (2013). doi:10.1007/s11192-012-0764-z

[82] Abbasi, A., Chung, K.S.K., Hossain, L.: Egocentric analysis of co-authorship network structure, position and performance. Information Processing Management **48**(4) (2012). doi:10.1016/j.ipm.2011.09.001

[83] Bordonsa, M., Apariciob, J., GonzálezAlbob, B., DiazFaesa, A.A.: The relationship between the research performance of scientists and their position in co-authorship networks in three fields. Journal of Informetrics **9**(1) (2015). doi:10.1016/j.joi.2014.12.001

[84] Ortega, J.L.: Influence of co-authorship networks in the research impact: Ego network analyses from microsoft academic search. Journal of Informetrics **8**(3), 728–737 (2014)

[85] de Vaan, M., Stark, D., Vedres, B.: Game changer: The topology of creativity. American Journal of Sociology **120**(4) (2015). doi:10.1086/681213

[86] Aggarwal, I., Woolley, A.W.: Do you see what i see? the effect of members' cognitive styles on team processes and errors in task execution. Organizational Behavior and Human Decision Processes **122**(1), 92–99 (2013)

[87] Joshi, A.: By whom and when is women's expertise recognized? the interactive effects of gender and education in science and engineering teams. Administrative Science Quarterly **59**(2), 202–239 (2014)

[88] Bear, J.B., Woolley, A.W.: The role of gender in team collaboration and performance. Interdisciplinary Science Reviews **36**(2), 146–153 (2011). doi:10.1179/030801811X13013181961473

[89] Kochan, T., Bezrukova, K., Ely, R., Jackson, S., Joshi, A., Jehn, K., Leonard, J., Levine, D., Thomas, D.: The effects of diversity on business performance: Report of the diversity research network. Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management **42**(1), 3–21 (2003)

[90] Baugh, S.G., Graen, G.B.: Effects of team gender and racial composition on perceptions of team performance in cross-functional teams. Group & Organization Management **22**(3), 366–383 (1997)

[91] Triana, M.d.C., Miller, T.L., Trzebiatowski, T.M.: The double-edged nature of board gender diversity: Diversity, firm performance, and the power of women directors as predictors of strategic change. Organization Science **25**(2), 609–632 (2014)

[92] Richard, O.C., Kirby, S.L., Chadwick, K.: The impact of racial and gender diversity in management on financial performance: How participative strategy making features can unleash a diversity advantage. The International Journal of Human Resource Management **24**(13), 2571–2582 (2013)

[93] Lauring, J., Villeseche, F.: The performance of gender diverse teams: What is the relation between diversity attitudes and degree of diversity? European Management Review **16**(2), 243–254 (2019)

[94] Bassett-Jones, N.: The paradox of diversity management, creativity and innovation. Creativity and innovation management **14**(2), 169–175 (2005)

[95] Montilla, E.: Google's Ideological Echo Chamber (2020). `https://www.forbes.com/sites/forbestechcouncil/2020/03/10/top-three-reasons-we-need-more-women-in-tech/#3adced8615fb`

[96] Wikipedia: Google's Ideological Echo Chamber (2017). ttps://en.wikipedia.org/wiki/Google%27s_Ideological_Echo_Chamber

[97] Sherbin, L., Rashid, R.: Diversity doesn't stick without inclusion. Harvard Business Review **1** (2017)

[98] Patterson, E.: Mary Somerville. The British Journal for the History of Science. **4**, 311–339 (1969). doi:10.1017/S0007087400010232

[99] Clayton, K.L., von Hellens, L.A., Nielsen, S.H.: Gender stereotypes prevail in ict: A research review. In: Proceedings of the Special Interest Group on Management Information System's 47th Annual Conference on Computer Personnel Research. SIGMIS CPR '09, pp. 153–158. ACM, New York, NY, USA (2009). doi:10.1145/1542130.1542160. http://doi.acm.org/10.1145/1542130.1542160

[100] Fuegi, J., Francis, J.: Lovelace babbage and the creation of the 1843 'notes. Annals of the History of Computing **25**(4), 26–26 (2003)

[101] Watts, R.: Women in Science: a Social and Cultural History. Routledge, ??? (2013)

[102] Nosek, B.A., Banaji, M.R., Greenwald, A.G.: Math= male, me= female, therefore math$\neq$ me. Journal of personality and social psychology **83**(1), 44 (2002)

[103] Fernando, D., Cohen, L., Duberley, J.: The problem of visibility of women in engineering and how they manage it. HBR (2018)

[104] National Center for Education Statistics = "Table 318.45: Number and Percentage Distribution of Science, Technology, Engineering, and Mathematics (STEM) Degrees/Certificates Conferred by Postsecondary Institutions, by Race/Ethnicity, Level of Degree/Certificate, and Sex of Student: 2008-09 through 2015-16, Digest of Education Statistics: 2016 Tables and Figures (2017) https://nces.ed.gov/programs/digest/d17/tables/dt17_318.45.asp?current=yes, note = Accessed: 2020-02-01

[105] Graduates by education level, programme orientation, sex and field of education, Eurostat = https://ec.europa.eu/eurostat/web/products-datasets/product?code=edu_uoe_grad02 , note = Accessed: 2020-02-01

[106] Xie, Y., Shauman, K.A., Shauman, K.A.: Women in Science: Career Processes and Outcomes vol. 26. Harvard university press Cambridge, MA, ??? (2003)

[107] Cvencek, D., Meltzoff, A.N., Greenwald, A.G.: Math–gender stereotypes in elementary school children. Child development **82**(3), 766–779 (2011)

[108] Eccles, J.S., Wang, M.-T.: What motivates females and males to pursue careers in mathematics and science? International Journal of Behavioral Development **40**(2), 100–106 (2016)

[109] Eccles, J.S., Jacobs, J.E., Harold, R.D.: Gender role stereotypes, expectancy effects, and parents' socialization of gender differences. Journal of social issues **46**(2), 183–201 (1990)

[110] Eccles, J.S., Jacobs, J.E.: Social forces shape math attitudes and performance. Signs: Journal of women in culture and society **11**(2), 367–380 (1986)

[111] Fryer Jr, R.G., Levitt, S.D.: An empirical analysis of the gender gap in mathematics. American Economic Journal Applied Economics **2**(2), 210–40 (2010)

[112] Cheng, A., Kopotic, K., Zamarro, G.: Can parents' growth mindset and role modelling address stem gender gaps? (2017)

[113] Lavy, V., Sand, E.: On the origins of gender human capital gaps: Short and long term consequences of teachers' stereotypical biases. Technical report, National Bureau of Economic Research (2015)

[114] Cornwell, C., Mustard, D.B., Van Parys, J.: Noncognitive skills and the gender disparities in test scores and teacher assessments: Evidence from primary school. Journal of Human resources **48**(1), 236–264 (2013)

[115] Bottia, M.C., Stearns, E., Mickelson, R.A., Moller, S., Valentino, L.: Growing the roots of stem majors: Female math and science high school faculty and the participation of students in stem. Economics of Education Review **45**, 14–27 (2015)

[116] Soe, L., Yakura, E.K.: What's wrong with the pipeline? assumptions about gender and culture in it work. Women's Studies **37**(3), 176–201 (2008)

[117] Camp, T.: The incredible shrinking pipeline. ACM SIGCSE Bulletin **34**(2), 129–134 (2002)

[118] Adya, M., Kaiser, K.M.: Early determinants of women in the it workforce: a model of girls' career choices. Information Technology & People (2005)

[119] Bartol, .A.W. K. M.: The state of research on girls and it. In: Aspray, J.C..W. (ed.) Women and Information Technology: Research on Under-representation, pp. 3–54. MIT Press, Cambridge, MA, USA (2006)

[120] Cohoon, .A.W. J. M.: A critical review of the research on women's participation in postsecondary computing education. In: Aspray, J.C..W. (ed.) Women and Information Technology: Research on Under-representation, pp. 137–180. MIT Press, Cambridge, MA, USA (2006)

[121] Babin, R., Grant, K.A., Sawal, L.: Identifying influencers in high school student ict career choice. Information Systems Education Journal **8**(26), 26 (2010)

[122] Vekiri, I., Chronaki, A.: Gender issues in technology use: Perceived social support, computer self-efficacy and value beliefs, and computer use beyond school. Computers & education **51**(3), 1392–1404 (2008)

[123] Robnett, R.D., Leaper, C.: Friendship groups, personal motivation, and gender in relation to high school students' stem career interest. Journal of Research on Adolescence **23**(4), 652–664 (2013)

[124] Cheryan, S., Plaut, V.C., Handron, C., Hudson, L.: The stereotypical computer scientist: Gendered media representations as a barrier to inclusion for women. Sex roles **69**(1-2), 58–71 (2013)

[125] Sele, L.: Talking nerdy: The invisibility of female computer nerds in popular culture and the subsequent fewer number of women and girls in the computer sciences. Journal of Integrated Studies **1**(3), 1–14 (2012)

[126] Sarsons, H.: Recognition for group work: Gender differences in academia. American Economic Review **107**(5), 141–45 (2017)

[127] Samek, A.S.: A University-Wide Field Experiment on Gender Differences in Job Entry Decisions. SSRN Electronic Journal (2015). doi:10.2139/ssrn.2579257

[128] Cotton, C., McIntyre, F., Price, J.: Gender differences in repeated competition: Evidence from school math contests. Journal of Economic Behavior & Organization **86**, 52–66 (2013)

[129] Tharenou, P., Latimer, S.: Academy of Management. Acad. Manag. J. **37**(4), 899–931 (1994)

[130] opensource.com Homepage= `https://opensource.com/` , note = Accessed: 2020-02-18

[131] Octoverse, Official GitHub Statistics Homepage=https://octoverse.github.com/#the-world-of-open-source , note = Accessed: 2020-02-18

[132] Ford, D., Smith, J., Guo, P.J., Parnin, C.: Paradise unplugged: Identifying barriers for female participation on stack overflow. In: Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering, pp. 846–857 (2016)

[133] Ortu, M., Destefanis, G., Counsell, S., Swift, S., Tonelli, R., Marchesi, M.: How diverse is your team? investigating gender and nationality diversity in github teams. Journal of Software Engineering Research and Development **5**(1), 1–18 (2017)

[134] Imtiaz, N., Middleton, J., Chakraborty, J., Robson, N., Bai, G., Murphy-Hill, E.: Investigating the effects of gender bias on github. In: 2019 IEEE/ACM 41st International Conference on Software Engineering (ICSE), pp. 700–711 (2019). IEEE

[135] Wang, Z., Wang, Y., Redmiles, D.: Competence-confidence gap: A threat to female developers' contribution on github. In: 2018 IEEE/ACM 40th International Conference on Software Engineering: Software Engineering in Society (ICSE-SEIS), pp. 81–90 (2018). IEEE

[136] stackoverflow Homepage= https://stackoverflow.com/ , note = Accessed: 2020-02-09

[137] Why are there so few women in tech? The truth behind the Google memo=https://www.theguardian.com/lifeandstyle/2017/aug/08/why-are-there-so-few-women-in-tech/-the-truth-behind-the-google-memo/ , note = Accessed: 2020-02-20

[138] The Dangers of Keeping Women Out of Tech= https://www.wired.com/story/dangers-keeping-women-out-of-tech/ , note = Accessed: 2020-02-20

[139] Women and Minorities in Tech, By the Numbers= https://www.wired.com/story/computer-science-graduates-diversity/ , note = Accessed: 2020-02-20

[140] Making Gains for Women in STEM Fields Will Take More Effort= https:/www.nytimes.com/2018/11/20/world/europe/women-in-stem.html , note = Accessed: 2020-02-20

[141] The Gender Gap in Computer Science Research Won't Close for 100 Years = https://www.nytimes.com/2019/06/21/technology/gender-gap-tech-computer-science.html , note = Accessed: 2020-02-20

[142] Women in Software Engineering stats, Crowd-sourced data= https://https://docs.google.com/spreadsheets/d/1BxbEifUr1z6HwY2_IcExQwUpKPRZY3FZ4x4ZFzZU-5E/edit#gid=0 , note = Accessed: 2020-02-20

[143] Stewart, S.: Video game industry silently taking over entertainment world= http://www.ejinsight.com/20191022-video-game-industry/-silently-taking-over-entertainment-world/ , note = Accessed: 2020-02-20

[144] Greenberg, B.S., Sherry, J., Lachlan, K., Lucas, K., Holmstrom, A.: Orientations to video games among gender and age groups. Simulation & Gaming **41**(2), 238–259 (2010)

[145] Dietz, T.L.: An examination of violence and gender role portrayals in video games: Implications for gender socialization and aggressive behavior. Sex roles **38**(5-6), 425–442 (1998)

[146] Williams, D., Martins, N., Consalvo, M., Ivory, J.D.: The virtual census: Representations of gender, race and age in video games. New Media & Society **11**(5), 815–834 (2009)

[147] Burgess, M.C., Stermer, S.P., Burgess, S.R.: Sex, lies, and video games: The portrayal of male and female characters on video game covers. Sex roles **57**(5-6), 419–433 (2007)

[148] Beasley, B., Collins Standley, T.: Shirts vs. skins: Clothing as an indicator of gender role stereotyping in video games. Mass Communication & Society **5**(3), 279–293 (2002)

[149] Fox, J., Tang, W.Y.: Sexism in online video games: The role of conformity to masculine norms and social dominance orientation. Computers in Human Behavior **33**, 314–320 (2014)

[150] Cunningham, C.: Unbeatable? debates and divides in gender and video game research. Communication Research Trends **37**(3), 4 (2018)

[151] Cassell, J., et al.: Genderizing hci. The Handbook of Human–Computer Interaction. Mahwah, NJ: Erlbaum, 402–411 (2002)

[152] Purple Moon, Wikipedia Page= https://en.wikipedia.org/wiki/Purple_Moon , note = Accessed: 2020-02-20

[153] Kafai, Y.B., et al.: Beyond Barbie & Mortal Kombat: New Perspectives on Gender and Gaming. Ed. YB Kafai, C. Heeter, J. Denner, and JY Sun. Cambridge, MA: MIT Press (2008)

[154] Women in get in the game= https://www.aauw.org/2015/03/24/women-get-in-the-game/ , note = Accessed: 2020-02-20

[155] Gender Equality Sells: Women in the Games Industry= https://games.usc.edu/news/gender-equality-sells-women-in-the-games-industry/ , note = Accessed: 2020-02-20

[156] Anita Sarkeesian, Carolyn Petit: Female Representation in Videogames Isn't Getting Any Better= https://www.wired.com/story/e3-2019-female-representation-videogames/ , note = Accessed: 2020-02-20

[157] emale-led films outperform at box office for 2014-2017= https://shift7.com/media-research , note = Accessed: 2020-02-20

[158] Bechdal Test, Wikipedia= https://en.wikipedia.org/wiki/Bechdel_test#cite_note-2 , note = Accessed: 2020-02-20

[159] Lewis, H.: Do videogames need their own version of the Bechdel test?= https://www.newstatesman.com/culture/2014/01/do-videogames-need-their-own-version-bechdel-test , note = Accessed: 2020-02-20

[160] Nixon, S.: Applying the Bechdel Test to Video Games= https://www.nymgamer.com/?p=3184 , note = Accessed: 2020-02-20

[161] Nutt, C.: Game devs negative on job outlook, positive on diversity, says IGDA survey= https://www.gamasutra.com/view/news/250317/Game_devs_negative_on_job_outlook_positive_on_diversity_says_IGDA_survey.php , note = Accessed: 2020-02-20

[162] NuForsdick, S.: Dark side of working in the video game industry: 100-hour weeks and on-the-spot sackingsy= https://www.ns-businesshub.com/business/working-conditions-in-the-video-game-industry/, note = Accessed: 2020-02-20

[163] Frank, J.: How to attack a woman who works in video gaming= https://www.theguardian.com/technology/2014/sep/01/how-to-attack-a-woman-who-works-in-video-games, note = Accessed: 2020-02-20

[164] Ley, T.J., Hamilton, B.H.: The gender gap in nih grant applications. Science **322**(5907), 1472–1474 (2008)

[165] Van der Lee, R., Ellemers, N.: Gender contributes to personal research funding success in the netherlands. Proceedings of the National Academy of Sciences **112**(40), 12349–12353 (2015)

[166] Bornmann, L., Mutz, R., Daniel, H.-D.: Gender differences in grant peer review: A meta-analysis. Journal of Informetrics **1**(3), 226–238 (2007)

[167] Wenneras, C., Wold, A.: Nepotism and sexism in peer-review. In: Women, Science, and Technology, pp. 64–70. Routledge, ??? (2010)

[168] Larivière, V., Ni, C., Gingras, Y., Cronin, B., Sugimoto, C.R.: Bibliometrics: Global gender disparities in science. Nature **504**(7479), 211–213 (2013). doi:10.1038/504211a

[169] Campbell, G., Mehtani, S., Dozier, M., Rinehart, J.: Gender-heterogeneous working groups produce higher quality science. PLoS ONE **8 (10)** (2013). doi:10.1371/journal.pone.0079147

[170] Moss-Racusin, C.A., Dovidio, J.F., Brescoll, V.L., Graham, M.J., Handelsman, J.: Science faculty's subtle gender biases favor male students. Proceedings of the national academy of sciences **109**(41), 16474–16479 (2012)

[171] Weisshaar, K.: Publish and perish? an assessment of gender gaps in promotion to tenure in academia. Social Forces **96**(2), 529–560 (2017)

[172] Cole, J.R., Zuckerman, H.: The productivity puzzle. Advances in Motivation and Achievement. Women in Science. JAI Press, Greenwich, CT (1984)

[173] Long, J.S.: Measures of sex differences in scientific productivity. Social Forces **71**(1), 159–178 (1992)

[174] Ledin, A., Bornmann, L., Gannon, F., Wallon, G.: A persistent problem. EMBO reports **8**(11), 982–987 (2007)

[175] Peñas, C.S., Willett, P.: Brief communication: Gender differences in publication and citation counts in librarianship and information science research. Journal of Information Science **32**(5), 480–485 (2006)

[176] Tower, G., Plummer, J., Ridgewell, B.: A multidisciplinary study of gender-based research productivity in the worlds best journals. Journal of Diversity Management (JDM) **2**(4), 23–32 (2007)

[177] Huang, J., Gates, A.J., Sinatra, R., Barabási, A.-L.: Historical comparison of gender inequality in scientific careers across countries and disciplines. Proceedings of the National Academy of Sciences (2020). doi:10.1073/pnas.1914221117. https://www.pnas.org/content/early/2020/02/14/1914221117.full.pdf

[178] Prozesky, H.: A career-history analysis of gender differences in publication productivity among south african academics. Science & Technology Studies (2008)

[179] Fuchs, S., Von Stebut, J., Allmendinger, J.: Gender, science, and scientific organizations in germany. Minerva **39**(2), 175–201 (2001)

[180] Hunter, L.A., Leahey, E.: Parenting and research productivity: New evidence and methods. Social Studies of Science **40**(3), 433–451 (2010)

[181] Stack, S.: Gender, children and research productivity. Research in higher education **45**(8), 891–920 (2004)

[182] Clauset, A., Larremore, D.B., Sinatra, R.: Data-driven predictions in the science of science. Science **355**(6324), 477–480 (2017)

[183] Deville, P., Wang, D., Sinatra, R., Song, C., Blondel, V.D., Barabási, A.-L.: Career on the move: Geography, stratification, and scientific impact. Scientific reports **4**, 4770 (2014)

[184] Sarigöl, E., Pfitzner, R., Scholtes, I., Garas, A., Schweitzer, F.: Predicting scientific success based on coauthorship networks. EPJ Data Science **3**(1), 9 (2014)

[185] Fortunato, S., Bergstrom, C.T., Börner, K., Evans, J.A., Helbing, D., Milojević, S., Petersen, A.M., Radicchi, F., Sinatra, R., Uzzi, B., *et al.*: Science of science. Science **359**(6379), 0185 (2018)

[186] Sinatra, R., Wang, D., Deville, P., Song, C., Barabási, A.-L.: Quantifying the evolution of individual scientific impact. Science **354**(6312), 5239 (2016)

[187] van Arensbergen, P., van der Weijden, I., Van den Besselaar, P.: Gender differences in scientific productivity: a persisting phenomenon? Scientometrics **93**(3), 857–868 (2012)

[188] Lerchenmueller, M.J., Sorenson, O., Jena, A.B.: Gender differences in how scientists present the importance of their research: observational study. bmj **367** (2019)

[189] Udry, J.R.: The nature of gender. Demography **31**(4), 561–573 (1994)

[190] Lorber, J.: Paradoxes of Gender. Yale University Press, ??? (1994)

[191] Srivastava, D.: Gendered behavior. In: Nadal, K. (ed.) The SAGE Encyclopedia of Psychology and Gender, pp. 790–7920. SAGE Publications, Thousand Oaks, CA, USA (2017)

[192] West, C., Zimmerman, D.H.: Doing gender. Gender & society **1**(2), 125–151 (1987)

[193] Sengupta, R.: Reading representations of black, east asian, and white women in magazines for adolescent girls. Sex roles **54**(11-12), 799–808 (2006)

[194] Hicks, M.: Programmed Inequality: How Britain Discarded Women Technologists and Lost Its Edge in Computing. MIT Press, ??? (2017)

[195] Dastin, J.: Amazon scraps secret AI recruiting tool that showed bias against women. Available at: `https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-too-that-showed-bias-against/-women-idUSKCN1MK08G`. Accessed: 2018-11-03 (2018)

[196] Joshi, A., Roh, H.: The role of context in work team diversity research: a meta-analytic review. Acad. Manag. J. **52**(3), 599–627 (2009)

[197] Ames, E.: What if the Women Who Work at Google... Didn't? = `https://anitab.org/blog/women-work-google-didnt/` , note = Accessed: 2020-02-01

[198] The Awakening, Women and Power in the Academy = `https://www.chronicle.com/interactives/the-awakening` , note = Accessed: 2020-02-01

[199] Kanter, R.M.: Some effects of proportions on group life. In: The Gender Gap in Psychotherapy, pp. 53–78. Plenum Press, New York, NY (1977)

[200] Merton, R.K.: The Matthew Effect in Science: The reward and communication systems of science are considered. **159**(3810), 56–63 (1968). doi:10.1126/science.159.3810.56. Accessed 2016-02-10

[201] Padgett, J.F., Ansell, C.K.: Robust Action and the Rise of the Medici, 1400-1434. Am. J. Sociol. **98**(6), 1259–1319 (1993)

[202] Uzzi, B., Spiro, J.: Collaboration and Creativity: The Small World Problem. Am. J. Sociol. **111**(2), 447–504 (2005). doi:10.1086/432782

[203] Ritter, T.: The Networking Company: Antecedents for Coping with Relationships and Networks Effectively. Ind. Mark. Manag. **28**(5), 467–479 (1999). doi:10.1016/S0019-8501(99)00075-9

[204] McMullan, W.E., Kenworthy, T.P.: Creativity and Entrepreneurial Performance: A General Scientific Theory, pp. 1–207. Springer, Springer, Cham, Heidelberg, New York, Dordrecht, London (2015). doi:10.1007/978-3-319-04726-3

[205] Zhang, X., Gloor, P.a., Grippa, F.: Measuring Creative Performance of Teams Through Dynamic Semantic Social Network Analysis. Int. J. Organ. Des. Eng. **3**(2), 165 (2013). doi:10.1504/IJODE.2013.057014

[206] Zheng, W.: A social capital perspective of innovation from individuals to nations: Where is empirical literature directing us? Int. J. Manag. Rev. **12**(2), 151–183 (2010). doi:10.1111/j.1468-2370.2008.00247.x

[207] Coleman, J.S.: Social Capital in the Creation of Human Capital. Am. J. Sociol. **94**(1988), 95–210 (1988). doi:10.1017/CBO9781107415324.004. arXiv:1011.1669v3

[208] Yang, H.-L., Tang, J.-H.: Team structure and team performance in is development: a social network perspective. Information & management **41**(3), 335–349 (2004)

[209] Harrison, D.A., Balkundi, P.: Ties, Leaders, and Time in Teams: Strong Inference about Network Structure's Effects on Team Viability and Performance. Acad. Manag. J. **49**(1), 49–68 (2006)

[210] Reagans, R., Zuckerman, E., McEvily, B.: How to make the team: Social Networks vs. Demography as Criteria for Designing Effective Teams. Adm. Sci. Q. **49**(1), 101–133 (2004). doi:10.2307/4131457

[211] Lucius, R.H., Kuhnert, K.W.: Using sociometry to predict team performance in the work place. The journal of Psychology **131**(1), 21–32 (1997)

[212] Sparrowe, R.T., Liden, R.C., Wayne, S.J., Kraimer, M.L.: Social networks and the performance of individuals and groups. Academy of management journal **44**(2), 316–325 (2001)

[213] Shaw, M.E., Rothschild, G.H., Strickland, J.F.: Decision processes in communication nets. The Journal of Abnormal and Social Psychology **54**(3), 323 (1957)

[214] Luo, J.-D.: Social network structure and performance of improvement teams. International Journal of Business Performance Management **7**(2), 208–223 (2005)

[215] Leenders, R.T.A., Van Engelen, J.M., Kratzer, J.: Virtuality, communication, and new product team creativity: a social network perspective. Journal of Engineering and technology management **20**(1-2), 69–92 (2003)

[216] Oh, H., Chung, M.-H., Labianca, G.: Group social capital and group effectiveness: The role of informal socializing ties. Academy of management journal **47**(6), 860–875 (2004)

[217] Burt, R.S.: Decay functions. Social Networks **22**(1), 1–28 (2000). doi:10.1016/S0378-8733(99)00015-5

[218] Burt, R.S.: Theory and Research-Structural Holes versus Network Structure as Social Capital (May 2000), 31–56 (2001). doi:Burt$_2$001

[219] Balkundi, P., Kilduff, M., Barsness, Z.O.E.I., Michael, J.H.: Demographic antecedents and performance consequences of structural holes in work teams. J. Organ. Behav. **260**(28), 241–260 (2007). doi:10.1002/job

[220] Berman, S.L., Down, J., Hill, C.: Tacit knowledge as a source of competitive advantage.pdf (2002). doi:10.2307/3069282. `http://classes.bus.oregonstate.edu/spring-05/ba569/Materials/CompetitiveAdvantageintheNBA.pdf`

[221] Fleming, L., Matt Marx: Managing Creativity in Small Worlds. Calif. Manage. Rev. **48**(4), 6–28 (2006). doi:10.1109/EMR.2009.5384055

[222] Vedres, B., Bruszt, L.: Fostering developmental agency from without. Stato e Mercato (2) (2010)

[223] Wong, S.-S.: Task knowledge overlap and knowledge variety: The role of advice network structures and impact on group effectiveness. Journal

of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior **29**(5), 591–614 (2008)

[224] Tröster, C., Mehra, A., van Knippenberg, D.: Structuring for team success: The interactive effects of network structure and cultural diversity on team potency and performance. Organizational Behavior and Human Decision Processes **124**(2), 245–255 (2014)

[225] Myaskovsky, L., Unikel, E., Dew, M.A.: Effects of gender diversity on performance and interpersonal behavior in small work groups. Sex Roles **52**(9-10), 645–657 (2005)

[226] Horwitz, S.K., Horwitz, I.B.: The Effects of Team Diversity on Team Outcomes: A Meta-Analytic Review of Team Demography. J. Manage. **33**(6), 987–1015 (2007). doi:10.1177/0149206307308587

[227] Hoogendoorn, S., Oosterbeek, H., Van Praag, M.: The impact of gender diversity on the performance of business teams: Evidence from a field experiment. Management Science **59**(7), 1514–1528 (2013)

[228] Fenwick, G.D., Neal, D.J.: Effect of gender composition on group performance. Gender, Work & Organization **8**(2), 205–225 (2001)

[229] Kang, H.-R., Yang, H.-D., Rowley, C.: Factors in team effectiveness: Cognitive and demographic similarities of software development team members. Human Relations **59**(12), 1681–1710 (2006)

[230] Shore, L.M., Chung-herrera, B.G., Dean, M.A., Ehrhart, K.H., Jung, D.I., Randel, A.E., Singh, G.: Diversity in organizations: Where are we now and where are we going? Hum. Resour. Manag. Rev. **19**(2), 117–133 (2009). doi:10.1016/j.hrmr.2008.10.004

[231] Granovetter, M.: The Strength of Weak Ties. American Journal of Sociology **78**(6), 1360–1380 (1973)

[232] Ibarra, H., Andrews, S.B.: Power, social influence, and sense making: Effects of network centrality and proximity on employee perceptions. Administrative science quarterly, 277–303 (1993)

[233] McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a feather: Homophily in social networks. Annual review of sociology **27**(1), 415–444 (2001)

[234] Ibarra, H.: Paving an alternative route: Gender differences in managerial networks. Social psychology quarterly, 91–102 (1997)

[235] McPherson, J.M., Smith-Lovin, L.: Women and weak ties: Differences by sex in the size of voluntary organizations. American Journal of Sociology **87**(4), 883–904 (1982)

[236] Kleinbaum, A.M., Stuart, T.E., Tushman, M.L.: Discretion within the constraints of opportunity: gender homophily and structure in a formal org. In: Academy of Management Proceedings, vol. 2011, pp. 1–6 (2011). Academy of Management Briarcliff Manor, NY 10510

[237] Van den Brink, M., Benschop, Y.: Gender in academic networking: The role of gatekeepers in professorial recruitment. Journal of Management Studies **51**(3), 460–492 (2014)

[238] McPherson, J.M., Smith-Lovin, L.: Homophily in voluntary organizations: Status distance and the composition of face-to-face groups. American sociological review, 370–379 (1987)

[239] Brass, D.J.: Men's and women's networks: A study of interaction patterns and influence in an organization. Academy of Management journal **28**(2), 327–343 (1985)

[240] McPherson, J.M., Smith-Lovin, L.: Sex segregation in voluntary associations. American Sociological Review, 61–79 (1986)

[241] McGuire, G.M., Bielby, W.T.: The variable effects of tie strength and social resources: how type of support matters. Work and Occupations **43**(1), 38–74 (2016)

[242] Greenberg, J., Mollick, E.: Leaning in or leaning on? gender, homophily, and activism in crowdfunding. In: Academy of Management Proceedings (2015)

[243] Burt, R.S., Jannotta, J.E., Mahoney, J.T.: Personality correlates of structural holes. Social Networks **20**, 63–87 (1998). doi:10.1016/S0378-8733(97)00005-1

[244] Askin, N., Mauskapf, M., Koppman, S., Uzzi, B.: Are women more creative than men? the gendered effects of networks and genres on musical creativity. Technical report, Working Paper (2019)

[245] Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., *et al.*: Computational social science. Science **323**(5915), 721–723 (2009)

[246] Szell, M., Thurner, S.: How women organize social networks different from men. Scientific reports **3**, 1214 (2013)

[247] Hannon, C.: Gender and status in voice user interfaces. interactions **23**(3), 34–37 (2016)

[248] Obinali, C.: The perception of gender in voice assistants. Perception **3**, 22–2019 (2019)

[249] Woods, H.S.: Asking more of siri and alexa: feminine persona in service of surveillance capitalism. Critical Studies in Media Communication **35**(4), 334–349 (2018)

[250] Hannák, A., Wagner, C., Garcia, D., Mislove, A., Strohmaier, M., Wilson, C.: Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr. In: Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, pp. 1914–1933 (2017)

[251] Chen, L., Ma, R., Hannák, A., Wilson, C.: Investigating the impact of gender on rank in resume search engines. In: Proceedings of the 2018 Chi Conference on Human Factors in Computing Systems, pp. 1–14 (2018)

[252] The top 500 sites on the web = `https://www.alexa.com/topsites`. Accessed: 2020-02-09

[253] Wikipedia on Wikipedia= `https://en.wikipedia.org/wiki/Wikipedia`, note = Accessed: 2020-02-09

[254] Reagle, J., Rhue, L.: Gender bias in wikipedia and britannica. International Journal of Communication **5**, 21 (2011)

[255] Iosub, D., Laniado, D., Castillo, C., Morell, M.F., Kaltenbrunner, A.: Emotions under discussion: Gender, status and communication in online collaboration. PloS one **9**(8) (2014)

[256] Robles, G., Reina, L.A., Gonzalez-Barahona, J.M., Dominguez, S.D.: Women in Free/Libre/Open Source Software: The Situation in the 2010s, pp. 163–173. Springer (2016). doi:10.1007/978-3-319-39225-7-13. `http://link.springer.com/10.1007/978-3-319-39225-7{_}13`

[257] Blau, F.D., Kahn, L.M.: The Gender Wage Gap: Extent, Trends, and Explanations. Journal of Economic Literature **55**(3), 789–865 (2017). doi:10.1257/jel.20160995. arXiv:1011.1669v3

[258] Katherine Michelmore, Sharon Sassler: Explaining the Gender Wage Gap in STEM: Does Field Sex Composition Matter? RSF: The Russell Sage Foundation Journal of the Social Sciences **2**(4), 194 (2016). doi:10.7758/rsf.2016.2.4.07

[259] Ashcraft, C., Mclain, B., Eger, E.: Women in Tech : The Facts 2016 Update. Available at: `https://www.ncwit.org/sites/default/files/resources/womenintech{_}facts{_}fullreport{_}05132016.pdf`. Accessed: 2018-09-04 (2016)

[260] Powell, K.: These labs are remarkably diverse — here's why they're winning at science. Nature **558**(7708), 19–22 (2018). doi:10.1038/d41586-018-05316-5

[261] Nielsen, M.W., Alegria, S., Börjeson, L., Etzkowitz, H., Falk-Krzesinski, H.J., Joshi, A., Leahey, E., Smith-Doerr, L., Woolley, A.W., Schiebinger, L.: Opinion: Gender diversity leads to better science. Proceedings of the National Academy of Sciences **114**(8), 1740–1742 (2017). doi:10.1073/pnas.1700616114

[262] Hacker, H.M.: Women as a Minority Group. Social Forces **30**(1), 60–69 (1951). doi:10.2307/2571742

[263] Udry, J.R.: The Nature of Gender. Demography **31**(4), 561 (1994). doi:10.2307/2061790

[264] West, C., Fenstermaker, S.: Doing difference. Gender & Society **9**(1), 8–37 (1995). doi:10.1177/089124395009001002. 0803973233

[265] Lemons, M.A., Parzinger, M.: Gender Schemas: A Cognitive Explanation of Discrimination of Women in Technology. Journal of Business and Psychology **22**(1), 91–98 (2007). doi:10.1007/s10869-007-9050-0

[266] Rosenbloom, J.L., Ash, R.A., Dupont, B., Coder, L.: Why are there so few women in information technology? Assessing the role of personality in career choices. Journal of Economic Psychology **29**(4), 543–554 (2008). doi:10.1016/J.JOEP.2007.09.005

[267] Wajcman, J.: Managing Like a Man : Women and Men in Corporate Management, p. 180. Pennsylvania State University Press, ??? (1998)

[268] Cross, S., Bagilhole, B.: Girls' Jobs for the Boys? Men, Masculinity and Non-Traditional Occupations. Gender, Work and Organization **9**(2), 204–226 (2002). doi:10.1111/1468-0432.00156

[269] McEwen, M.: Is Frontend Web Development Sexist? Available at: https://medium.com/@melissamcewen/is-frontend-development-sexist-220040c952b1. Accessed: 2018-09-04 (2017)

[270] Google pay discrimination case: judge dismisses women's class action — Technology — The Guardian. Available at: https://www.theguardian.com/technology/2017/dec/06/google-women-pay-discrimination-lawsuit. Accessed: 2018-09-04 (2017)

[271] Abbate, J.: Recoding Gender : Women's Changing Participation in Computing, p. 247. MIT Press, Boston, Ma (2012)

[272] Terrell, J., Kofink, A., Middleton, J., Rainear, C., Murphy-Hill, E., Parnin, C., Stallings, J.: Gender differences and bias in open source: pull request acceptance of women versus men. PeerJ Computer Science **3**, 111 (2017). doi:10.7717/peerj-cs.111

[273] Udry, J.R.: Biological Limits of Gender Construction. American Sociological Review **65**(3), 443 (2000). doi:10.2307/2657466

[274] Terman, L.M., Miles, C.C.: Sex and Personality, First edit edn. McGraw-Hill Book Company, New York, New York, USA (1936)

[275] Wachs, J., Hannak, A., Voros, A., Daróczy, B.Z.: Why do men get more attention? Exploring factors behind success in an online design community. In: 11th International Conference on Web and Social Media, ICWSM 2017, pp. 299–308. AAAI Press, Montreal (2017). http://eprints.sztaki.hu/9326/

[276] Rosenfeld, A., Sina, S., Sarne, D., Avidov, O., Kraus, S.: A Study of WhatsApp Usage Patterns and Prediction Models without Message Content. Computing Research Repository **02** (2018)

[277] Miguel-Hurtado, O., Stevenage, S.V., Bevan, C., Guest, R.: Predicting sex as a soft-biometrics from device interaction swipe gestures. Pattern Recognition Letters **79**, 44–51 (2016). doi:10.1016/j.patrec.2016.04.024

[278] Turkle, S.: Life on the Screen : Identity in the Age of the Internet. Simon & Schuster, New York, New York, USA (1995)

[279] Wajcman, J.: TechnoFeminism. Polity, Cambridge, UK

[280] Reagans, R.: Network Structure and Knowledge Transfer : The Effects of Cohesion and Range Bill McEvily. Administrative Science Quarterly **48**(2), 240–267 (2002)

[281] Coffman, K.B.: Evidence on self-stereotyping and the contribution of ideas. Quarterly Journal of Economics **129**(4), 1625–1660 (2014). doi:10.1093/qje/qju023

[282] Karimi, F., Wagner, C., Lemmerich, F., Jadidi, M., Strohmaier, M.: Inferring Gender from Names on the Web: A Comparative Evaluation of Gender Detection Methods. Proceedings of the 25th International Conference Companion on World Wide Web - WWW '16 Companion, 53–54 (2016). doi:10.1145/2872518.2889385. 1603.04322

[283] Tiwsakul, R.A., Hackley, C.: Postmodern paradoxes in Thai-Asian consumer identity. Journal of Business Research (2012). doi:10.1016/j.jbusres.2011.02.027

[284] Smith, L.E.: English is an Asian Language. Asian Englishes **1**(1), 172–174 (1998). doi:10.1080/13488678.1998.10801003org/10.1080/13488678.1998.10801003

[285] Chen, L.N.H.: Choices and Patterns of English Names among Taiwanese Students. Names (2015). doi:10.1179/0027773815Z.000000000122

[286] Computing Krippendorff's Alpha-Reliability. Available at: `https://repository.upenn.edu/asc_papers/43`. Accessed: 2019-03-29 (2011)

[287] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research **12**, 2825–2830 (2011)

[288] Farmer, T.A., Christiansen, M.H., Monaghan, P.: Phonological typicality influences on-line sentence comprehension. Proceedings of the National Academy of Sciences of the United States of America **103**(32), 12203–8 (2006). doi:10.1073/pnas.0602173103

[289] Askin, N., Mauskapf, M.: What Makes Popular Culture Popular? Product Features and Optimal Differentiation in Music. American Sociological Review **82**(5), 910–944 (2017). doi:10.1177/0003122417728662

[290] Kleinbaum, A.M.: Organizational misfits and the origins of brokerage in intrafirm networks. Administrative Science Quarterly **57**(3), 407–452 (2012). doi:10.1177/0001839212461141

[291] Zuckerman, E.W.: The Categorical Imperative: Securities Analysts and the Illegitimacy Discount. American Journal of Sociology **104**(5), 1398–1438 (1999). doi:10.1086/210178

[292] Kovács, B., Johnson, R.: Contrasting alternative explanations for the consequences of category spanning: A study of restaurant reviews and menus in San Francisco. Strategic Organization **12**(1), 7–37 (2014). doi:10.1177/1476127013502465

[293] Scott, I.M., Clark, A.P., Josephson, S.C., Boyette, A.H., Cuthill, I.C., Fried, R.L., Gibson, M.A., Hewlett, B.S., Jamieson, M., Jankowiak, W., Honey, P.L., Huang, Z., Liebert, M.A., Purzycki, B.G., Shaver, J.H., Snodgrass, J.J., Sosis, R., Sugiyama, L.S., Swami, V., Yu, D.W., Zhao, Y., Penton-Voak, I.S.: Human preferences for sexually dimorphic faces may be evolutionarily novel. Proceedings of the National Academy of Sciences **111**(40), 14388–14393 (2014). doi:10.1073/pnas.1409643111. arXiv:1408.1149

[294] Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani: An Introduction to Statistical Learning: with Applications in R, 1st edn., p. 184. Springer, New York, New York, USA (2013)

[295] Max Kuhn, Kjell Johnson: Applied Predictive Modeling, 1st edn., p. 70. Springer, New York, New York, USA (2013)

[296] Constantinople, A.: 'masculinity-femininity: An exception to a famous dictum?' **80**, 389–407 (1973)

[297] Hoffman, R.M.: The Measurement of Masculinity and Femininity: Historical Perspective and Implications for Counseling. Journal of Counseling & Development **79**(4), 88–101 (2001). doi:10.1002/j.1556-6676.2001.tb01995.x

[298] Jensen, K., Kovács, B., Sorenson, O.: Gender differences in obtaining and maintaining patent rights. Nature Biotechnology **36**(4), 307–309 (2018). doi:10.1038/nbt.4120

[299] Posner, M.: We can teach women to code, but that just creates another problem. Available at: `https://www.theguardian.com/technology/2017/mar/14/tech-women-code-workshops-developer-jobs`. Accessed: 2018-1-04

[300] National Center for Education Statistics, IPEDS Data Center, "Full-Time Instructional Staff, by Faculty and Tenure Status, Academic Rank, Race/Ethnicity, and Gender (Degree-Granting Institutions): Fall 2018," Fall Staff 2018 Survey (2018). Available at: https://nces.ed.gov/ipeds/Search/ViewTable?tableId=26398&returnUrl=%2Fipeds%2FSearch%2FView%3FresultType%3Dtable%26sortBy%3Drelevance%26query%3DFull-Time%2BInstructional%2BStaff%26query2%3DFull-Time%2BInstructional%2BStaff%26dataYears%3D2018-19%26dataYears%3D2017-18. Accessed: 2020-02-10 (2018)

[301] Ahuja, M.K.: Women in the information technology profession: a literature review, synthesis and research agenda. European Journal of Information Systems **11**(1), 20–34 (2002). doi:10.1057/palgrave.ejis.3000417

[302] West, J.D., Jacquet, J., King, M.M., Correll, S.J., Bergstrom, C.T.: The role of gender in scholarly authorship. PloS one **8**(7) (2013)

[303] Larivière, V., Ni, C., Gingras, Y., Cronin, B., Sugimoto, C.R.: Bibliometrics: Global gender disparities in science. Nature News **504**(7479), 211 (2013)

[304] Holman, L., Stuart-Fox, D., Hauser, C.E.: The gender gap in science: How long until women are equally represented? PLoS biology **16**(4), 2004956 (2018)

[305] Bear, J.B., Woolley, A.W.: The role of gender in team collaboration and performance. Interdisciplinary Science Reviews **36**(2), 146–153 (2011). doi:10.1179/030801811X13013181961473

[306] Rowlands, I., Nicholas, D., Russell, B., Canty, N., Watkinson, A.: Social media use in the research workflow. Learned Publishing **24**(3), 183–195 (2011)

[307] Tenopir, C., Volentine, R., W. King, D.: Social media and scholarly reading. Online Information Review **37** (2013). doi:10.1108/OIR-04-2012-0062

[308] Van Eperen, L., Marincola, F.: How scientists use social media to communicate their research. Journal of translational medicine **9**, 199 (2011). doi:10.1186/1479-5876-9-199

[309] Van Noorden, R.: Online collaboration: Scientists and the social network. Nature News **512**(7513), 126–130 (2014). doi:10.1038/512126a

[310] Eysenbach, G.: Can tweets predict citations? metrics of social impact based on twitter and correlation with traditional metrics of scientific impact. Journal of medical Internet research **13**(4), 123 (2011)

[311] Holmberg, K., Thelwall, M.: Disciplinary differences in twitter scholarly communication. Scientometrics **101**(2), 1027–1042 (2014)

[312] Priem, J., Groth, P., Taraborelli, D.: The altmetrics collection. PloS one **7**(11) (2012)

[313] Bowman, T.D.: Investigating the use of affordances and framing techniques by scholars to manage personal and professional impressions on twitter. Indiana University (2015)

[314] Hadgu, A.T., Jäschke, R.: Identifying and analyzing researchers on twitter. In: Proceedings of the 2014 ACM Conference on Web Science, pp. 23–32 (2014)

[315] Sugimoto, C.R., Work, S., Larivière, V., Haustein, S.: Scholarly use of social media and altmetrics: A review of the literature. Advances in Information Science **68**(9) (2017). doi:10.1098/rsta.2010.0155

[316] Fox, C.W., Paine, C.T.: Gender differences in peer review outcomes and manuscript impact at six journals of ecology and evolution. Ecology and Evolution **9**(6), 3599–3619 (2019)

[317] Bornmann, L., Daniel, H.-D.: Does the h-index for ranking of scientists really work? Scientometrics **65**(3), 391–392 (2005)

[318] Barnes, C.: The h-index debate: an introduction for librarians. The Journal of Academic Librarianship **43**(6), 487–494 (2017)

[319] Altmetrics Manifesto (2019). http://altmetrics.org/manifesto/

[320] Brossard, D.: New media landscapes and the science information consumer. Proceedings of the National Academy of Sciences **110**, 14096–14101 (2013). doi:10.1073/pnas.1212744110

[321] Scheufele, D.A.: Communicating science in social settings. Proceedings of the National Academy of Sciences **110**, 14040–14047 (2013). doi:10.1073/pnas.1213275110

[322] Büchi, M.: Microblogging as an extension of science reporting. Public Understanding of Science **26**(8), 953–968 (2017). doi:10.1177/0963662516657794. https://doi.org/10.1177/0963662516657794

[323] Hargittai, E., Füchslin, T., Schäfer, M.S.: How do young adults engage with science and research on social media? Some preliminary findings and an agenda for future research. Social Media + Society **4**(3) (2018). doi:10.1177/2056305118797720. https://doi.org/10.1177/2056305118797720

[324] Milkman, K.L., Berger, J.: The science of sharing and the sharing of science. Proceedings of the National Academy of Sciences **111**(Supplement 4), 13642–13649 (2014)

[325] Moss-Racusin, C.A., Rudman, L.A.: Disruptions in women's self-promotion: The backlash avoidance model. Psychology of women quarterly **34**(2), 186–202 (2010)

[326] Oladejo, M.A., Adelua, O.O., Ige, N.A.: Age, gender, and computer self-efficacy as correlates of social media usage for scholarly works in nigeria. In: Proceedings of the International Conference on e-Learning, Cape Town, South Africa, pp. 316–320 (2013)

[327] Procter, R., Williams, R., Stewart, J., Poschen, M., Snee, H., Voss, A., Asgari-Targhi, M.: Adoption and use of web 2.0 in scholarly communications. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences **368**(1926), 4039–4056 (2010)

[328] Coffman, K.B.: Evidence on self-stereotyping and the contribution of ideas. The Quarterly Journal of Economics **129**(4), 1625–1660 (2014)

[329] Haustein, S., Peters, I., Sugimoto, C.R., Thelwall, M., Larivière, V.: Tweeting biomedicine: An analysis of tweets and citations in the biomedical literature. Journal of the Association for Information Science and Technology **65**(4), 656–669 (2014)

[330] Costas, R., Zahedi, Z., Wouters, P.: Do "altmetrics" correlate with citations? extensive comparison of altmetric indicators with citations from a multidisciplinary perspective. Journal of the Association for Information Science and Technology **66**(10), 2003–2019 (2015)

[331] Zagovora, O., Weller, K., Janosov, M., Wagner, C., Peters, I.: What increases (social) media attention: Research impact, author prominence or title attractiveness? In: 23rd International Conference on Science and Technology Indicators (STI 2018), September 12-14, 2018, Leiden, The Netherlands (2018). Centre for Science and Technology Studies (CWTS)

[332] Abbasi, A., Chung, K.S.K., Hossain, L.: Egocentric analysis of co-authorship network structure, position and performance. Information Processing & Management **48**(4), 671–679 (2012)

[333] Abramo, G., D'Angelo, C.A., Murgia, G.: Gender differences in research collaboration. Journal of Informetrics **7**(4), 811–822 (2013)

[334] Clauset, A., Arbesman, S., Larremore, D.B.: Systematic inequality and hierarchy in faculty hiring networks. Science Advances **1**(1) (2015)

[335] Karimi, F., Génois, M., Wagner, C., Singer, P., Strohmaier, M.: Homophily influences ranking of minorities in social networks. Scientific reports **8**(1), 1–12 (2018)

[336] Lee, E., Karimi, F., Wagner, C., Jo, H.-H., Strohmaier, M., Galesic, M.: Homophily and minority-group size explain perception biases in social networks. Nature human behaviour **3**(10), 1078–1087 (2019)

[337] Tang, J., Zhang, J., Yao, L., Li, J., Zhang, L., Su, Z.: Arnetminer: extraction and mining of academic social networks. In: Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 990–998 (2008)

[338] Guimera, R., Uzzi, B., Spiro, J., Amaral, L.A.N.: Team assembly mechanisms determine collaboration network structure and team performance. Science **308**(5722), 697–702 (2005)

[339] Karimi, F., Wagner, C., Lemmerich, F., Jadidi, M., Strohmaier, M.: Inferring gender from names on the web: A comparative evaluation of gender detection methods. In: Proceedings of the 25th International Conference Companion on World Wide Web, pp. 53–54 (2016)

[340] Fisher, R.A.: On the interpretation of χ 2 from contingency tables, and the calculation of p. Journal of the Royal Statistical Society **85**(1), 87–94 (1922)

[341] Signorella, M.L., Vegega, M.E.: A note on gender stereotyping of research topics. Personality and Social Psychology Bulletin **10**(1), 107–109 (1984)

[342] Kortelainen, T., Katvala, M.: "everything is plentiful—except attention". attention data of scientific journals on social web tools. Journal of Informetrics **6**(4), 661–668 (2012)

[343] Boulos, M.N.K., Anderson, P.F.: Preliminary survey of leading general medicine journals' use of facebook and twitter. Journal of the Canadian

Health Libraries Association/Journal de l'Association des bibliothèques de la santé du Canada **33**(2), 38–47 (2012)

[344] Webster, G.D., Jonason, P.K., Schember, T.O.: Hot topics and popular papers in evolutionary psychology: Analyses of title words and citation counts in evolution and human behavior, 1979–2008. Evolutionary Psychology **7**(3), 147470490900700301 (2009)

[345] Jacques, T.S., Sebire, N.J.: The impact of article titles on citation hits: an analysis of general and specialist medical journals. JRSM short reports **1**(1), 1–5 (2010)

[346] Breiman, L.: Random forests. Machine Learning **45**(1), 5–32 (2001). doi:10.1023/A:1010933404324. /dx.doi.org/10.1023%2FA%3A1010933404324

[347] Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T., Zeileis, A.: Conditional variable importance for random forests. BMC Bioinformatics **9**(307) (2008)

[348] Parr, T., Turgutlu, K., Csiszar, C., Howard, J.: Beware default random forest importances. March **26**, 2018 (2018)

[349] Lutter, M.: Do women suffer from network closure? the moderating effect of social capital on gender inequality in a project-based labor market, 1929 to 2010. American Sociological Review **80**(2), 329–358 (2015)

[350] Sugimoto, C.R., Work, S., Larivière, V., Haustein, S.: Scholarly use of social media and altmetrics: A review of the literature. Journal of the Association for Information Science and Technology **68**(9), 2037–2062 (2017)

[351] Fausto, S., Machado, F.A., Bento, L.F.J., Iamarino, A., Nahas, T.R., Munger, D.S.: Research blogging: indexing and registering the change in science 2.0. PloS one **7**(12) (2012)

[352] Kadriu, A.: Discovering value in academic social networks: A case study in researchgate. In: Proceedings of the ITI 2013 35th International Conference on Information Technology Interfaces, pp. 57–62 (2013). IEEE

[353] Marc Jr, B., Egan, M.L., Lanier, L.: The business case for diversity and the perverse practice of matching employees to customers. Personnel Review **39**(4), 468–486 (2010)

[354] Sabharwal, M.: Is diversity management sufficient? organizational inclusion to further performance. Public Personnel Management **43**(2), 197–217 (2014)

[355] Llopis, G.: 3 Reasons Diversity Does Not Solve For Inclusion = `https://www.forbes.com/sites/glennllopis/2018/02/12/3-reasons-diversity-does-not-solve-for-inclusion/#59357c040adb` , year=2018, note = Accessed: 2020-03-18

[356] Díaz-García, C., González-Moreno, A., Jose Saez-Martinez, F.: Gender diversity within r&d teams: Its impact on radicalness of innovation. Innovation **15**(2), 149–160 (2013)

[357] Østergaard, C.R., Timmermans, B., Kristinsson, K.: Does a different view create something new? the effect of employee diversity on innovation. Research policy **40**(3), 500–509 (2011)

[358] Chua, R.Y.: Innovating at cultural crossroads: How multicultural social networks promote idea flow and creativity. Journal of Management **44**(3), 1119–1146 (2018)

[359] Barak, M.E.M.: Beyond affirmative action: Toward a model of diversity and organizational inclusion. Administration in Social Work **23**(3-4), 47–68 (1999)

[360] Chrobot-Mason, D.L.: Keeping the promise. Journal of Managerial Psychology (2003)

[361] Mor Barak, M.E.: Inclusion is the key to diversity management, but what is inclusion? Human Service Organizations: Management, Leadership & Governance **39**(2), 83–88 (2015)

[362] Roberson, Q.M.: Disentangling the meanings of diversity and inclusion in organizations. Group & Organization Management **31**(2), 212–236 (2006)

[363] Mor Barak, M.E., Cherin, D.A., Berkman, S.: Organizational and personal dimensions in diversity climate: Ethnic and gender differences in employee perceptions. The Journal of Applied Behavioral Science **34**(1), 82–104 (1998)

[364] Pless, N., Maak, T.: Building an inclusive diversity culture: Principles, processes and practice. Journal of business ethics **54**(2), 129–147 (2004)

[365] Tajfel, H., Turner, J.C., Austin, W.G., Worchel, S.: An integrative theory of intergroup conflict. Organizational identity: A reader **56**, 65 (1979)

[366] Alderfer, C.P., Smith, K.K.: Studying intergroup relations embedded in organizations. Administrative Science Quarterly, 35–65 (1982)

[367] Lyra, O., Karapanos, E., Kostakos, V.: Intelligent playgrounds: measuring and affecting social inclusion in schools. In: IFIP Conference on Human-Computer Interaction, pp. 560–563 (2011). Springer

[368] Hennessey, B.A., Amabile, T.M.: Reality, intrinsic motivation, and creativity. (1998)

[369] Isaksen, S.G., Lauer, K.J.: The climate for creativity and change in teams. Creativity and innovation management **11**(1), 74–86 (2002)

[370] Hoever, I.J., Van Knippenberg, D., Van Ginkel, W.P., Barkema, H.G.: Fostering team creativity: perspective taking as key to unlocking diversity's potential. Journal of applied psychology **97**(5), 982 (2012)

[371] Stovel, K., Shaw, L.: Brokerage. Annual review of sociology **38**, 139–158 (2012)

[372] Moby Games Wikipedia = `https://en.wikipedia.org/wiki/MobyGames` , year= 2018, note = Accessed: 2020-03-18

[373] Freeman, L.C.: Segregation in social networks. Sociological Methods & Research **6**(4), 411–429 (1978)

[374] Global Women in Data Science (WiDS) Initiative homepage = `https://www.widsconference.org/` , year=2018, note = Accessed: 2020-04-03

[375] Perez, C.C.: Invisible Women: Exposing Data Bias in a World Designed for Men, pp. 10–30. Random House, UK (2019)

[376] Barabási, A.-L.: The Formula: The Universal Laws of Success, pp. 98–123. Hachette UK, New York, NY (2018). Chap. Superstars and Power Laws

[377] Federal Court of the United States ruled that discrimination studies do not violate federal anti-hacking law = `https://www.aclu.org/press-releases/federal-court-rules-big-data-discrimination-studies-do/-not-violate-federal-anti` , note = Accessed: 2020-04-03

[378] Lewis, H.: The Coronavirus Is a Disaster for Feminism = `https://amp-theatlantic-com.cdn.ampproject.org/c/s/amp.theatlantic.com/amp/article/608302/` , year=2020, note = Accessed: 2020-04-05

[379] Alon, T., Doepke, M., Olmstead-Rumsey, J., Tertilt, M., et al.: The impact of covid-19 on gender equality. Technical report, Northwestern University, USA, IL, Evanston (2020). Accessed: 2018-09-04

CHAPTER 8

APPENDICES

8.1 Gendered Behaviour as a disadvantage in Open Source Software Development

8.2 Gender diversity in collaboration networks and the online popularity of scientists

8.3 The role of gender diversity and inclusion in success and creativity in the video game industry

	Dependent Variable: Success (number of stars)															
	(1) Controls				(2) Controls + Languages				(3) Controls + DT classes				(4) 5% gender swaps		(5) 10% gender swaps	
	Zero-inflation model		Count model		Zero-inflation model		Count model		Zero-inflation model		Count model		Count model		Count model	
	Coef.	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**95% CI**	**Coef.**	**95% CI**
Female	0.666		0.618	*	0.766	*	0.704	*	0.517		0.424		0.645	-0.646, 1.774	0.526	-1.379, 2.051
	(0.357)		(0.314)		(0.350)		(0.309)		(0.375)		(0.308)					
Femaleness	1.492	***	−4.123	***	1.326	**	−3.108	***	0.996	*	−4.152	***	−3.416	-4.432, -1.724	−3.741	-5.027, -1.663
	(0.404)		(0.273)		(0.406)		(0.297)		(0.496)		(0.381)					
Female:Femaleness	1.031	*	1.503	***	0.599		0.823	*	1.274	*	1.258	**	0.976	-2.771, 2.705	1.149	-2.433, 3.472
	(0.484)		(0.403)		(0.480)		(0.418)		(0.513)		(0.409)					
Name frequency	−0.048		0.034		−0.186		−0.293		0.172		0.290		0.111	-0.481, 0.568	0.134	-0.665, 1.054
	(0.279)		(0.191)		(0.273)		(0.192)		(0.288)		(0.203)					
Female:Name frequency	−0.966	*	−1.841	***	−0.918	*	−0.061	***	−1.013	*	−1.579	***	−1.651	-2.722, 0.053	−1.573	-3.241, 0.826
	(0.394)		(0.341)		(0.390)		(0.014)		(0.410)		(0.340)					
Followers (log)	−0.678	***	0.669		−0.651	***	0.718	***	−0.610	***	0.735	***	0.624	0.596, 0.663	0.630	0.598, 0.670
	(0.032)		(0.016)		(0.032)		(0.018)		(0.032)		(0.017)					
Tenure	−0.903	***	−0.502	***	−0.850	***	−0.418	***	−0.911	***	−0.397	***	−0.318	-0.372, -0.266	−0.311	-0.407, -0.184
	(0.050)		(0.055)		(0.051)		(0.053)		(0.054)		(0.056)					
No of own repositories (log)	−0.119		0.327	***	−0.290	**	0.097		−0.407	***	0.173	*	0.347	0.241, 0.412	0.333	0.218, 0.429
	(0.098)		(0.076)		(0.093)		(0.078)		(0.097)		(0.076)					
No of touched repositories (log)	−0.590	***	−0.287	**	−0.628	***	−0.044		−0.227		−0.421	***	−0.227	-0.330, -0.113	−0.205	-0.360, -0.064
	(0.134)		(0.110)		(0.143)		(0.117)		(0.138)		(0.110)					
No of collaborators (log)	−0.349	***	0.393	***	−0.377	***	0.244	***	−0.156	*	0.353	***	0.354	0.280, 0.438	0.334	0.244, 0.428
	(0.068)		(0.060)		(0.069)		(0.062)		(0.073)		(0.063)					
Potential bookmarkers	0.140	**	0.021		0.059		−0.031		0.127	**	0.004		0.054	0.026, 0.077	0.053	0.022, 0.079
	(0.046)		(0.030)		(0.046)		(0.034)		(0.047)		(0.032)					
Intercept	4.706	***	2.658	***	5.818	***	2.449	***	4.434	***	2.620	***	1.702	0.834, 2.417	1.825	0.673, 2.881
	(0.453)		(0.355)		(0.499)		(0.401)		(0.559)		(0.471)					
Observations	20000				20000				20000				20000		20000	
Languages included	*No*				*Yes*				*No*				*No*		*No*	
DT classes included	*No*				*No*				*Yes*				*No*		*No*	

Note: *p<0.05; **p<0.01; ***p<0.001

Zero-inflated negative binomial models

Figure 8.1. *Zero-inflated negative binomial models of success for men and women*

	Dependent Variable: Success (log(stars+1))									
	(1) Controls		(2) Controls + Languages		(3) Controls + DT classes		(4) 5% gender swaps		(5) 10% gender swaps	
	Coef.	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**95% CI**	**Coef.**	**95% CI**
Female	−0.041		−0.051		−0.059	*	0.645	-0.646, 1.774	0.526	-1.379, 2.051
	(0.027)		(0.027)		(0.027)					
Femaleness	−0.367	***	−0.295	***	−0.343	***	−3.416	-4.432, -1.724	−3.741	-5.027, -1.663
	(0.029)		(0.030)		(0.032)					
Female:Femaleness	0.060		0.075	*	0.089	**	0.976	-2.771, 2.705	1.149	-2.433, 3.472
	(0.033)		(0.033)		(0.033)					
Name frequency	0.014		0.012		0.010		0.111	-0.481, 0.568	0.134	-0.665, 1.054
	(0.022)		(0.022)		(0.022)					
Female:Name frequency	−0.037		−0.004	***	0.089		−1.651	-2.722, 0.053	−1.573	-3.241, 0.826
	(0.028)		(0.028)		(0.028)					
Followers (log)	0.131	***	0.125	***	0.130	***	0.624	0.596, 0.663	0.630	0.598, 0.670
	(0.004)		(0.004)		(0.004)					
Tenure	0.003		0.004		0.005		−0.318	-0.372, -0.266	−0.311	-0.407, -0.184
	(0.003)		(0.003)		(0.003)					
No of own repositories (log)	0.019	***	0.013	**	0.020	***	0.347	0.241, 0.412	0.333	0.218, 0.429
	(0.004)		(0.004)		(0.004)					
No of touched repositories (log)	0.085	***	0.085	***	0.055	***	−0.227	-0.330, -0.113	−0.205	-0.360, -0.064
	(0.007)		(0.008)		(0.007)					
No of collaborators (log)	0.034	***	0.028	***	0.032	***	0.354	0.280, 0.438	0.334	0.244, 0.428
	(0.004)		(0.004)		(0.004)					
Potential bookmarkers	−0.011	***	−0.017	***	−0.009	**	0.054	0.026, 0.077	0.053	0.022, 0.079
	(0.003)		(0.003)		(0.003)					
Intercept	−0.174	***	−0.157	***	−0.091	**	1.702	0.834, 2.417	1.825	0.673, 2.881
	(0.031)		(0.034)		(0.033)					
Observations	20000		20000		20000		20000		20000	
Adjusted R2	0.298		0.312		0.311					
Languages included	*No*		*Yes*		*No*		*No*		*No*	
DT classes included	*No*		*No*		*Yes*		*No*		*No*	

Note: *p<0.05; **p<0.01; ***p<0.001

OLS models

Figure 8.2. *OLS models of log(success+1)*

	Dependent Variable: Survival (yes=1, no=0)									
	(1) Controls		(2) Controls + Languages		(3) Controls + DT classes		(4) 5% gender swaps		(5) 10% gender swaps	
	Coef.	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**95% CI**	**Coef.**	**95% CI**
Female	−0.286		−0.173		0.009		−0.380	-0.633, -0.089	−0.346	-0.650, -0.047
	(0.256)		(0.259)		(0.257)					
Femaleness	−2.934	***	−2.769	***	−2.592	***	−2.748	-3.150, -2.445	−3.021	-3.43, -2.623
	(0.290)		(0.297)		(0.331)					
Female:Femaleness	0.010		−0.156		−0.409		0.234	-0.112, 0.627	0.236	-0.167, 0.789
	(0.326)		(0.331)		(0.269)					
Name frequency	0.072		0.076		0.107		0.109	-0.013, 0.279	0.124	-0.025, 0.273
	(0.213)		(0.214)		(0.208)					
Female:Name frequency	−0.323		0.128	***	−0.409		−0.329	-0.610, -0.115	−0.295	-0.544, -0.050
	(0.274)		(0.016)		(0.269)					
Followers (log)	0.219	***	0.210	***	0.207	***	0.219	0.215, 0.224	0.221	0.214, 0.228
	(0.024)		(0.024)		(0.024)					
Tenure	−0.635	***	−0.571	***	−0.615	***	−0.465	-0.472, -0.456	−0.454	-0.467, -0.445
	(0.033)		(0.034)		(0.034)					
No of own repositories (log)	−0.061		−0.091	*	0.048		−0.082	-0.094, -0.068	−0.088	-0.104, -0.069
	(0.046)		(0.046)		(0.046)					
No of touched repositories (log)	0.205	**	0.177	*	0.140		0.245	0.219, 0.273	0.257	0.226, 0.290
	(0.074)		(0.082)		(0.074)					
No of collaborators (log)	0.420	***	0.432	***	0.218	***	0.341	0.322, 0.356	0.327	0.305, 0.351
	(0.041)		(0.042)		(0.045)					
Potential bookmarkers	0.472	***	0.421	***	−0.391		0.463	0.453, 0.473	0.460	0.447, 0.474
	(0.019)		(0.021)		(0.337)					
Intercept	1.177	***	1.118	***	3.842	***	0.778	0.512, 1.021	0.867	0.601, 1.146
	(0.297)		(0.318)		(0.329)					
Observations	20000		20000		20000		20000		20000	
Languages included	*No*		*Yes*		*No*		*No*		*No*	
DT classes included	*No*		*No*		*Yes*		*No*		*No*	

Note: *p<0.05; **p<0.01; ***p<0.001

Logit models

Figure 8.3. *Logit models of survival*

	Dependent Variable: Success (number of stars)															
	(1) Controls				(2) Controls + Languages				(3) Controls + DT classes				(4) Controls, Users without name			
	Zero-inflation model		Count model		Zero-inflation model		Count model		Zero-inflation model		Count model		Zero-inflation model		Count model	
	Coef.	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**
Femaleness	6.113	***	−4.329	***	5.314	***	−4.701	***	2.907	*	−5.805	***	7.930	***	−0.516	
	(1.076)		(0.897)		(1.157)		(0.905)		(1.355)		(1.165)		(1.360)		(1.363)	
Followers (log)	−0.763	***	0.575	***	−0.747	***	0.635	***	−0.624	***	0.651	***	−0.858	***	0.544	***
	(0.054)		(0.027)		(0.058)		(0.032)		(0.054)		(0.031)		(0.074)		(0.037)	
Tenure	−1.285	***	−0.846	***	−1.229	***	−0.752	***	−1.272	***	−0.617	***	−1.344	***	−0.966	***
	(0.070)		(0.083)		(0.075)		(0.081)		(0.076)		(0.086)		(0.089)		(0.119)	
No of own repositories (log)	0.023		0.181		−0.053		0.196		−0.427	**	0.029		0.270		0.520	*
	(0.092)		(0.132)		(0.095)		(0.143)		(0.109)		(0.134)		(0.114)		(0.217)	
No of touched repositories (log)	−0.420	*	0.835	***	−0.258		0.830	***	0.182		0.603	***	−0.888	**	0.256	
	(0.184)		(0.172)		(0.207)		(0.180)		(0.191)		(0.174)		(0.271)		(0.270)	
No of collaborators (log)	−0.455	***	−0.035		−0.425	***	0.029		−0.448	***	−0.229	**	−0.234	*	0.430	**
	(0.092)		(0.091)		(0.105)		(0.093)		(0.109)		(0.088)		(0.114)		(0.132)	
Potential bookmarkers	0.199	***	−0.221	***	0.214	***	−0.245	***	0.148	***	−0.243	***	0.272	***	−0.173	***
	(0.027)		(0.023)		(0.033)		(0.028)		(0.032)		(0.028)		(0.033)		(0.028)	
Intercept	1.773	*	3.305	***	1.783	*	3.143	***	3.275	**	4.196	***	1.090		1.369	
	(0.753)		(0.656)		(0.845)		(0.667)		(1.020)		(0.867)		(0.945)		(0.988)	
Observations	10000				10000				10000				7231			
Languages included	*No*				*Yes*				*No*				*No*			
DT classes included	*No*				*No*				*Yes*				*No*			

Note: *p<0.05; **p<0.01; ***p<0.001

Zero-inflated negative binomial models

Figure 8.4. *Zero-inflated negative binomial models of success for users with unknown gender*

	Dependent Variable: Success (log(stars+1))							
	(1) Controls		(2) Controls + Languages		(3) Controls + DT classes		(4) Controls, Users without name	
	Coef.	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**
Femaleness	−0.584	***	−0.535	***	−0.599	***	−0.479	***
	(0.067)		(0.072)		(0.075)		(0.070)	
Followers (log)	0.124	***	0.119	***	0.122	***	0.114	***
	(0.006)		(0.006)		(0.006)		(0.008)	
Tenure	0.028	***	0.024	***	0.027	***	0.026	***
	(0.003)		(0.003)		(0.003)		(0.003)	
No of own repositories (log)	0.012	*	0.014	**	0.019	***	0.013	**
	(0.005)		(0.005)		(0.005)		(0.005)	
No of touched repositories (log)	0.104	***	0.091	***	0.069	***	0.085	***
	(0.009)		(0.010)		(0.010)		(0.010)	
No of collaborators (log)	0.029	***	0.028	***	0.022	***	0.028	***
	(0.005)		(0.005)		(0.006)		(0.005)	
Potential bookmarkers	−0.023	***	−0.023	***	−0.022	***	−0.021	***
	(0.002)		(0.002)		(0.002)		(0.002)	
Intercept	−0.002		0.012		0.103		−0.004	
	(0.054)		(0.056)		(0.061)		(0.058)	
Observations	10000		10000		10000		7231	
Languages included	*No*		*Yes*		*No*		*No*	
DT classes included	*No*		*No*		*Yes*		*No*	

Note: Heteroscedasticity-robust SEs are in parentheses.

p<0.05; **p<0.01; ***p<0.001

OLS models

Figure 8.5. *OLS models of log(success+1) for users with unknown gender*

	Dependent Variable: Survival (yes=1, no=0)							
	(1) Controls		(2) Controls + Languages		(3) Controls + DT classes		(4) Controls, Users without name	
	Coef.	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**	**Coef.**	**Sign.**
Femaleness	−2.987	***	−2.110	**	−1.684	*	−3.341	***
	(0.639)		(0.697)		(0.749)		(0.707)	
Followers (log)	0.446	***	0.410	***	0.363	***	0.416	***
	(0.038)		(0.039)		(0.039)		(0.045)	
Tenure	−0.486	***	−0.474	***	−0.515	***	−0.487	***
	(0.035)		(0.036)		(0.036)		(0.039)	
No of own repositories (log)	−0.015		−0.020		0.045		−0.069	
	(0.056)		(0.057)		(0.060)		(0.062)	
No of touched repositories (log)	0.221	*	0.115		0.066		0.261	*
	(0.092)		(0.098)		(0.098)		(0.103)	
No of collaborators (log)	0.209	***	0.206	***	0.197	***	0.180	***
	(0.049)		(0.050)		(0.059)		(0.054)	
Potential bookmarkers	0.649	***	0.583	***	0.651	***	0.637	***
	(0.017)		(0.020)		(0.020)		(0.018)	
Intercept	−0.323		−0.451		−0.678		−0.079	
	(0.477)		(0.513)		(0.572)		(0.529)	
Observations	10000		10000		10000		7231	
Adjusted R2	0.265		0.278		0.282		0.227	
Languages included	*No*		*Yes*		*No*		*No*	
DT classes included	*No*		*No*		*Yes*		*No*	

Note: *p<0.05; **p<0.01; ***p<0.001

Logit models

Figure 8.6. *Logit models of survival for users with unknown gender*

Dependent Variable:
Success (count)

	Zero-inflation model		Count model	
	Coef.	**Sign.**	**Coef.**	**Sign.**
Female	0.956	*	1.030	**
	(0.382)		(0.327)	
Femaleness	2.578	***	−3.313	***
	(0.457)		(0.271)	
Female:Femaleness	1.096		1.624	***
	(0.565)		(0.433)	
2015-16	2.886	***	4.364	***
	(0.616)		(0.742)	
Female:2015-16	−0.862		−1.668	
	(0.773)		(0.914)	
Femaleness:2015-16	−2.561	*	−6.854	***
	(1.212)		(1.342)	
Female:Femaleness:2015-16	0.742		2.082	
	(1.438)		(1.597)	
Name frequency	0.072		0.247	
	(0.294)		(0.204)	
Female:Name frequency	−1.271	**	−2.434	***
	(0.403)		(0.353)	
Followers (log)	2.886	***	4.364	
	(0.616)		(0.742)	
Tenure	−0.716	***	0.649	***
	(0.032)		(0.016)	
No of own repositories (log)	−0.077		0.364	***
	(0.106)		(0.079)	
No of touched repositories (log)	−0.603	***	−0.283	*
	(0.146)		(0.115)	
No of collaborators (log)	−0.394	***	0.360	***
	(0.072)		(0.063)	
Potential bookmarkers	0.149	**	0.046	
	(0.049)		(0.030)	
Intercept	1.681	***	0.627	
	(0.468)		(0.331)	
Observations	20000		20000	
Languages included	*No*		*No*	
DT classes included	*No*		*No*	

Note: *p<0.05; **p<0.01; ***p<0.001
Zero-inflated negative binomial models

Figure 8.7. *Differences between the 2013-14 and 2015-16 cohorts*

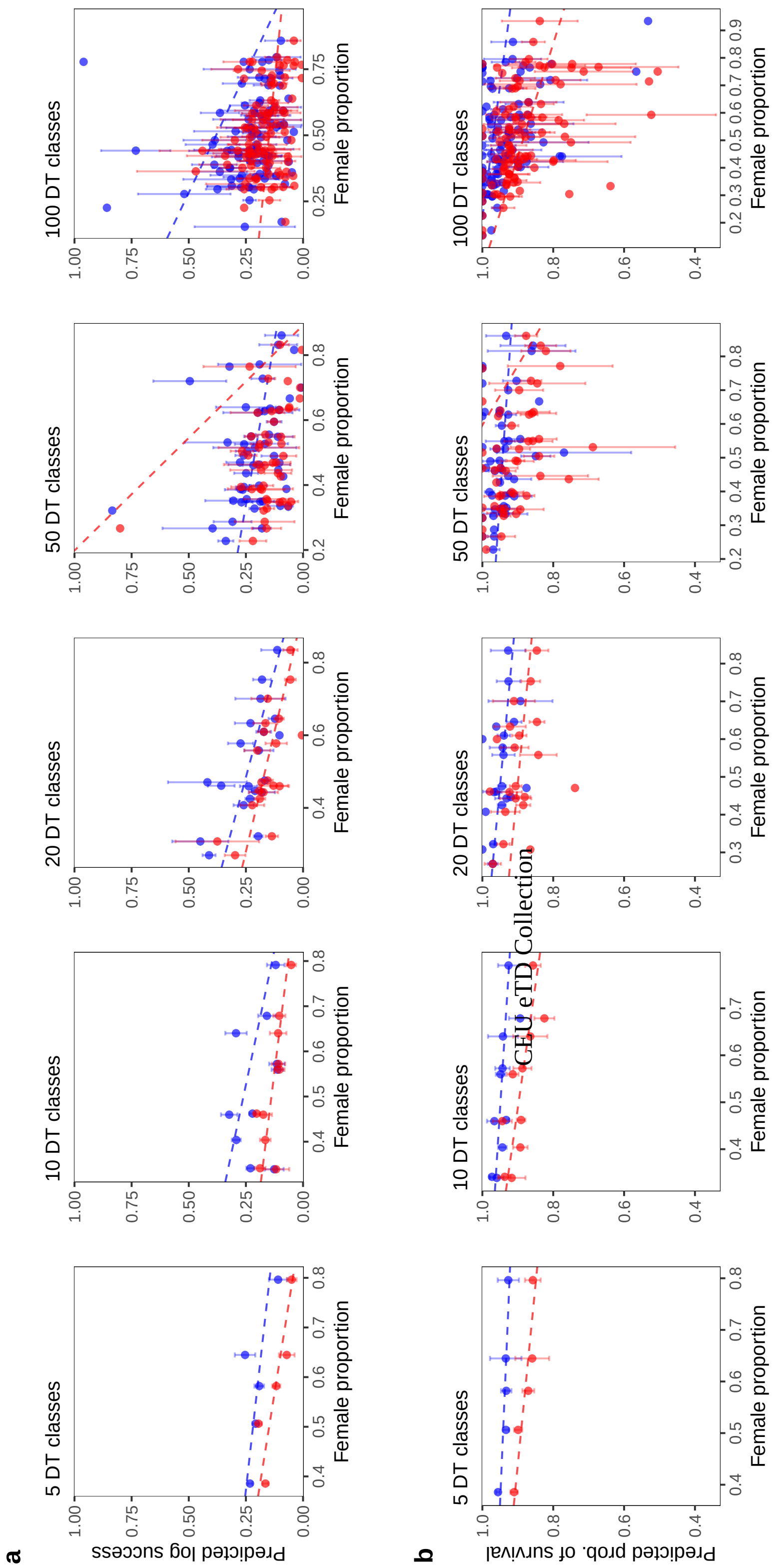

Figure 8.8. *OLS model of log(success+1 and Logit model of survival with classes of gendered behavior*

Dependent Variables:
Success (log) & Survival (yes=1, no=0)

	OLS model		Logit model	
	Coef.	**Sign.**	**Coef.**	**Sign.**
Female	−0.021		−0.343	
	(0.028)		(0.209)	
DT Female Propotion	−0.279	***	−1.976	* * *
	(0.031)		(0.213)	
Name frequency (log)	0.017		0.103	
	(0.020)		(0.142)	
Female:Name frequency (log)	−0.042		0.089	
	(0.028)		(0.221)	
Female:DT Female Propotion	0.000		−0.143	
	(0.040)		(0.230)	
Followers (log)	0.130	***	0.620	* * *
	(0.002)		(0.014)	
Tenure	0.027	***	0.698	* * *
	(0.004)		(0.030)	
No of own repositories (log)	0.017	***	0.292	* * *
	(0.008)		(0.039)	
No of touched repositories (log)	0.081	***	0.052	
	(0.008)		(0.068)	
No of collaborators (log)	0.029	***	0.137	* * *
	(0.013)		(0.040)	
Potential Bookmarkers	0.0285	*	0.682	* * *
	(0.040)		(0.114)	
Intercept	−0.448	***	−8.278	* * *
	(0.063)		(0.542)	
Observations	20000		20000	
Adjusted R2 / McFadden's pseudo R2	0.293		0.269	

Note: *p<0.05; **p<0.01; ***p<0.001

Figure 8.9. *Robustness of classes of gendered behavior*

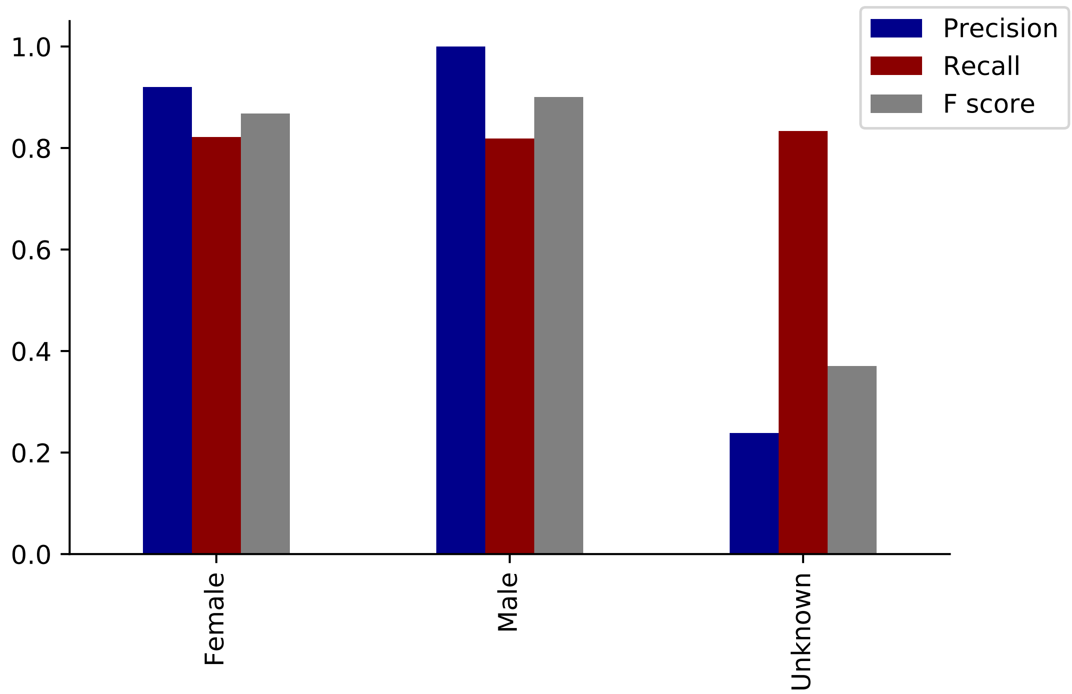

Figure 8.10. *Accuracy of the used gender inference algorithmby Ford et al [4] against the baseline. Precision (a) measures for each category how many categorized items are relevant, and recall (b) captures how many relevant items are selected from all good ones, F score (c) takes the harmonic average of precision and recall, reaches 1 when both metrics are perfect*

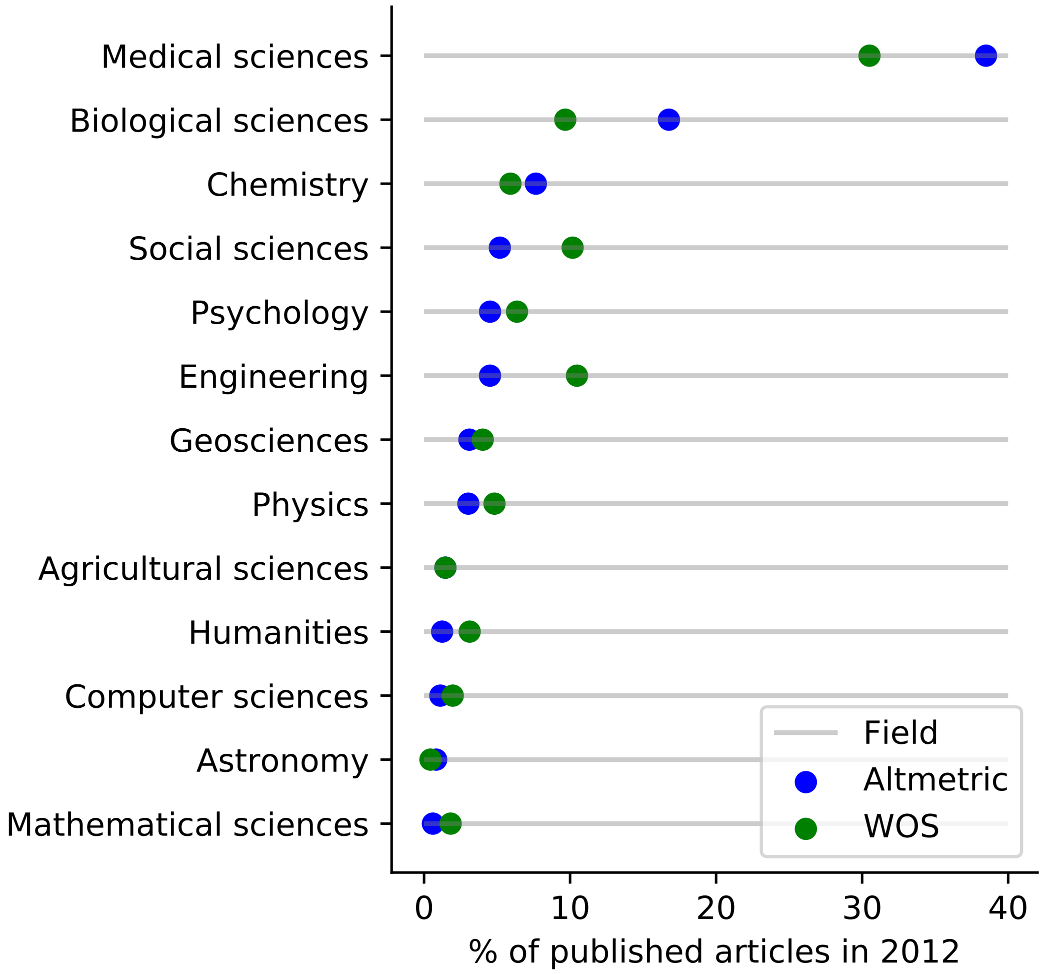

Figure 8.11. *Ratio of articles published in WOS in 2012 and shared in Altmetric by broad research fields.*

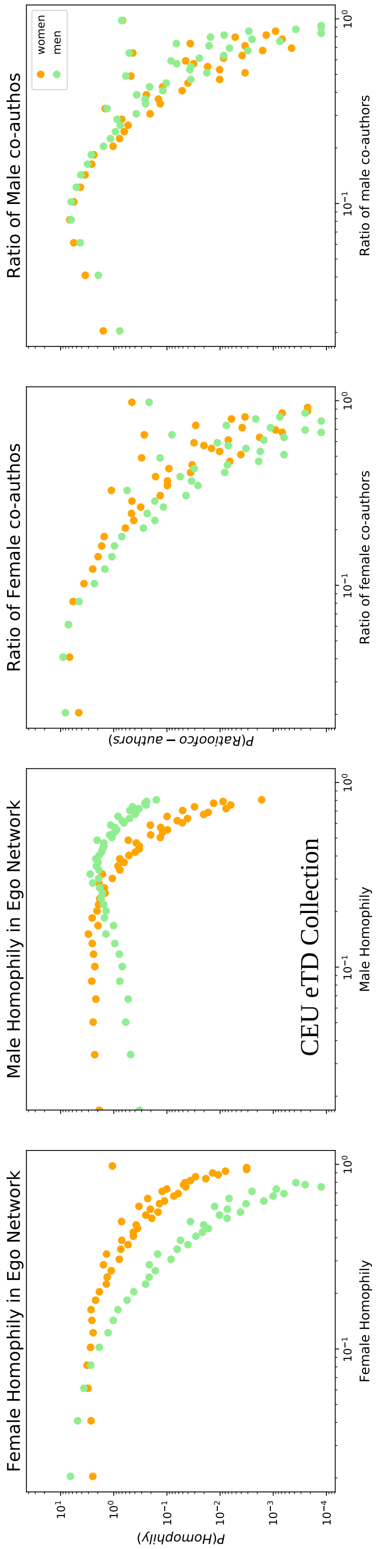

Figure 8.12. *Distribtuion of variables capturing Gender Homophily in Ego networks by gender.*

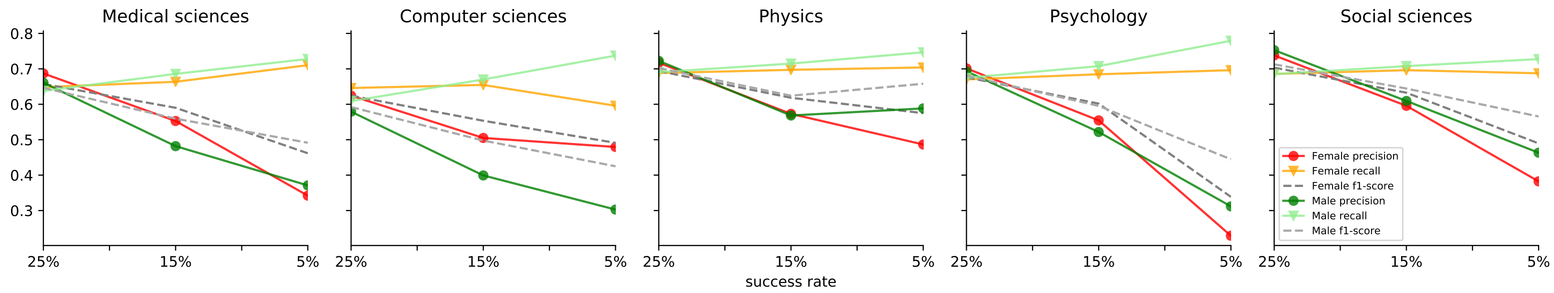

Figure 8.13. *Recall and F1-scores of 100 models predicting popular success by various thresholds in chosen research fields by gender. Models were ran 100 times separately by field, gender, success and threshold.*

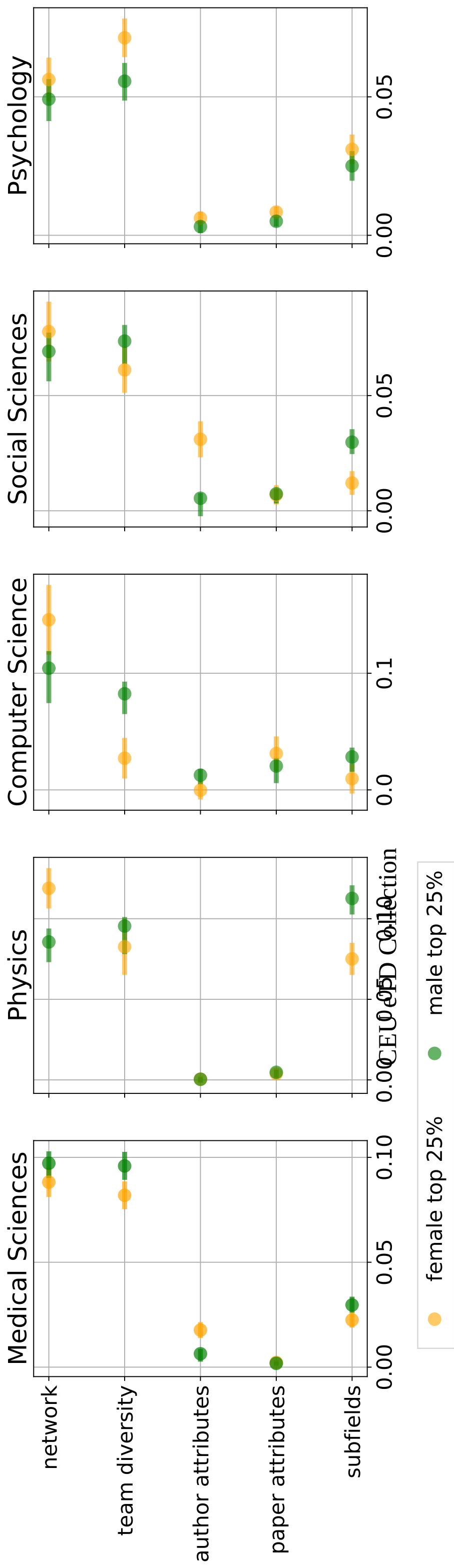

Figure 8.14. *Group variable importances' of 100 Random Forest Models. The importance of a variable group is the difference between the baseline overall accuracy, and the accuracy of re-ran model without the given feature set. Points indicates the average variable importance, lines the standard deviation of 100 runs.*

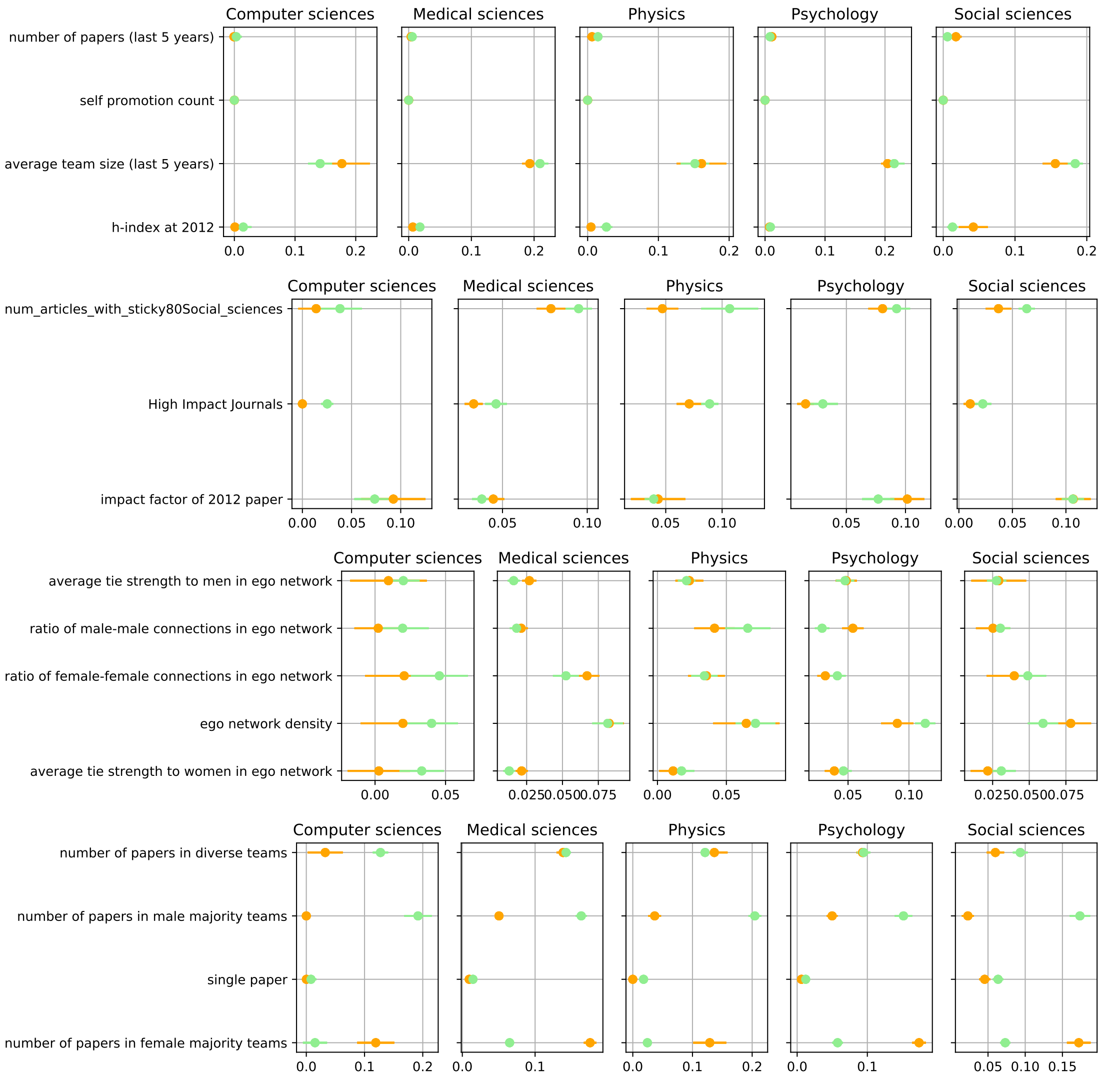

Figure 8.15. *Relative variable importances of features for predicting top 25 % of most successful scientists on each field. Line indicates standard deviation, based on 100 separate models*

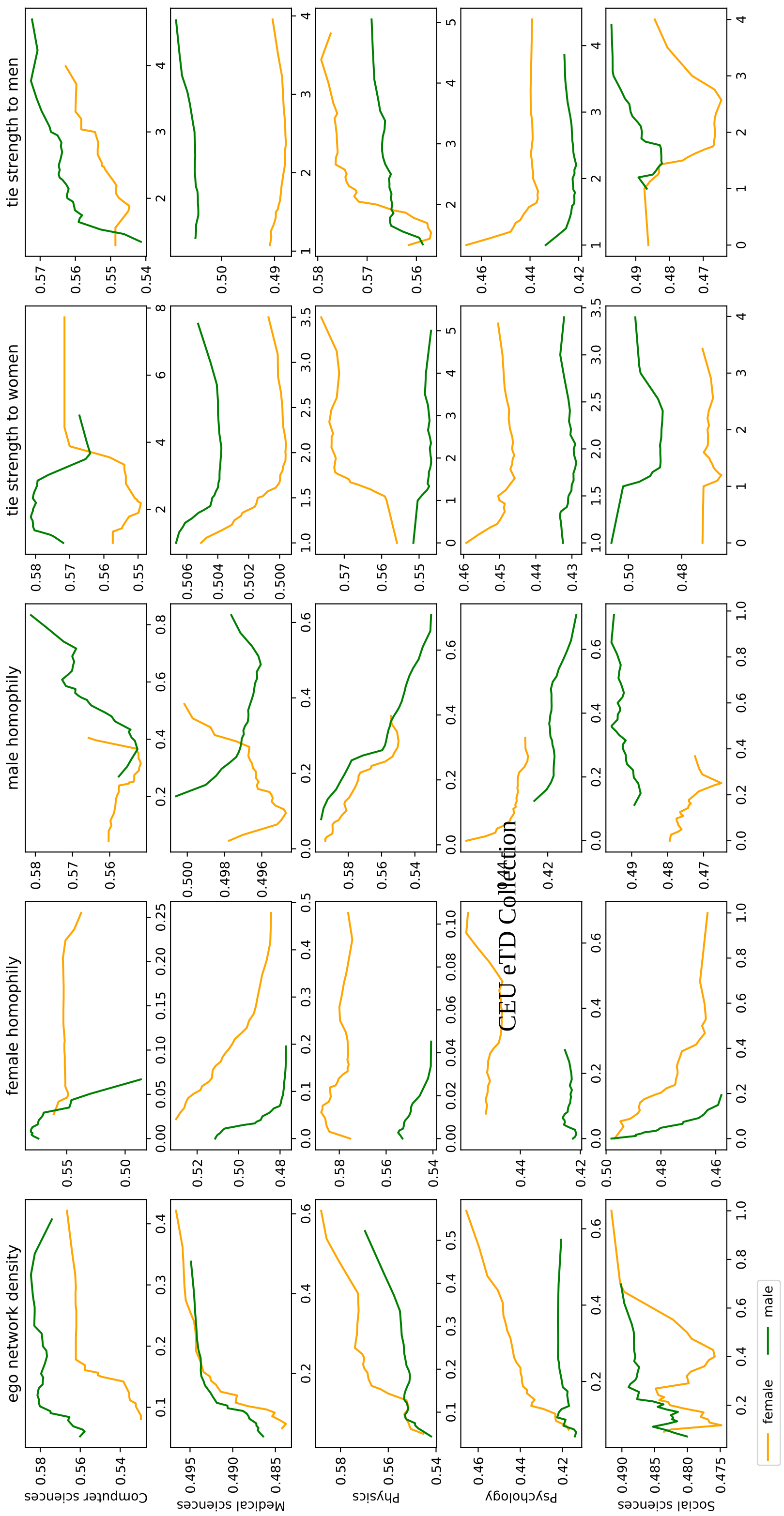

Figure 8.16. *Partial Dependency Plots of variables capturing ego network structure for predicting top 25 % of most successful scientists on each field.*

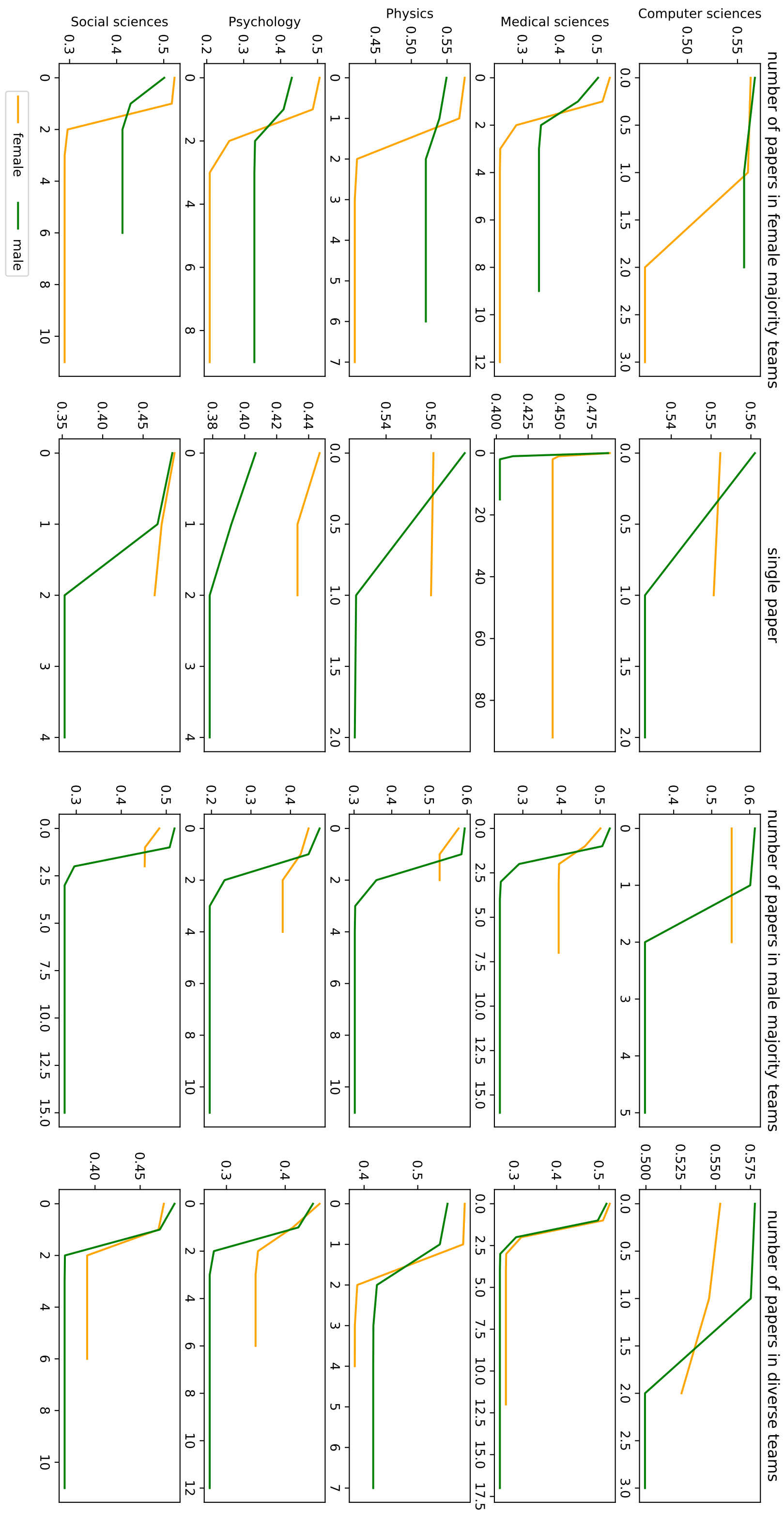

Figure 8.17. *Partial Dependency Plots of variables capturing team diversity for predicting top 25 % of most successful scientists on each field.*

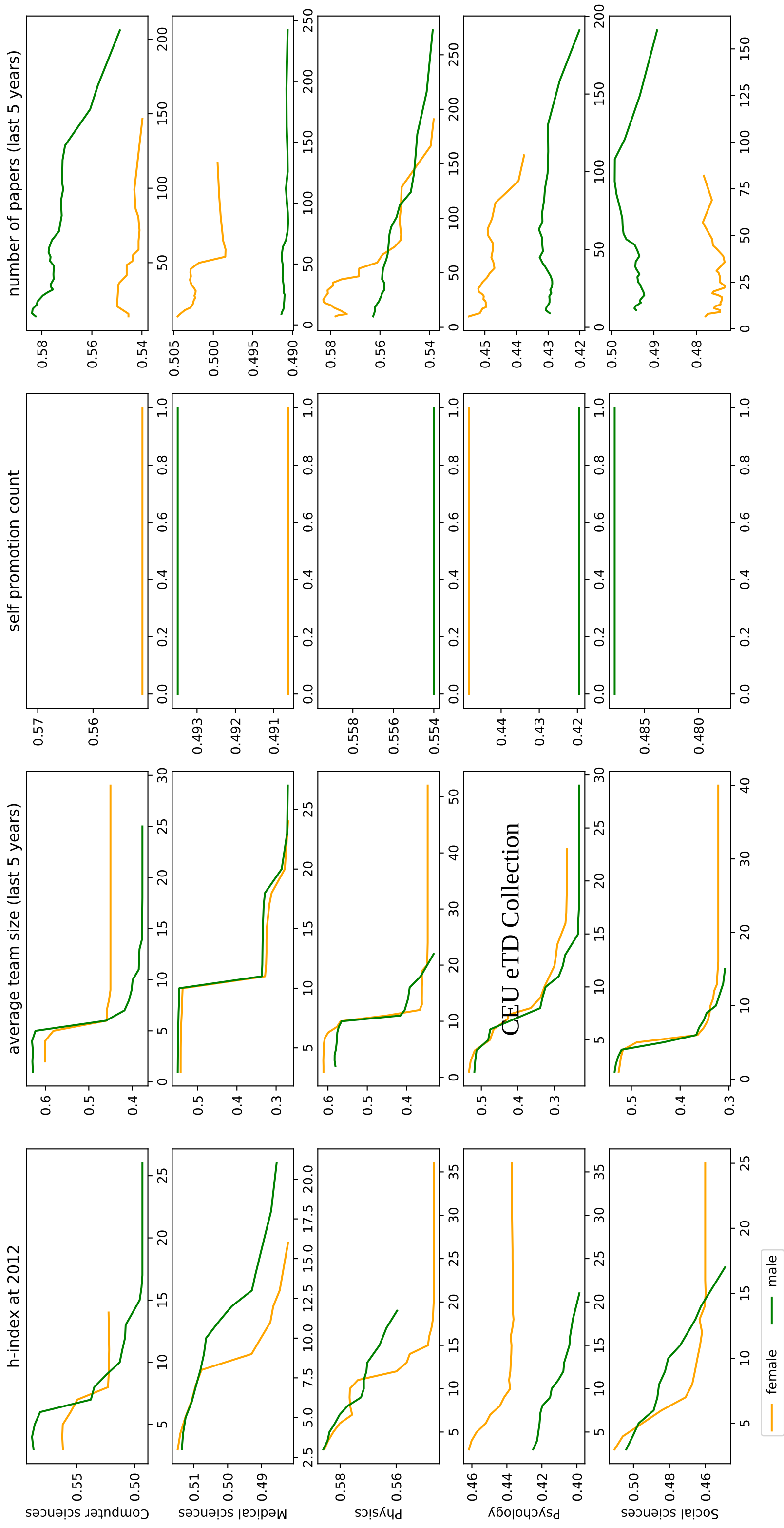

Figure 8.18. *Partial Dependency Plots of variables capturing author attributes for predicting top 25 % of most successful scientists on each field.*

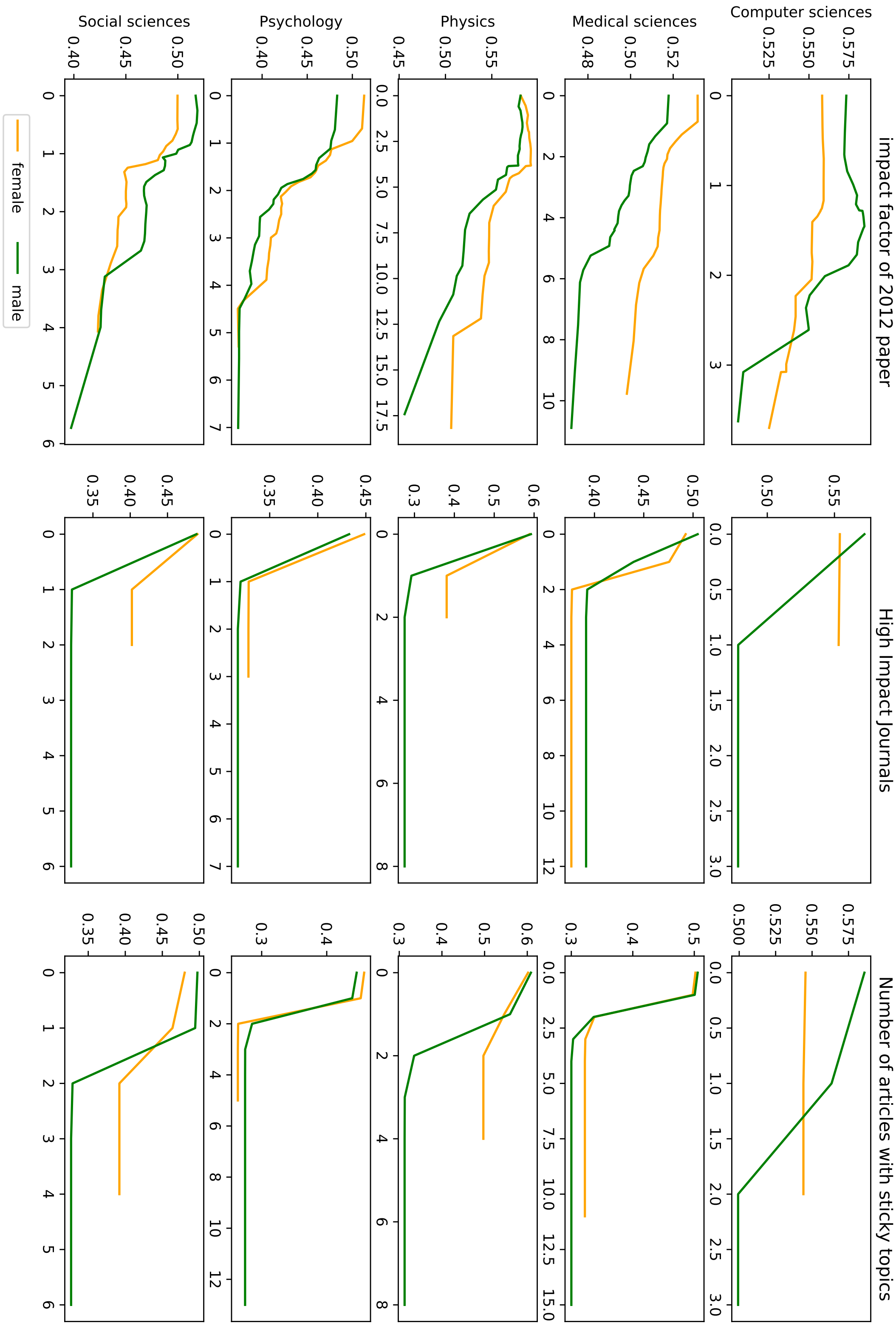

Figure 8.19. *Partial Dependency Plots of variables capturing paper attributes for predicting top 25 % of most successful scientists on each field.*

	Altmetric 2012		WOS sample		OAG	
	N	%	N	%	N	%
female	216 646	28.60%	274 681	23.07%	390 891	29.35%
male	391 013	51.61%	465 185	39.06%	642 507	48.24%
unknown	149 868	19.78%	451 004	37.80%	298 569	22.42%
total	757 527		1 190 870		1 331 967	

Table 8.1. *Gender inferring results*

Data points	N
Number of articles Altmetric 2012	241 386
Number of unique authors	757 527
Number of unique authors with shares	537 486
Number of authors in collaboration network	1 331 967
Number of shares in social media	4 689 423
Number of shares on Twitter	3 634 714 (77%)
Number of shares on FB	473 884 (10%)
Number of shares on news sites	206 456 (4.4%)

Table 8.2. *Descriptive Statistics*

	Male			Female			Unknown			Mann-Whitney U test (men & women)		
Platform	Mean	Std	Median	Mean	Std	Median	Mean	Std	Median	Mann–Whitney U	p	Cliff's D
Blogs	0.16	1.60	0.00	0.21	1.37	0.00	0.28	0.98	0.00	41667635928	0.00	0.02
Facebook	0.51	10.74	0.00	0.66	11.07	0.00	0.65	12.99	0.00	42125385417	0.00	0.01
GooglePlus	0.09	2.85	0.00	0.11	2.10	0.00	0.14	1.96	0.00	42183168975	0.00	0.01
News	0.16	2.95	0.00	0.29	3.74	0.00	0.30	2.10	0.00	42104178645	0.00	0.01
Q&A	0.00	0.08	0.00	0.00	0.06	0.00	0.00	0.06	0.00	42305911228	0.00	0.00
Reddit	0.01	0.29	0.00	0.02	0.24	0.00	0.02	0.24	0.00	42270259224	0.00	0.00
Twitter	3.31	35.09	1.00	4.72	29.26	1.00	5.41	26.98	1.00	42242668422	0.04	0.00
Video	0.02	0.39	0.00	0.02	0.37	0.00	0.02	0.24	0.00	42248502386	0.00	0.00
Wikipedia	0.08	1.20	0.00	0.08	0.81	0.00	0.11	0.54	0.00	41781989981	0.00	0.01
Total shares	4.34	43.59	1.00	6.12	37.89	1.00	6.94	35.28	1.00	41960163702	0.00	0.01

Table 8.3. *Average, median, and standard deviation of the number shares by gender and different platforms and the results of the Mann-Whitney U test between female and male scientists' shares by platform*

Research Field	Top 25%	Top 5%	Top 1%	Almtetric	WOS
Agricultural sciences	22%	13%	9%	19%	20%
Biological sciences	25%	22%	19%	23%	25%
Astronomy	13%	14%	10%	12%	2%
Chemistry	17%	14%	16%	15%	18%
Computer sciences	16%	14%	18%	14%	13%
Engineering	14%	11%	4%	12%	11%
Geosciences	19%	17%	17%	17%	17%
Humanities	26%	17%	7%	27%	37%
Mathematical sciences	15%	18%	5%	11%	12%
Medical sciences	33%	32%	29%	28%	22%
Physics	12%	10%	8%	10%	3%
Professional fields	33%	33%	38%	30%	36%
Social_sciences	26%	23%	16%	24%	26%
Psychology	38%	34%	25%	36%	38%

Table 8.4. *Ratio of most successful women by research fields, and the ratio of women in Altmetric and on WOS in 2012*

Field	Women	Men	KS	P
Agricultural sciences	0.25	0.40	0.11	0.00
Astronomy	0.17	0.42	0.19	0.00
Biological sciences	0.31	0.52	0.12	0.00
Chemistry	0.58	1.13	0.27	0.00
Computer sciences	0.20	0.43	0.21	0.00
Engineering	0.27	0.53	0.20	0.00
Geosciences	0.41	0.64	0.15	0.00
Humanities	0.16	0.21	0.04	0.92
Mathematical sciences	0.13	0.30	0.14	0.00
Medical sciences	0.40	0.59	0.11	0.00
Physics	0.47	0.81	0.21	0.00
Psychology	0.58	0.81	0,09	0.00
Social sciences	0.29	0.45	0,12	0.00

Table 8.5. *Average number of articles writing in sticky topic by gender and Kolmogorov-Smirnoff 2 sample test results*

	High-Femaleness			Low-Femaleness		
	Topic	OR	P	Topic	OR	P
Social Sciences	diversity	27.62	0.00	usa	0.00	0.04
	language	19.29	0.00	greenhouse+gas+emission	0.00	0.04
	attachment	13.76	0.01	issue	0.00	0.04
	gender+difference	12.42	0.00	prevention	0.00	0.04
	reframing	11.00	0.02	trade	0.10	0.00
	neighbourhood	9.64	0.00	economic	0.22	0.00
	definition	9.64	0.00	environmental	0.23	0.03
	ngo	8.26	0.01	uncertainty	0.24	0.04
	educational+attainment	8.26	0.01	information	0.25	0.01
	preschool+children	8.26	0.01	market	0.38	0.03
	Topic	OR	P	Topic	OR	P
Physics	exit+tunnelling+barrier	18.51	0.01	communication	0.00	0.04
	optical+excitation	18.51	0.01	molecule	0.16	0.04
	photoluminescence	9.28	0.00			
	bonding	9.26	0.02			
	spin+hall	9.26	0.02			
	composition	9.26	0.02			
	sky	9.26	0.02			
	voltage	6.18	0.01			
	response	6.17	0.02			
	field+enhancement	6.17	0.04			
	Topic	OR	P	Topic	OR	P
Medical Sciences	dairy+intake	20.62	0.00	nsaid	0.00	0.00
	australian+women	17.53	0.00	navigation	0.00	0.00
	chondroitin	12.37	0.01	reverse+shoulder+arthroplasty	0.00	0.00
	hiv+service	12.37	0.01	prasugrel	0.00	0.00
	increased+serum+hydroxyvitamin	12.37	0.01	tomography+computed+tomography	0.00	0.00
	cry	12.37	0.01	oncology+drug	0.00	0.01
	women+experience	11.00	0.00	retinal+detachment	0.00	0.01
	mental+health+disorder	9.28	0.00	marathon+runner	0.00	0.01
	childbirth	8.94	0.00	mimic	0.00	0.01
	african+american+women	8.77	0.00	partial+nephrectomy	0.00	0.01
	Topic	OR	P	Topic	OR	P
Psychology	word+learning	11.04	0.01	integrative	0.00	0.00
	pursuit	7.88	0.04	gambling	0.00	0.00
	receptive	7.88	0.04	computational	0.00	0.01
	maternal+sensitivity	7.88	0.04	integrating	0.00	0.01
	corporal+punishment	5.52	0.03	monkey	0.00	0.03
	school+aged+children	5.26	0.01	red	0.00	0.03
	gesture	5.13	0.00	psychopathic+trait	0.00	0.05
	sibling	4.97	0.00	asymmetry	0.00	0.05
	lesbian	4.74	0.00	narcissism	0.00	0.05
	gaze	4.73	0.01	autonomy	0.00	0.05
	Topic	OR	P	Topic	OR	P
Computer Science	comprehensive+sample	15.84	0.01			
	thermohaline+instability	15.84	0.01			
	sight+line	15.84	0.01			
	pks	15.84	0.01			
	red+supergiant	15.84	0.01			
	examining	15.84	0.01			
	light+element	15.84	0.01			
	electron	13.27	0.00			
	chemical+abundance	10.53	0.07			
	unraveling	10.53	0.07			

Table 8.6. *Top 10 significant topics with highest and lowest femaleness by broad research area*

Research Field	Ratio of significant topics	Average of the number of total shares on topic			N
		Low Femaleness	High Femaleness	Non- genderedn	
Social Sciences	0.93%	82.00	14.55	3.25	14905
Physics	1.10%	51.00	4.15	2.67	15518
Medical Sciences	1.13%	154.30	182.43	132.92	8000
Psychology	0.75%	40.03	48.49	3.80	25174
Computer Science	1.23%	0.00	0.00	0.18	3178

Table 8.7. *Overall Genderedness, and the average number of total shares by genderedness. Please note that data points for Medical Sciences are based on a sample that covers topics with higher total number of shares than average in that area (mean* $= 11.29$, $N = 8000$)

	Social Sciecnes		Physics		Medical Sciences	
Genderedness	Median	IQR	Median	IQR	Median	IQR
Low-Femaleness	38	22-46	51	46-56	39	22-104
High-Femaleness	15	7-39	13	7-35	50	23-157
Non-gendered	81	65-146	1	0-2	24	16-50

Table 8.8. *Genderedness of visualized topics, the median number and the IQR (inter quartile range) of total shares by genderedness.*

Not popular						
Network Metric	Male Med.	Female Med.	Mann–Whitney U	P	Cliff D	Effect size
Degree	31.00	19.00	18413082537.00	0.00	0.16	small
Ego Network Density	0.31	0.46	18084518511.00	0.00	-0.18	small
Ratio of Female co-authors	0.05	0.07	17271220458.00	0.00	-0.22	small
Ratio of Male co-authors	0.13	0.11	19015954095.50	0.00	0.14	negligible
Tie strength to women	1.20	1.17	21913544689.00	0.00	0.01	negligible
Tie strength to women	1.55	1.33	19247485827.50	0.00	0.13	negligible
Female Homophily	0.02	0.13	10106200846.50	0.00	-0.54	large
Male Homophily	0.35	0.13	10037029435.50	0.00	0.54	large
Top 25%						
Degree	47.00	24.00	2546400407.00	0.00	0.23	small
Ego Network Density	0.20	0.35	2494923619.50	0.00	-0.24	small
Ratio of Female co-authors	0.06	0.08	2448208596.50	0.00	-0.26	small
Ratio of Male co-authors	0.13	0.11	2784207774.50	0.00	0.15	small
Tie strength to women	1.50	1.41	3157607897.00	0.00	0.04	negligible
Tie strength to men k	1.78	1.57	2819869884.50	0.00	0.14	negligible
Female Homophily	0.04	0.17	1279769983.00	0.00	-0.61	large
Male Homophily	0.37	0.15	1118329754.00	0.00	0.66	large

Table 8.9. *Medians of different ego network metrics by gender and success, and the results of the Mann-Whitney tests, which shows significant difference between men' and women' ego network metrics. Ego networks are created based on 5 years of collaboration history of each author.*

	NOT POPULAR						POPULAR					
Computer Science	Male	Female	Mann–Whitney U	p	cliff	effect size	Male	Female	Mann–Whitney U	p	cliff	effect size
Ego network density	0.31	0.36	534737.50	0.02	-0.06	negligible	0.25	0.25	208012.50	0.50	0.00	negligible
Tie strength to women	1.33	1.50	518505.00	0.00	-0.09	negligible	1.50	1.50	208012.50	0.50	0.00	negligible
Tie strength to men	2.00	2.00	533364.50	0.01	0.06	negligible	2.00	2.00	208012.50	0.50	0.00	negligible
Female homophily	0.00	0.07	203855.50	0.00	-0.64	large	0.00	0.00	208012.50	0.50	0.00	negligible
Male homophily	0.55	0.18	141339.50	0.00	0.75	large	0.50	0.50	208012.50	0.50	0.00	negligible
Medical Science	Male	Female	Mann–Whitney U	p	cliff	effect size	Male	Female	Mann–Whitney U	p	cliff	effect size
Ego network density	0.29	0.46	1453330507.00	0.00	-0.22	small	0.25	0.18	17259868.50	0.00	0.14	negligible
Tie strength to women	1.35	1.33	1813976286.50	0.00	0.03	negligible	1.50	1.56	19144517.00	0.02	-0.05	negligible
Tie strength to men	1.67	1.46	1593322048.50	0.00	0.14	negligible	2.00	1.83	17622921.50	0.00	0.12	negligible
Female homophily	0.03	0.15	783774328.00	0.00	-0.58	large	0.00	0.05	10543195.50	0.00	-0.48	large
Male homophily	0.35	0.14	755729956.00	0.00	0.59	large	0.50	0.35	11844116.50	0.00	0.41	medium
Physics	Male	Female	Mann–Whitney U	p	cliff	effect size	Male	Female	Mann–Whitney U	p	cliff	effect size
Ego network density	0.293	0.412	7446749.500	0.000	-0.143	negligible	0.25	0.18	1168436.50	0.00	0.14	negligible
Tie strength to women	1.200	1.167	8543515.000	0.121	0.017	negligible	1.50	1.57	1306752.00	0.08	-0.03	negligible
Tie strength to men	2.000	1.875	7938389.500	0.000	0.087	negligible	2.00	2.25	1179240.50	0.00	-0.13	negligible
Female homophily	0.000	0.028	4221968.000	0.000	-0.514	large	0.00	0.00	1220415.50	0.00	0.10	negligible
Male homophily	0.360	0.143	4021136.500	0.000	0.537	large	0.50	0.41	1012909.50	0.00	0.25	small
Psychology	Male	Female	Mann–Whitney U	p	cliff	effect size	Male	Female	Mann–Whitney U	p	cliff	effect size
Ego network density	0.33	0.54	5506398.50	0.00	-0.24	small	0.25	0.21	1965241.00	0.02	0.05	negligible
Tie strength to women	1.27	1.25	7098475.00	0.13	0.02	negligible	1.50	1.50	2013352.00	0.13	-0.03	negligible
Tie strength to men	1.57	1.27	6000517.50	0.00	0.17	small	2.00	1.89	1852767.50	0.00	0.10	negligible
Female homophily	0.05	0.30	2560109.50	0.00	-0.64	large	0.00	0.07	1061520.50	0.00	-0.49	large
Male homophily	0.36	0.07	2063817.00	0.00	0.71	large	0.50	0.35	1305785.00	0.00	0.37	medium
Social Sciences	Male	Female	Mann–Whitney U	p	cliff	effect size	Male	Female	Mann–Whitney U	p	cliff	effect size
Ego network density	0.40	0.53	5670683.50	0.00	-0.14	negligible	0.25	0.31	1279183.50	0.00	-0.10	negligible
Tie strength to women	1.00	1.00	6508346.00	0.09	-0.02	negligible	1.50	1.00	1117313.00	0.00	0.21	small
Tie strength to men	1.33	1.00	5512027.00	0.00	0.17	small	2.00	1.50	975792.50	0.00	0.31	small
Female homophily	0.00	0.17	2963601.00	0.00	-0.55	large	0.00	0.00	1410460.50	0.43	0.00	negligible
Male homophily	0.50	0.00	1874953.00	0.00	0.72	large	0.50	0.50	1382877.00	0.17	0.02	negligible

Table 8.10. *Medians of different ego network metrics by field, gender and success level, and the results of the Mann-Whitney tests, which shows significant difference between men' and women' ego network metrics. Ego networks are created based on 5 years of collaboration history of each author.*

	Female popular	Female not popular	Male popular	Male not popular
Total shares	519.00	3.00	4626.00	3.00
H-index (2012)	7.00	3.00	27.00	4.00
Number of papers (2012)	4.00	1.00	6.00	1.00
Degree	184.00	24.00	139.00	26.00
Ego netowrk density	0.17	0.39	0.05	0.67
Tie strength to women	2.26	1.27	2.07	1.40
Tie strength to men	2.07	1.25	2.69	2.33
Female homophily	0.28	0.43	0.15	0.03
Male homophily	0.15	0.03	0.25	0.32

Table 8.11. *Ego Network statistics of example scientists*

	Altmetric 2012		WOS sample	
	N	%	N	%
diverse	97 828	34%	104 739	46%
male majority	81 295	41%	70 908	31%
female majority	62 263	26%	49 526	22%

Table 8.12. *Team gender diversity of articles in Altmetric and in our WOS matching sample in 2012. Matching sample was created...*

		Female						Male					
				Top 25%		Below Top 25%				Top 25%		Below Top 25%	
	Research Field	KS	P	Mean	Std	Mean	Std	KS	P	Mean	Std	Mean	Std
Female majority	Agricultural sciences	0.16	0.04	0.04	0.06	0.03	0.05	0.10	0.01	0.01	0.03	0.01	0.02
	Astronomy	0.10	0.27	0.02	0.04	0.01	0.03	0.04	0.33	0.00	0.01	0.00	0.01
	Biological sciences	0.12	1.00	0.05	0.07	0.04	0.06	0.10	0.00	0.01	0.03	0.01	0.03
	Chemistry	0.21	0.00	0.04	0.06	0.03	0.05	0.10	1.00	0.01	0.02	0.00	0.02
	Computer sciences	0.28	0.00	0.04	0.06	0.02	0.03	0.08	0.11	0.00	0.01	0.00	0.01
	Engineering	0.20	0.00	0.03	0.04	0.02	0.03	0.10	0.00	0.00	0.02	0.00	0.01
	Geosciences	0.13	0.00	0.04	0.06	0.03	0.05	0.10	1.00	0.01	0.02	0.00	0.02
	Humanities	0.49	0.00	0.05	0.04	0.02	0.03	0.11	0.54	0.01	0.02	0.00	0.01
	Mathematical sciences	0.28	0.01	0.05	0.08	0.02	0.03	0.15	0.00	0.01	0.02	0.00	0.01
	Medical sciences	0.19	0.00	0.04	0.07	0.03	0.05	0.14	0.00	0.01	0.02	0.00	0.02
	Physics	0.20	0.00	0.02	0.04	0.01	0.04	0.06	1.00	0.00	0.01	0.00	0.01
	Professional fields	0.13	0.00	0.06	0.07	0.05	0.06	0.12	0.00	0.01	0.04	0.01	0.03
	Psychology	0.16	0.00	0.07	0.08	0.04	0.06	0.18	0.00	0.01	0.03	0.01	0.02
	Social sciences	0.17	0.00	0.06	0.08	0.04	0.06	0.13	0.12	0.01	0.03	0.01	0.02
Male majority	Agricultural sciences	0.17	0.01	0.01	0.03	0.01	0.02	0.21	0.00	0.05	0.07	0.03	0.04
	Astronomy	0.07	0.66	0.00	0.02	0.00	0.01	0.16	0.00	0.03	0.05	0.02	0.04
	Biological sciences	0.10	1.00	0.01	0.04	0.01	0.03	0.21	0.00	0.04	0.07	0.03	0.05
	Chemistry	0.11	0.00	0.01	0.03	0.00	0.02	0.25	1.00	0.04	0.07	0.03	0.05
	Computer sciences	0.07	0.96	0.00	0.02	0.00	0.00	0.21	0.00	0.03	0.04	0.02	0.03
	Engineering	0.13	0.11	0.01	0.03	0.00	0.01	0.20	0.00	0.03	0.04	0.02	0.03
	Geosciences	0.10	0.00	0.01	0.02	0.00	0.02	0.18	1.00	0.04	0.05	0.02	0.04
	Humanities	0.03	1.00	0.00	0.01	0.00	0.00	0.30	0.00	0.03	0.04	0.02	0.04
	Mathematical sciences	0.11	0.71	0.00	0.01	0.00	0.02	0.25	0.00	0.04	0.07	0.02	0.03
	Medical sciences	0.08	0.00	0.01	0.03	0.01	0.02	0.18	0.00	0.03	0.05	0.02	0.04
	Physics	0.15	0.00	0.01	0.02	0.00	0.02	0.18	1.00	0.03	0.05	0.02	0.04
	Professional fields	0.09	0.01	0.01	0.03	0.00	0.02	0.18	0.00	0.04	0.06	0.03	0.04
	Psychology	0.11	0.00	0.01	0.04	0.01	0.03	0.22	0.00	0.05	0.07	0.03	0.04
	Social sciences	0.08	0.01	0.01	0.02	0.00	0.02	0.15	0.12	0.04	0.06	0.02	0.04
Diverse	Agricultural sciences	0.16	0.02	0.03	0.04	0.02	0.04	0.23	0.00	0.02	0.04	0.01	0.03
	Astronomy	0.10	0.28	0.04	0.04	0.03	0.05	0.10	0.00	0.02	0.04	0.02	0.03
	Biological sciences	0.16	1.00	0.04	0.06	0.03	0.05	0.16	0.00	0.02	0.04	0.02	0.04
	Chemistry	0.20	0.00	0.04	0.06	0.03	0.05	0.23	1.00	0.02	0.05	0.02	0.04
	Computer sciences	0.08	0.83	0.02	0.02	0.01	0.03	0.13	0.00	0.01	0.02	0.01	0.02
	Engineering	0.21	0.00	0.04	0.08	0.02	0.04	0.25	0.00	0.02	0.04	0.01	0.02
	Geosciences	0.12	0.00	0.04	0.06	0.03	0.05	0.12	1.00	0.02	0.04	0.02	0.03
	Humanities	0.15	0.72	0.01	0.02	0.00	0.01	0.18	0.07	0.01	0.02	0.00	0.01
	Mathematical sciences	0.26	0.02	0.03	0.04	0.02	0.03	0.25	0.00	0.02	0.03	0.01	0.02
	Medical sciences	0.13	0.00	0.03	0.05	0.03	0.05	0.19	0.00	0.02	0.04	0.02	0.03
	Physics	0.11	0.00	0.03	0.04	0.03	0.04	0.13	1.00	0.01	0.03	0.01	0.03
	Professional fields	0.17	0.00	0.03	0.05	0.01	0.03	0.15	0.00	0.02	0.04	0.01	0.03
	Psychology	0.21	0.00	0.03	0.05	0.02	0.04	0.24	0.00	0.02	0.04	0.01	0.03
	Social sciences	0.12	0.00	0.02	0.04	0.01	0.03	0.16	0.12	0.01	0.03	0.01	0.02

Table 8.13. *Average number of articles written in different team composition by gender and success, and the Kolmogorov-Smirnoff 2 sample test results between success groups*

		Below Top 25%				Top 25%			
		Male		Female		Male		Female	
Research field	Team composition	OR	P	OR	P	OR	P	OR	P
Agricultural Sciences	female majority	0.25	0.00	3.55	0.00	0.13	0.00	7.59	0.00
	male majority	6.00	0.00	0.25	0.00	12.18	0.00	0.08	0.00
	diverse	0.93	0.00	1.08	0.00	0.93	0.75	1.08	0.75
Astronomy	female majority	0.25	0.00	3.54	0.00	0.13	0.00	7.98	0.00
	male majority	5.98	0.00	0.25	0.00	28.70	0.00	0.03	0.00
	diverse	0.93	0.00	1.08	0.00	0.40	0.00	2.47	0.00
Biological Sciences	female majority	0.25	0.00	3.83	0.00	0.20	0.00	5.00	0.00
	male majority	6.05	0.00	0.28	0.00	9.53	0.00	0.10	0.00
	diverse	0.94	0.00	1.15	0.00	0.88	0.00	1.13	0.00
Chemistry	female majority	0.25	0.00	3.58	0.00	0.12	0.00	8.10	0.00
	male majority	5.89	0.00	0.26	0.00	18.52	0.00	0.05	0.00
	diverse	0.93	0.00	1.10	0.00	0.70	0.00	1.44	0.00
Computer Sciences	female majority	0.25	0.00	3.55	0.00	0.05	0.00	19.07	0.00
	male majority	5.99	0.00	0.25	0.00	37.98	0.00	0.03	0.00
	diverse	0.93	0.00	1.08	0.00	0.66	0.14	1.51	0.14
Engineering	female majority	0.25	0.00	3.55	0.00	0.10	0.00	9.58	0.00
	male majority	5.99	0.00	0.25	0.00	21.88	0.00	0.05	0.00
	diverse	0.93	0.00	1.08	0.00	0.49	0.00	2.05	0.00
Geosciences	female majority	0.25	0.00	3.56	0.00	0.15	0.00	6.50	0.00
	male majority	5.95	0.00	0.25	0.00	13.33	0.00	0.08	0.00
	diverse	0.93	0.00	1.09	0.00	0.62	0.00	1.60	0.00
Humanities	female majority	0.25	0.00	3.55	0.00	0.07	0.00	15.38	0.00
	male majority	6.00	0.00	0.25	0.00	45.07	0.00	0.02	0.00
	diverse	0.93	0.00	1.08	0.00	1.70	0.36	0.59	0.36
Mathematical Sciences	female majority	0.25	0.00	3.55	0.00	0.05	0.00	19.34	0.00
	male majority	6.00	0.00	0.25	0.00	28.30	0.00	0.04	0.00
	diverse	0.93	0.00	1.08	0.00	0.57	0.06	1.76	0.06
Medical Sciences	female majority	0.30	0.00	3.88	0.00	0.17	0.00	5.88	0.00
	male majority	6.51	0.00	0.31	0.00	9.79	0.00	0.10	0.00
	diverse	1.02	0.07	1.26	0.00	1.11	0.00	0.90	0.00
Physics	female majority	0.25	0.00	3.53	0.00	0.11	0.00	9.13	0.00
	male majority	5.93	0.00	0.25	0.00	17.52	0.00	0.06	0.00
	diverse	0.93	0.00	1.08	0.00	0.26	0.00	3.85	0.00
Professional fields	female majority	0.25	0.00	3.55	0.00	0.14	0.00	7.40	0.00
	male majority	6.00	0.00	0.25	0.00	11.64	0.00	0.09	0.00
	diverse	0.93	0.00	1.08	0.00	1.10	0.38	0.91	0.38
Psychology	female majority	0.26	0.00	3.57	0.00	0.13	0.00	7.85	0.00
	male majority	6.13	0.00	0.25	0.00	10.80	0.00	0.09	0.00
	diverse	0.93	0.00	1.09	0.00	1.43	0.00	0.70	0.00
Social Sciences	female majority	0.25	0.00	3.56	0.00	0.11	0.00	9.47	0.00
	male majority	5.97	0.00	0.25	0.00	13.76	0.00	0.07	0.00
	diverse	0.93	0.00	1.08	0.00	1.32	0.00	0.76	0.00

Table 8.14. *Odds Ratios and significance tests of female and male scientists publishing at least one article in a given gender composition*

		Medical Sciences		Computer Sciences		Physics		Psychology		Social Science	
Metric	Success	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
F1-Score	5%	0.46	0.49	0.49	0.43	0.57	0.66	0.34	0.44	0.49	0.57
	10%	0.59	0.61	0.56	0.47	0.69	0.74	0.44	0.57	0.56	0.62
	15%	0.59	0.56	0.55	0.50	0.62	0.62	0.60	0.60	0.63	0.64
	20%	0.70	0.72	0.64	0.64	0.78	0.80	0.65	0.68	0.70	0.68
	25%	0.66	0.65	0.62	0.59	0.69	0.70	0.68	0.68	0.70	0.71
Accuracy	5%	0.78	0.80	0.95	0.89	0.77	0.78	0.87	0.87	0.82	0.83
	10%	0.75	0.77	0.89	0.84	0.75	0.78	0.82	0.84	0.76	0.79
	15%	0.82	0.79	0.86	0.80	0.80	0.79	0.81	0.79	0.78	0.78
	20%	0.75	0.76	0.84	0.83	0.75	0.76	0.79	0.80	0.74	0.73
	25%	0.78	0.77	0.80	0.77	0.77	0.77	0.77	0.77	0.76	0.76

Table 8.15. *Averages of Accuracy and F1-scores of 100 models predicting popular success by various thresholds in chosen research fields by gender. Models were ran 100 times separately by field, gender, success and threshold.*

	Creativity Model 3.		
	Coef.	**Std error**	**P**
Intercept	.428	.080	.000
Diversity	.050	.019	.009
Inclusion	.022	.019	.250
Diversity:Inclusion	.065	.018	.000
Integration	.092	.017	.000
Diversity:Integration	.016	.016	.310
Community size	.044	.019	.019
Number of elements	−.152	.008	.000
Team size	−.001	.000	.000
Ratio of newbies	.270	.110	.014
Game tenure	.042	.019	.029
Star prior	.291	.126	.022
Single firm	.094	.028	.001
Firm age	−.001	.002	.841
1994	.155	.072	.031
1995	.224	.063	.000
1996	.251	.059	.000
1997	.163	.055	.003
1998	.106	.051	.039
1999	.105	.049	.032
2000	.150	.045	.001
2001	.093	.045	.039
2002	.126	.045	.005
2003	.061	.046	.186
2004	.049	.048	.305
2005	−.110	.047	.020
2006	−.138	.047	.003
2007	−.269	.049	.000
2008	−.185	.055	.001
2009	−.354	.071	.000
Xbox 360	.258	.062	.000
Windows	.297	.029	.000
PlayStation 3	−.182	.043	.000
Macintosh	.103	.057	.070
PlayStation 2	−.275	.054	.000
PlayStation	−.164	.062	.008
Nintendo 64	−.418	.091	.000
Observations	5042		
R^2	.227		
Signif. codes: *:p<.05 **: p<.01 ***: p<.01			

Table 8.16. *Final OLS model of Creativity*

	Success Model 3.		
	Coef.	**Std error**	**P**
Intercept	−.474	.072	.000
Creativity	.099	.013	.000
Diversity	−.021	.017	.217
Integration	.027	.016	.080
Diversity:Integration	−.013	.014	.373
Inclusion	−.084	.018	.000
Diversity:Inclusion	−.002	.016	.882
Community_Size	.035	.017	.042
# of elements	.017	.007	.023
Team size	.001	.000	.000
Ratio of newbies	.283	.100	.005
Game tenure	.027	.017	.116
Star prior	.116	.115	.311
Single firm	.165	.025	.000
Firm age	.016	.002	.000
1994	.182	.065	.005
1995	−.110	.057	.055
1996	.038	.053	.482
1997	.107	.050	.032
1998	.115	.046	.013
1999	.101	.044	.023
2000	−.051	.041	.209
2001	.004	.041	.926
2002	.016	.041	.695
2003	−.068	.042	.105
2004	−.016	.043	.721
2005	−.148	.043	.001
2006	−.217	.042	.000
2007	−.183	.045	.000
2008	−.118	.050	.019
2009	−.127	.065	.049
Xbox 360	.056	.056	.322
Windows	−.060	.027	.025
PlayStation 3	−.212	.039	.000
Macintosh	−.111	.052	.031
PlayStation 2	−.148	.049	.003
PlayStation	.006	.056	.919
Nintendo 64	−.013	.083	.875
Observations	5042		
R^2	.108		
Signif. codes: *:p<.05 **: p<.01 ***: p<.01			

Table 8.17. *Final OLS model of Success*

Kotaku		
Position	***Name***	***Gender***
editor-in-chief	Stephen Totilo	Male
deputy editor	Maddy Myers	Female
editor-at-large	Riley MacLeod	Male
news editor	Jason Schreier	Male
features editor	Chris Kohler	Male
senior editor	Natalie Degraffinried	Female
senior writer (nights)	Brian Ashcraft	Male
senior writer (nights)	Luke Plunkett	Male
senior reporter	Michael Fahey	Male
senior reporter	Nathan Grayson	Male
senior writer	Heather Alexandra	Female
staff writer	Ethan Gach	Male
staff writer	Ari Notis	Male
staff writer	Ian Walker	Male
weekend editor	Zack Zwiezen	Male
senior video producer	Chris Person	Male
video producer	Paul Tamayo	Male
contributor	GB Burford	Unknown
contributor	Kevin Wong	Male
contributor	Joshua Calixto	Male
contributor	S.E. Doster	Unknown
contributor	Lee Yancy	Unknown
contributor	Kate Gray	Female
contributor	Harris O'Malley	Male
contributor	Kirk Hamilton	Male
art director	Jim Cooke	Male
staff illustrator	Angelica Alzona	Female
staff illustrator	Chelsea Beck	Female
staff illustrator	Elena Scotti	Female

Table 8.18. *Position, name and gender of the staff at Kotaku Source: https://kotaku.com/whats-a-kotaku-who-works-here-4586*

Gaminformer		
Position	***Name***	***Gender***
editor-in-chief	Andy McNamara	Male
executive editor	Andrew Reine	Male
senior reviews editor	Joe Jubel	Male
senior previews editor	Matt Miller	Male
digital editor	Brian Shea	Male
pc editor	Daniel Tack	Male
features editor	Kimberley Wallace	Female
senior editor	Matthew Kato	Male
senior editor	Jeff Cork	Male
senior editor	Ben Reeves	Male
video producer	Leo Vader	Male
video editor	Alex Stadnik	Male
advertising manager	Janey Stringer	Female
marketing coordinator	Rachel Castle	Female
circulation services	Ted Katzung	Male
fulfillment specialist	Michelle Biros	Female
office manager	Sarah Hansen	Female
creative director	Jeff Akervik	Male
senior production director	Curtis Fung	Male
senior graphic designer	Laleh Tobin	Male
graphic designer	Jen Vinson	Female
web designer/programmer	Margaret Andrews	Female
web designer/programmer	Kristin Williams	Female
software engineer	Shawn Gilligan	Male

Table 8.19. *Position, name and gender of the staff at Gaminformer Source: https://www.gameinformer.com/staff*

Eurogames		
Position	***Name***	***Gender***
editor	Oli Welsh	Male
deputy editor	Wesley Yin-Poole	Male
feature and reviews editor	Martin Robinson	Male
news editor	Tom Phillips	Male
features editor	Christian Donlan	Male
guides editor	Matthew Reynolds	Male
senior staff writer	Robert Purchese	Male
staff writer	Chris Tapsell	Male
reporter	Matt Wales	Male
reporter	Emma Kent	Female
video team	Ian Higton	Male
video team	Johnny Chiodini	Male
video team	Aoife Wilson	Female
technology editor, digital foundry	Richard Leadbetter	Male
senior staff writer, digital foundry	Tom Morgan	Male
staff writer, digital foundry	John Linneman	Male
audience development director	Jon Hicks	Male

Table 8.20. *Position, name and gender of the staff at eurogamers https://www.eurogamer.net/articles/the-eurogamer-staff*