

# Breaking Gender Code:

## Visibility, power, and gender in creative coding cultures

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## **Abstract**

This project is a radically multidisciplinary examination of how gender intervenes in programming culture. Through three studies, I level a feminist challenge to the meritocracy of technology. I show how gender norms prescribe individual capacity for action, perpetuating “natural” masculine ability. By reviewing existing scholarship, I show how academia has perpetuated the narrative of a gendered difference. I explore how computational studies have quantified success and attributed womens lack of representation to feminine behaviour as opposed to categorical discrimination.

In Study I, I conduct a survey into the perceptions of gender stereotypes in sites that afford anonymity. Comparing Reddit, Twitter, and 4chan, I show that gender norms dictate perceptions of hostility and technical knowledge. The exploratory analysis finds male-dominated spaces are social read as hostile, even for men. Study II examines gender on Stack Overflow. I combine computational approaches with a non-binary inference of gender to analyse how gendered identity dictates interaction. Using social network analysis, I find that even in anonymity communities are organised by gender. I also show that the inferred gender of a user can be predicted by how they are spoken to. I conclude that Stack Overflow obscures rampant sexism behind narratives of being hostile to new users. In Study III, I observe gender performance and boundary making at hackathons. I participate in the coding competitions to the fullest extent, programming alongside my teammates for an intensive 24-hour period. Through the sharing of memes and ironic jokes I show that gender is the mediator of legitimate technical knowledge. I delineate how masculinity is embodied in tech start-ups and geeks to define femininity as incompatible with computers. Overall, this feminist project conducts a social structural analysis to reveal that sexism is fundamental to technology culture.

*“Women, on the other hand, had to wield their intellects like a scythe, hacking away against the stubborn underbrush of low expectations.”*

- Margot Lee Shetterly, *Hidden Figures*

# Acknowledgements

*“She got on with her education. In her opinion, school kept trying to interfere with it”*

- Terry Pratchett

I never expected to enjoy education. This might seem strange, even contradictory, given the document on which this is printed; bound in a doctoral thesis submitted to the University of Oxford. But education was difficult. Schools came full of mounting pressures, challenging to navigate with my own catalogue of impairments. Learning, however, was never a problem. When I was thirteen, my dad told me that I should be proud of how I consistently mispronounced words. It was evidence, he said, of all the reading and learning I had done on my own. At sixteen, I first learnt what a doctorate was. Sat in the very back of my History class, one of the other students shot up a hand, and asked why a particular text was written by a “Doctor”. Our teacher patiently explained that it was a title given to those who had been awarded a PhD and that you could be a doctor of whatever you liked, “as long as you were good enough”. I was utterly enticed by the concept - the promise of learning so much that your name could reflect it. Yet, I quickly forgot this personal revelation. When I finally attended University (after a misspent year thinking I wanted to be an accountant), I fell in love. The debating and questioning which got me into such trouble at school, was now valued and even prized. Speaking to my mum on the phone one evening she referred to learning as “my food, my fuel”, the implication being that it was completely necessary to my survival. Through every difficulty, loss, and heartbreak, I was completely certain what I wanted to do. I didn’t know how to do it, or even what subject I wanted to do it in, but I was sure (again) I was going to follow my sixteen-year-old dream and become Dr. Brooke.

Over a decade later, and I am well on my way. I have gone from Politics, to International Relations, to Sociology, to the work encompassed in these pages. But I would be amiss to attribute this achievement to my own individual effort. First, I would like to thank my supervisors, Dr. Bernie Hogan and Dr. Joss Wright. To my primary advisor, Dr. Hogan, I especially thank you for pushing me outside of my comfort zone and always challenging me to do better. Thank you for introducing me to Python, and helping me take my first tentative steps. I am grateful to my supervisors, and assessors throughout the stages of my doctorate who have provided vital feedback that allowed this project to grow.

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*"There is a curse. They say: May you live in interesting times."*

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# INTRODUCTION

## “HELLO WORLD!”

---

*“A new, a vast, and a powerful language is developed for the future use of analysis, in which to wield its truths so that these may become of more speedy and accurate practical application for the purposes of mankind than the means hitherto in our possession have rendered possible.”*

- Ada Lovelace

In 1843, the first manifesto of the computer was published. The treatise was Ada Lovelace’s (1843) *Notes from the Translator*, a series of notes on the description of the “Analytical Engine”, which set out the first conception of a computer.<sup>1</sup> Signed only with her initials, Lovelace’s appendices comprised forty-one pages of the sixty-six page document. What they contained was not merely a translation, but the first computer programme - a detailed explanation of the computation of Bernoulli numbers according to instructions on punched cards.<sup>2</sup> Lovelace’s contribution was an overview of the practical engineering of data, memory, and programming, the computation of which is still understandable nearly two hundred years later.

In contemporary accounts, much virtuous effort has been spent in ensuring that the contributions of Ada Lovelace are not forgotten. She is reimagined in comic books, featured in period dramas, and is

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<sup>1</sup> *Notes from the Translator* was an addendum to the English translation of Luigi Menabrea's *Sketch of the Analytical Machine*, a reaction to engine proposed by Charles Babbage (“the Father of Computing”).

<sup>2</sup> Bernoulli numbers are particularly amenable to machine calculations because they are defined *recursively*. This means that each number is determined using the one before it, requiring the storing of numbers in a memory.

the eponym of University classroom and technology company boardrooms alike.<sup>3</sup> There is the *Ada Lovelace Institute*, which works to promote informed public understandings on the use of artificial intelligence in different societal groups. The contribution of women to the progression of technology has become a new conventional wisdom, with figures such as Katherine Jackson, Grace Hopper, and Adele Goldberg commonly referenced as “forgotten female programmers” (Haigh & Priestley, 2015, p. 21).<sup>4</sup> This collective remembering does show that women’s involvement and systematic exclusion from computing is not new, or without history. Whilst the popular imagination is so seduced by the ideological act of remembering women’s contributions, this becomes conceited if the same critical eye is not applied to the current state of affairs. Women are *still* excluded from computing. This thesis provides recommendations for the inclusion of women in creative coding culture. I map how we can dismantle gender prejudice in this culture, resulting in women’s tangible inclusion in technological developments that extends beyond historical projects of remembering

The cause for the absence of women in technological careers is widely explained by the metaphor of the “leaky pipeline”.<sup>5</sup> The proposition being that if you pour water (young women) into a pipe, and it leaks along its length (women exiting at various points), very little water (professional woman leaders) will emerge at the end. The purpose of the metaphor is to argue that if only later leaks are patched, then there will still be a relatively small number of women “emerging” at the end, as there are leakages all along the pipeline. The metaphor is also used to substantiate the claim that until the earlier (educational) leaks are fixed, there is no point paying attention to the lack of women in leadership and professional positions.<sup>6</sup> The pipeline metaphor connotes a belief that the “end” is a

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<sup>3</sup> An example of the reimagining of Lovelace in a graphic novel is *The Thrilling Adventures of Lovelace and Babbage: The (Mostly) True Story of the First Computer*, by Sydney Padua. The novel has done much to elevate Lovelace and an important historical figure, based on thorough research on the biographies of and correspondence between her and Babbage.

<sup>4</sup> Katherine Jackson (along with Dorothy Vaughan and Mary Jackson) has been immortalised in a 2016 book by Margot Lee Shetterly entitled *Hidden Figures: The American Dream and the Untold Story of the Black Women Who Helped Win the Space Race*. It was made into a film of the same name later same that year.

<sup>5</sup> “Technological” relates to the general use of technology by people, whereas “technical” refers to specific applications and outcomes.

<sup>6</sup> This has the underlying assumption that one must start programming at a very young age.

desirable place for women, as if the achievement of high-status position negates a field rife with sexism and culturally engrained bigotry. The moral imperative of encouraging women into technology is flawed if the pipeline leads to a “sewage treatment plant” or “meat grinder”.<sup>7</sup> The “pipeline” metaphor is not useful. It simplifies a picture of historical and cultural biases into individual experiences of “leaking out”, placing the onus with those who leave technical fields. This language of “pipes”, “leaks”, and “drips” distracts from structural discrimination, prejudice, and agency in the process of exclusion. Women are not trickling out of the system, they are forced out by sexist institutions that associate technical expertise with anti-social, erratic young men.

## **Research Questions and Thesis Structure**

The remainder of this Introduction provides an overview of the structure and context of this project and summarises its main conclusions and contributions to academic discourse. I use the phrase *creative coding culture* throughout this thesis to investigate technological communities, without the masculine stereotypes associated with terms such as “hacker” or “developer”. The overarching question of this project is *how does gender intervene in creative coding culture?* In first outlining existing scholarship the literature review (Chapter I) will present the case for gender as intervention, situating the project within the academy. The project is then divided into three distinct studies, each of which focuses on a particular point of informal participation in creative coding. Study I focuses on how perceptions of gender and hostility mediate legitimate knowledge in anonymous spaces. Study II examines the forms in which gender is visible in programming forums, and the impact it has on knowledge sharing. Study III looks at lived experience, analysing how gender is performed in the embodied space of coding competitions called hackathons. Table 1 outlines the research questions associated with each distinct study.

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<sup>7</sup> These comments were tweeted by a woman who work in high status positions in technology companies in the USA, and then widely reported across media outlets (Pagano, 2014).

*Table 1 Outline of Chapters, Studies, and Research Questions*

<b>Chapter I</b>	<b>Literature Review</b>	
<b>Chapter II</b>	<b>Study I:</b> Perceptions of Gender and Hostility	<b>RQ1</b> Does the gender majority of a platform affect perceptions of hostility?
		<b>RQ2</b> Do gender-based stereotypes affect perceptions of hostility?
		<b>RQ3</b> What are the gendered assumptions of technical knowledge in anonymous spaces?
<b>Chapter III</b>	<b>Study II:</b> Reception to Gender on Stack Overflow	<b>RQ4</b> How salient is users' gender on Stack Overflow?
		<b>RQ5</b> Is there a gendered difference in Answer effort and reward?
		<b>RQ6</b> Is there a gendered difference in users' interactions on Stack Overflow?
		<b>RQ7</b> Is condescension gendered?
<b>Chapter IV</b>	<b>Study III:</b> Gender Expectations at Hackathons	<b>RQ8</b> How is gender visible at hackathons?
		<b>RQ9</b> What does communication at hackathons look like?
<b>Chapter V</b>	<b>Conclusion</b>	

Chapter I begins by asking *How did we get here?* (Section I). Using historical and contemporary examples, I show how the development of technology has actively sought to exclude women, painting computers as “naturally” masculine. Starting with a definition of gender in the terms of Risman’s (2012) social structure, I show how technology has been shaped by social relations. Sexism is as fundamental to technology as the code, as will be shown to be foundational in both the informal and formal avenues of creative coding. The discussion here also looks at modern conceptions of gender in the technology industry, and how start-up, entrepreneurial narratives have recast gender norms. I conclude that gender-technology norms have also impacted how the history of technology is recorded and thought about.

Building on the situated approach, Section II, *The Gender Code*, dissects the gender norms that are currently associated with technology. I lay out the functioning of stereotypes and how they are internalised on an individual level, as well as operating on larger interactional and cultural bases. Additionally, I analyse how the masculine dominance of technology is perpetuated by stereotypical beliefs and categorical thinking. Adding to the critique in Section I that history has recorded computing as masculine, I problematize efforts within the academy to study the gender divide. I

argue that much work in the social data science nexus recreates a gender binary, and in some instances, justifies womens subjugation.<sup>8</sup>

Following the literature review in Chapter I, Chapter II is the introduction, methods, and results of Study I. Drawing largely on the classifications of stereotypes in Chapter II, Study I looks at the pre-existing perceptions that an individual may have prior to seeking to participate in creative coding culture. The point here is that a person is culturally situated, and their pre-established beliefs and norms of a culture will dictate whether they seek to *belong*. Is creative coding culture for someone like them? Using a survey, I examine assumptions of gender, hostility, and role-based expectations of competence. With much media coverage and academic reporting highlighting the exclusion of women, individuals are aware of the masculine dominance of technology. The study concludes that gender roles are fundamental to attributions of legitimate knowledge and perceptions of hostility.

In Chapter III, Study II builds on the gendered perceptions that are emphasised in the exploratory findings of the first study. The focus here is on the Question and Answer programming forum *Stack Overflow* [hereafter SO]. Commonly described as a “knowledge market”, SO is the most popular programming advice platform, often framed as indispensable to novice and expert programmers alike (Ford et al., 2016; May et al., 2019). However, it has a reputation for hostility, condescension, and sexism. The data used for this study is taken from the quarterly Internet Archive Data Dump. It consists of all of the interactions on the forum from its founding in 2008, to when the data was last updated in November 2019.<sup>9</sup> Modifying an established classifier, *genderComputer* (Vasilescu et al., 2012), Study II incorporates a five-level understanding of gender, including anonymous users. I conclude that gender salience is mediated by reputation and reception of users. I find that feminine users are unfairly evaluated on the basis of their gender, even when their Answer effort is comparably

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<sup>8</sup> Nexus as the meeting point for various other fields.

<sup>9</sup> Previous dumps were analysed before this, November 2019 reflects the last time that new data dumps were incorporated into the dataset.

higher than masculine users.<sup>10</sup> Overall, the culture of SO is permeated by bias against women, regardless of capability, which undermines the painting of SO as meritocratic.

In the final Study in Chapter IV, I complement the statistical methods of Study I and II with an ethnographic approach. I conduct observations of “hackathons”, intense events in which programmers in small teams compete over a straight 24 to 36-hour period. Building on the argument on cultural situating in Chapter I, I look at how the masculine nature of coding is justified and normalised in embodied spaces. As a *girl* at a hackathon, I reflect on how I become the subject of my own research, how my perception of my own ability is mediated by my gender, and how others interact with me in a technical competition. I outline how gender is characterised at hackathons, and how the multiple forms of masculinity work to establish the geek as the central character. I show how this tension is revealed in memes that are created and shared at events,<sup>11</sup> and contrast this with the performance of gender in start-up culture. In concluding Study III, I reveal how the individualism of technology culture works to refute claims of institutionalised, systemic discrimination.

In Chapter V I situate the conclusions of the project by first reflecting on my experiences as a woman programming. Informed by Haraway (1988), I reflect on my own situatedness and how this is ultimately beneficial to the feminist project. From this standpoint, I consider the thesis as a work of activism. Firstly, in terms of its theoretical and methodological contributions, but also in terms of providing tangible recommendations for gender inclusivity. Ultimately I conclude that despite appearances, the problem of inherent sexism cannot be solved using technical and individualistic solutions, as social problems require social solutions.

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<sup>10</sup> *Answer effort* is specifically operationalised in Study II based on features associated with a high quality Answer. For example, text/context given to links to specific documentation.

<sup>11</sup> In this case, image based jokes that reflect an in-joke. I conduct an in-depth discussion on the gender power of memes in *There are no girls on the internet* (Brooke, 2019a), which builds on the work of Ryan Milner (2016).

## Significance of Research

The contributions of this project are threefold. First, I show how gender as social structure is a useful framework for analysing gender power in creative coding culture. I account for how a portion of the literature has worked to recreate a binary understanding of gender in technology, and how qualifications of “success” and “ability” ultimately recreate the stereotype of incompetent femininity. Prejudice is symptomatic of wider power relations. An uncommitted chastising of individual instances of sexism does little to challenge wider power structures. I show how technology culture needs to be understood as fundamentally hostile to women. Only by acknowledging this can we take steps towards greater inclusivity.

Secondly, I show how computational and ethnographic approaches can be successfully combined to provide a multi-layered understanding of gender and culture. I illustrate how power needs to be analysed on the level of culture. Academic enquiry that is focused on particular manifestations of sexism localized in platforms fails to account for the wider picture of lived experience. A person is more than the sum of multiple users. As a “user” they are not fragments of identity but aspects of a wider whole. In taking platform-centric approaches, research also tacitly recreates ideas of Internet exceptionalism.<sup>12</sup> Rather, I emphasise that researchers should acknowledge what culture they are attuned to within a given platform, and that the incorporation of a multisite framework is beneficial to the study of a social phenomenon.

Finally, not only does this project make a valuable contribution to academic work, but it also extends beyond doctrines of masculine (computational) and feminine (ethnographic) approaches to academia itself. I problematise the male/female, quantitative/qualitative, computational/ethnographic dichotomies as unhelpful. Such binary structures in themselves impose political frameworks on academic research. I show how transgressing these boundaries offers rich information into how these

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<sup>12</sup> Internet exceptionalism is the idea that online interaction is unique in comparison to other communication technologies, such as telephones or SMS.

cultures operate by accounting for the situatedness of coding. In the following section, I provide the academic context for the challenging of these boundaries, and the implications of doing so within computational social science.

## Gender and Science

Explanations from within the academy for the lack of women's representation in the sciences frequently focus on the inherent masculinity of science. They argue that the positivist, empirically based, objective rationality of the discipline is largely closed off to women. There are four dominant perspectives in this category (adapted from Blickenstaff, 2005):

- *Feminist Standpoint Theory*: Harding (1991) proposes that women's positions outside of the dominant social group endow them with a more objective view of the world than men have. She proposes that power distorts the perspectives of those in the dominant position, and that knowledge claims should be judged taking account of the social context in which they were made.
- *Situated Knowledge*: Whilst agreeing with Harding that there are different perspectives, Haraway (1988, 1991) contends that these are not fixed, as individuals can take on different perspectives at different times. Haraway (1991) is a proponent of a varied research perspective that encompasses both blind spots (acknowledging what is omitted) and focal points (recognising limits).
- *Feminist Empiricism*: Longino (1990) argues for "contextual empiricism" in which claims to truth are aligned to available evidence, but where scientists use their politics to guide theoretical positions. She proposes that scientists should acknowledge their biases and work from their political position.
- *Binary Rationality*: Gilbert (2001) surmises that the origins of science in enlightenment rationality means that it is masculine by its very nature.<sup>13</sup> She positions scientific rationality as opposed to emotion, objectivity to subjectivity, and science to nature. The first category is associated with men, and its opposite with women. The emphasis is placed here on divorcing emotions from work in scientific activities.

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<sup>13</sup> Rationalism is the view that knowledge is rooted in human reason.

Moving to social sciences more specifically, Oakley (1998) shows how feminist paradigms have challenged the incorporation of quantitative methods as part of the “malestream”. Qualitative methods are perceived as aligned with a feminist perspective, while quantitative (computational) are inherently defensive of the (masculine) status quo. Dichotomies and binaries are neither a property of nature or human experience (Du Bois, 1983). The idea of opposition between two elements which denies any middle ground can not be empirically derived (Du Bois, 1983). It is a social construction informed by a basic rule of patriarchal societies; opposition between men and women (Butler, 1990; Oakley, 1998). As Oakley (1998) argues, a range of techniques can be rehabilitated into critical social research, and the gendering of methods is itself a social construction. For feminists to make a case against quantitative ways of knowing by rejecting rationality/science as masculine, whilst embracing embodiment/experience as feminine, they are “buying into the very paradox that [they are] protesting about” (Oakley, 1998, p. 725). She cautions against researchers losing themselves in debates on paradigms, rather than looking forward to the emancipatory potential of (social) science (Oakley, 1998). Across the feminist perspectives outlined above, is the conception that political and social power affects who possesses masculine knowledge, what kind of questions they seek to answer and how they interpret the results they obtain. Taking into account Oakley’s (1998) objections, if only one type of person is able to conduct the process of scientific enquiry then the field will be “narrow and inbred” (Blickenstaff, 2005). The framing of science as masculine is relevant to the development of technology for two reasons. First, if science is thought about as masculine this mediates who seeks to be a computer scientist. Secondly, the systematic exclusion of women from computing and technology is overwhelmingly justified by invoking *bad* scientific citations.<sup>14</sup> If women’s exclusion from technology is scientifically justifiable, it is natural, and it follows that it is unchangeable.

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<sup>14</sup> I start Chapter I with a recent (and infamous) example of such citations of *bad* science, namely James Damore’s memo, entitled *Google’s Ideology Echo Chamber*.

## The Feminist Project

This thesis contributes to a *feminist project* concerned with challenging the “natural” masculinity of technology, working to bridge the divide between academia and activism. In such projects, theoretical work is valuable if it can be taken into the public domain and bring about material, measurable, transformation. By naming “inequality” what has previously been considered as “natural” we create an impetus for change (Risman, 2004). My research shows that gender power operates on a cultural, interactional, and individual level to perpetuate the ordinary masculinity of technology. Not only do I show how this ideology is historically situated (Chapter I), I also show how research into gender norms has further perpetuated the dichotomy of the capable man and incompetent woman (Chapter II). This project also has a unique methodological contribution in its combination of computational and ethnographic analysis. My methodological approach encompasses not only the computational tools (knowledge production) of my research object, but also the subjectivity of lived experiences in an ethnographic account of programming events.

In three distinct studies I examine: (1) perception of gendered knowledge and hostility; (2) reception of gendered identities in programming forums; (3) expectations of gender in embodied programming competitions. Building on Oakley’s (1998) criticism of the “paradigm argument”, I use Haraway’s (1988, 1991) situatedness to guide my investigation into the politics of the tools I use. On an epistemological level, this reflects an effort to think outside of a duality of objectivity-relativism. Objectivity cannot live up to its promises of neutrality as a “view from nowhere” which masks a very specific white, male position (Haraway, 1988, p. 589). In this way situatedness is ontological and political in producing the conditions for imagining alternatives; a critical and *better* account of the world by acknowledging the biases inherent in experience. Visibility is vital. As Haraway (1988, p. 583) shows, “eyes are not passive instruments of seeing, they are actively organising the world”; ways of seeing (and who is seen) are “ways of life”. In researching power, we must ask questions on visibility: Who gets to see? Who is blinded? Who gets to have more than one point of view? This thesis considers the process and practice of objectivity and how a researcher’s methodological

choices are situated. This is not a totalising condemnation of objectivity, but a bid to recognise its limits.

An indispensable part of this project is a conversation in clear terms. Too often procedures of computation and abstractions of gender theory are discussed in languages of boundary making. I have argued elsewhere that gender studies and data science are portrayed as fundamentally incompatible subjects (Brooke, 2019b). Efforts to combine the paradigms can recreate binary classifications, and even fail to operationalise gender beyond anything other than “male” and “not-male” sensitive only to the algorithmic classification of male associated behaviour. This is not the same as researching gender. With this in mind, each statistical procedure, computation, and model in this project is explained in depth – as is every conceptualisation of gender and social theory. To some this may be unnecessary, yet the motivation is political, for both activism and boundary unmaking. Scholarship which rests on assumed knowledge fails to reach its full capacity of advocacy.

This project focuses on the Anglosphere, English-speaking nations that share a common cultural and historical ties to the UK. In not confining the project to a singular country, I am more faithfully representing how users interact across nationalities on online platforms. The sampling frame included America, Canada, and the UK. The common cultural heritage of these countries means that they broadly share conceptions of gender, allowing for a measure of generalisation (Butler, 1990; Haraway, 2006).<sup>15</sup> However, this is not to say the project is a complete picture of gender in creative coding cultures. A focus on the Anglosphere means that I limit my study to a Western, often white, conception of gender. I am not able to foreground intersectionality in my work, with ethnicity either obscured in my data or absent from my ethnographic procedures. I acknowledge this absence not to justify it, but rather to propose that the methods I use and the findings I present be taken forward.

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<sup>15</sup> It was not always practical to use the same geographic sample in each study. In Study III, I focus on hackathons in the UK. This is because of the practical costs that would be incurred by including countries from the USA and Canada.

My work considers power and domination across multiple contexts. It is the documenting of how this power functions and persists which can be of particular use to intersectional research. The high-status group in my studies were ubiquitously white, and this is not an observation that should go unnoticed. This is a feminist project, and where identity categories such as race, ethnicity, and class, mediated gender this is noted in the studies. I support any and all efforts to expand my critiques. Outside of intersectionality, my research focuses on informal avenues of creative coding – the space in between formalised institutions (University, companies) and more nefarious technological cultures (hacking, Open source).<sup>16</sup> It is my hope that in focusing on where these tenets meet, I am able to encapsulate elements of them both, and their effect on each other in bilateral causal relationship.

This project is a feminist challenge to the masculine dominance of technology. This provocation is first visible in the research subject, examining how gender creates barriers to legitimate participation in programming. This political stance is also apparent in the method and operationalisation of the project. In combining computation and ethnography, I am challenging the binary, hierarchical framings that are damaging in the pursuit of emancipatory social science, not only in gender categorisations, but also in methodological dichotomies. Noting the shortcomings of previous historical and academic accounts, this thesis refutes the natural masculinity of creative coding cultures.

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<sup>16</sup> As will be expanded upon in the next Chapter, the Open Source movement is arguably the most openly hostile cultural, in terms of sexist discourses.



# CHAPTER I

## LITERATURE REVIEW

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*“I think it’s very important to get more women into computing. My slogan is ‘Computing is too important to be left to men’.”*

- Karen Spärck Jones<sup>17</sup>

Sexism is fundamental to computer culture; it is visible everywhere. In 2017 James Damore, a Google software engineer, wrote an “anti-diversity manifesto”, entitled *Google’s Ideological Echo Chamber*. Drawing on theories of biological determinism, the memo asserts that women are intrinsically and innately different to men and are therefore less capable of working in the same industries (Damore, 2017). Painting gender roles as *natural* and invoking scientific claims as unassailable and irrefutable means rejecting demands for emancipation. However, what appears as “natural sex” is constructed through repeated performances, and these performances in turn reproduce traditional categories and expectations of gender (Butler, 1990), such as the expectation that women don’t write code. A year later, Damore attempted to sue Google for firing him, claiming that this was discrimination against white, conservative men (Wong, 2018).<sup>18</sup> In more recent developments, Google has significantly rolled back its diversity and inclusion initiatives in an attempt to avoid being perceived as “anti-conservative” (Glaser, 2020). The memo, and

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<sup>17</sup> Former professor of Computers and Information at Cambridge Computer Laboratory. Spärck Jones was a vocal advocate for women in computing and technology; she introduced the concept of inverse document frequency (IDF) used by most search engines today.

<sup>18</sup> In October 2018, Damore and the other former Google employee dismissed their claims in the lawsuit, in order to pursue private arbitration against Google.

subsequent press coverage, served to illuminate the hostilities to women that are embedded in technology culture. These hostilities are not focused on specific skills or incidents, but derive from a general emphasis on social domination and determinism, which is informed by an erroneous amplification of gendered differences.

Since reaching a peak of 37% in the academic year 1984-1985, the number of women involved in computer science has persistently declined, whilst other Science, Technology, Engineering, and Mathematics (STEM) disciplines have seen a rise in women's representation (Ford et al., 2017; Women in STEM UK, 2018). There is evidence for this picture being replicated in online spaces and informal cultures of programming as the proportion of women contributing decreases (Ford et al., 2016; Terrell et al., 2017; Vedres & Vasarhelyi, 2019). In the early days of the Internet, anonymous online spaces were heralded as an identity utopia, with a multiplicity of self-expression and removal of prejudice (Korobov, 2013; Kramarae, 2001; Turkle, 2017). But why is programming still such a "boys club"? How do perceptions of gender in technological and computational cultures intervene in women's participation? In this review of the literature, I will show how the history of creative coding has been documented as masculine and as the purview of men.<sup>19</sup> In turn, I argue that this literature has itself perpetuated sexism in technology culture, further contributing to the exclusion of women.

Technology is framed as naturally masculine. Implicit in this assumption is the "unnaturalness" of women working with computers, owing to an innately determined lack of technical ability. But this conception of "naturalness" comes from a social history whose construction reflects dominant

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<sup>19</sup> *Programming, hacking and developing* are terms that are often conflated. But they reflect a diversity in formal and informal conceptions of computer culture. Programmer is the overarching term, referring to an individual who can write scripts and solve problems using computer code. A hacker is synonymous with a creative coder. In this context, they create by programming computers and are defined by originality. A developer is a formally trained programmer. Whilst all developers are programmers, many formally trained developers are not creative enough to be considered hackers. Developer is the modern term that is often used to refer to programmers in a formal institutionalised setting, whereas hacker is more reflective of an informal passion and creativity in programming.

discourses that decide who gets to *legitimately* participate. The perceived naturalness of masculine affinity for technology in turn creates stereotypes that perpetuate a masculine history, and so the story is consolidated. In a self-perpetuating cycle, this has led researchers to equate *what* men and women do with technology to *why* there is a gendered difference. The lineage of this equivalency is examined in *Section I: How did we get here?*, as I explore the informal and formal history of computing. In *Section II: The Gender Code*, I turn to contemporary scholarship on gender stereotyping and technology, examining how work on gender difference has recreated a “natural” binary within the academy. Overall this project encompasses three elements in characterising the visibility of gender: perception of absence, reception of presence, and expectations of behaviour. Overall, this thesis follows the story of a creatively coding woman - from perceiving the space as an outsider, to her active, legitimate, engagement.

## **Section I: How did We Get Here?**

The history of technology extends beyond the invention of computers. We use technology to measure time, to qualify periods of change, and define generations. In recounting the development of computers, Mackenzie and Wajcman (1999) show how technical systems are classed as “deterministic”, seeming to follow trajectories that are comparable to natural laws. In this way, computers are seen as external to social hierarchies. The most famous example that they highlight is Moore’s Law (1965), named for the cofounder of Intel, Gordon Moore. The law describes how twice as many transistors can fit on a chip every year, adjusted to doubling every two years in 1975 (Mackenzie & Wajcman, 2006). But technical systems aren’t just technical, as such technology functions in networks of meaning creation. As discussed in the Introduction to this project, the history of scientific development is inherently masculine. Technical systems are

inscribed with meaning, and function within political, organisational, and ultimately social structures.

It is perhaps easiest to see how technology is shaped by economics. As Mackenzie and Wajcman (2006) show, technology is discussed in terms of goal orientation, without which such terms as “innovation” make little sense. Innovation here is prized above all else in a story of maximising *future* profits and fundamentally financial motivations. As shown by the dot-com bubble, an expanding user base and access significantly affects market projections.<sup>20</sup> The future of technologies is often determined by adoption, and this means that the history of technology has considerable significance for the study of the social shaping of technology. Mackenzie and Wajcman (2006) also highlight how technologies are path-dependent, where past events exercise continuing influence. The implications of this are extensive, deciding how technologies interact with ethnicity, race, class, and gender as well as other social striations. Social science has the capacity to be emancipatory (see Introduction) and thus it is imperative to be aware of how we arrived at a masculinist understanding of technology in order to critique current power relations. My focus here is on how women were, have been, and continue to be excluded from a field that has been accorded such priority. The following section serves to show how gender structure operates, how it has moulded technology into its current form, and how sexism is firmly rooted in technology.

## **Gender as Social Structure**

In this section I will argue that gender has moulded technology into its current form, and that sexism is firmly entrenched in technology. Technology is imbued with the value of its creators (Latour, 1999), but it is often framed outside of society, with social relations and hierarchies

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<sup>20</sup>The dot-com bubble (tech bubble/Internet bubble) was a stock market bubble caused by excessive speculation in Internet-related companies in the late 1990s, a period of massive growth in the use and adoption of the Internet.

imposed post-hoc. This externalisation allows for discussions in which gender is imposed on technology, as if the latter were value-neutral. In understanding the role of gender in technology, it is helpful to look at theorists who have described the way gender functions in Western society. In *Doing Gender*, West and Zimmerman (1987) argued that gender is something we *do*, not something that we *are*. Referencing the work of Goffman (1956), West and Zimmerman (1987) discuss how gender is exhibited through interaction. It is this “doing” that contributes to the formation of “natural” sex. They see *doing* gender as a micro-political activity that is “ongoing ... embedded in everyday interactions”.<sup>21</sup> In *Stigma*, Goffman (1963) establishes how the categorising of persons defines what is ordinary or natural for individual members of each of these categories; what is “normal” for how a male versus a female should act. This is their social identity, where an individual’s anticipations are transformed via normative expectations into “righteously presented demands” (Goffman, 1963). Following this, when an individual presents an attribute that marks them as different to the category of persons they seem to be in, they are stigmatised:

*“thus reduced in our minds from a whole and usual person to a tainted and discounted one”*

(Goffman, 1963)

In other words, within the gender performance framework, to *do* gender incorrectly is tantamount to a failure of identity. The overarching structure of gender defines the normative actions of the individual at a micro level, defining the tolerable and intolerable deviations.

More recently, Deutsch (2007) argues that the work of West and Zimmerman (1987) needs to be reframed. She shows that the theory of doing gender has become “a theory of persistence and the inevitability of inequality” (Deutsch, 2007, p.106). Gender operates at numerous levels (Deutsch,

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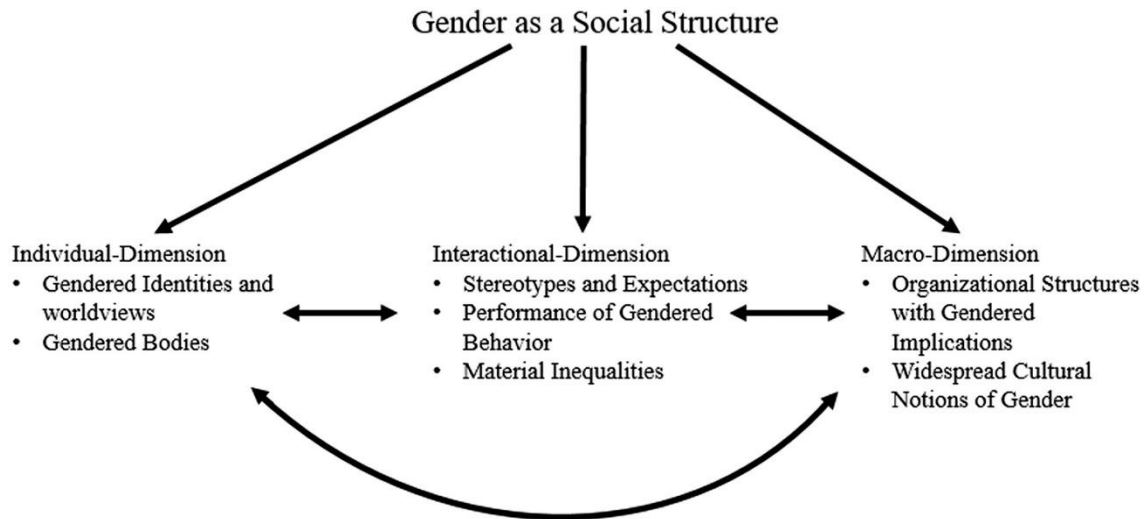
<sup>21</sup> I will return to the micro-political functioning of gender roles in a discussion of the work of Deleuze and Guattari (1989) in Chapter I, Section II, under the subheading “I am who I think you think I am”.

2007; Risman, 2004). Butler (2004) outlines that gender requires its own distinctive disciplinary regime, where conflation of biology with the matrix of masculine and feminine is precisely to miss the point that normative gender is a coherent binary. Masculine/feminine is not synonymous with male/female. In this framework Butler (1990) outlines heteronormativity in a “matrix”, where bodies, gender, and sexual desires are naturalised and stabilised.<sup>22</sup> In looking to how we might understand how to challenge this matrix, Deutsch (2007, pp. 117-118) argues that we need to research the relations between the structural (“society”) and interational (“action”) levels. Building on this scholarship, Risman (2009) argues that a tautology has emerged where whatever a group of men, boy, or women do is equivalent to *doing* gender. Paradoxically, gender performativity is discussed in terms tantamount to functional sex roles theory. Rather, she proposes, in *undoing* gender (see Deutsch, 2007), scholarship needs to challenge the essentialism of binary distinctions between people.

Gender is framed by Risman (2004; 2013) as *social structure*, on the same analytic plan as economics and politics – structures existing outside of individual desires or motivations. From this standpoint, both actions and the ability to choose are patterned by social structure (Risman, 2004).

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<sup>22</sup> Butler (1990, p. 151) proposes that a hegemonic model of “gender intelligibility” assumes that for bodies to cohere, there must be a stable sex expressed through a stable gender. Masculine expresses male and feminine expresses female. Here, the practice of heterosexuality is largely compulsory.



*Figure 1 Gender as Social Structure, Risman and Davis (2013, p. 745)*

As shown in Figure 1, we can see how cultural processes form stereotypes, and how this affects the ways in which individuals interpret the behaviour of others. Gender stereotyping and its effects are discussed in depth in Section II. Rather than a result of a determination, norms are developed when actors occupy similar positions in the social structure and evaluate their own options vis-à-vis the alternatives of similarly situated others (Risman & Davis, 2013). From this comparison, norms and feeling of relative deprivation/advantage evolve, as context creates action indirectly by shaping perception and directly constraining choice (Risman, 2004). Gender defines how one may see “similarly situated others”, meaning that women will be unlikely to compare their lives to men due to the prominent argument of biological or socialised sex-difference. For Risman (2004), therein lies the power of gender. As human beings are dichotomised (binarised) into types, the differentiation diffuses expectations for and claims to gender equality (Risman, 2004). Gender as social structure determines the shaping of labour and the shaping of technology, narrating difference as natural. Importantly, as Risman (2004) suggests, academics have the opportunity to not just reproduce gender structures, but to interrogate them. In viewing gender as social structure, feminist research can illuminate avenues by which the structure might be dismantled.

First it is important to ascertain the function of these gender perceptions (Study I) before going on to interrogate their role in social interaction (Study II) and culture (Study III).

## **Women and Technology**

A common view of technology is that it exists outside of social hierarchies, external to social interactions. However, the Internet and technology do not neutrally inform or simply reflect society, as its use and the very act of its creation involve bilateral shaping; technological advances shape culture, and culture shapes technological advances. The incorporation of this point is known as the Social Shaping of Technology (SCOT) (MacKenzie & Wajcman, 1999). In this approach, society and technology are not conceived of as distinct spaces, but are mutually constitutive. Building on my characterisation of gender above, gender social structure feeds into technological creation, and vice versa. As dissected in the Introduction to this project, scholars such as Haraway (1988) and Cockburn (2003) have argued that the history of technologies is masculine in the sense of their development and materiality. Cockburn describes this binary and the historical process of exclusions;

*“The construction of men as strong, manually able and technologically endowed, and women as physically and technically incompetent”*

(Cockburn as cited in Wajcman and Mackenzie, 2006, p. 25)

Cockburn (2003) points to how ways of knowing and ways of doing that are associated with women, such as the domestic sphere, are simply not regarded as technological. The exclusion of women from domains that are seen as technical alters the very design of tasks and of the machines themselves.

These exclusions have unforeseen impacts. In her examination of gender data bias, Caroline Criado Perez (2019, pp. 166–167) shows how the search term “computer programmer” can direct more views to a male programmer’s website, simply because a search algorithm has learnt that

masculine pronouns are more closely associated with the term “computer programmer”.<sup>23</sup> The same association was not true for feminine pronouns. Similarly, Noble (2018) shows that a Google search for the term “black girls” returns primarily pornographic results, in this way demonstrating racism and sexualisation in the wider culture. She comments that sexism and racism are built into technology, as it is built by people.

*“Structures of knowledge, and the results retrieved in a commercial search engine create their own particular material reality. Ranking is itself information that also reflects the political, social, and cultural values of the society that search engines operate within”*

(Noble, 2018, p. 148)

The concerns of Perez (2019) and Noble (2018) are the most recent iterations of a history of feminism’s engagement with technology, its adoption and applications.<sup>24</sup> It is hoped that this work can contribute to research that serves to unearth the informal functioning of prejudice in technology cultures, and also contribute to the increase of gender diversity in technological development.

### ***The Path-Dependency of Sexism and Technology***

Path-dependency refers to how technology and computers were committed to develop in specific manners due to cultures of sexism. Here I provide an account of the informal structures of creative coding in *hacking* and the erasure of women from its history. I will first provide an argument about the importance of storytelling, and how historical stories have led to legitimatisation of masculine participation in technology, at women’s expense. Then, I will outline the formal history of how women were erased from the institutions of technology. In the informal history of hackers

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<sup>23</sup> Algorithms themselves are shaped by culture and are not objective. For a valuable discussion on this, see Noble’s (2018) *Algorithms of Oppression*

<sup>24</sup> It is beyond the scope of this project to comment on ethnicity and mediating factors that adversely impact the social shaping of technology. As noted in the introduction, it is hoped that the method of enquiry and findings of this project can contribute to further emancipatory work.

and the creation of the Internet, hackers are acclaimed for developing many of the technological innovations that are so prized today.<sup>25</sup> Yet, it too was built on the social truth of the technologically endowed man and the incompetent woman.

## **The Story of Technology**

Stories are how we make the world make sense. They have a cast of complementary gendered characters, each defined in characteristics that are opposites of the other; the brave, strong white knight and the delicate, vulnerable princess. Stories seem democratic (“everyone has one”), aligned with common sense, and they seem engaging and appealingly authentic in providing simple causal explanations (Polletta et al., 2002). Yet, these stories feed into stereotypes and oversimplifications of causality, and *how we got here*. The stories that people live by are *narratives*, representing cause and effect through their sequencing of events rather than by appeals to logic and proof (Polkinghorne, 2010). Individuals claim to understand events when they have formulated a coherent story explaining how they believe an event was generated or how an action can be accounted for. Stories, and consequently narratives, are important here in understanding how we came to the current state of affairs, and understanding can lead to change. Narratives can provide an explanatory framework, an account of the lived texts of experience, involving the production, practice, and communication of understanding. From this standpoint, Lakoff (2013) proposed applying the approach of narrative enquiry to the social world, whereby people make sense of multi-causal events through the imposition of story structures.

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<sup>25</sup> In dissecting the embedding of sexism into technology, it is imperative to highlight that intuitional and economic actors do not dictate the culture. Rather, they have both a formal and informal lineage. Formal here refers to history as established in institutions and organisations. Once the promises of computer technology were beginning to be realised, there was opposition to the informal network of hackers, who were often without affiliations. The informal counterculture was fundamental in shaping technology development. It was deceptively anti-capitalist, anti-big business and, not uncommonly, anti-government (Jordan & Taylor, 2004). “Deceptively”, given the entrepreneurial enterprises hacking is seen to lead to, such as Steve Wozniak and the tech giant Apple.

## *Storytelling, Power, and Gender*

The propensity to identify simple stories typically leads to narrative fallacy, meaning a limited ability to look at a sequence of events without providing an explanation for them, or imposing a logical link to connect them (Lakoff & Johnson, 2013). Bakhtin (2017) argues that the construction of narratives involves coexistence and conflict between forms of speech, which he termed “heteroglossia”. Here, language represents distinct points of view, characterised by meaning and values “shot through with intentions and accents” (Bakhtin, 2017, p. 324). For instance, in referring to a young woman as *girl*, she is authored as juvenile - subordinate in status to the adult *man*.<sup>26</sup> Similarly, his term “monoglossia” refers to dominant forms of language that represent the interests and worldview of dominant social groupings. Language is a fluid process, fundamentally socially constructed, where meaning is created between the author/speaker and the reader/listener as they are situated in a social context. For instance, gender performance is often classified in a binarised, “monoglossic” linguistic system. Integral to the binarised account is the positioning of the *masculine* as subject and in-group, and the *feminine* as the other, or out-group.<sup>27</sup> The out-group often requires naming, as the in-group is a given (“Football” versus “Women’s Football”). In the phrase *Women in Tech*, women are narrated as the out-group, as the dominant form of *Tech* is masculine. The phrase *Men in Tech* points to different intentions, those espoused in Damore’s (2017) Google Memo as discussed in the Introduction to this Section. Such binarised accounts not only reflect an enduring predominance over alternative accounts but have also been successful in authoring the binary as an inevitable, natural system of sex.

Storytelling thus changes the meaning and power of words, redefining the established wisdom. As stories are given structure, their language reflects the relations of power in the context in which

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<sup>26</sup> This example will be discussed in more depth in Chapter I, Section II.

<sup>27</sup> The “in-group” is the dominant group in a given cultural context. These groups are typically set apart by a social identity category (such as race, ethnicity, gender, social class) from the “out-group”. The in-group is favoured over the out-group, expressed in the allocation of resources and evaluation of others.

they are told. These relations are a productive force, embedded in definitions of hierarchies and institutions espoused in discourses. Foucault defines discourses as “ways of constituting knowledge [that] constitute the ‘nature’ of the body, unconscious and conscious mind and emotional life of the subjects they seek to govern” (quoted in Weedon, 1987, p. 108). Discourse acts as a form of social power that shapes strategies of dominance and resistance and marks the normative and the marginalised. Foucault (1991, [1971]) sees knowledge as inextricably connected to power, with the formation of identities and practices being a function of historically specific discourses. An understanding of the discursive construction of power may therefore open the way for change and contestation in gender identities and heteroglossia.

Considering Foucault’s regulative discourse, Butler (1990) shows how disciplinary regimes dictate in advance what is possible and how gender is seen as natural, embodied in a person’s possessed “sex”.<sup>28</sup> Once the sexed body is established in discourse, it becomes a natural fact. According to this view, discourse is embodied since gender is embodied. The story here defines masculine and feminine as binarised opposites, and thus a hierarchy emerges. In this way narrative sensemaking and the power relations of discourse are assertions of visibility. Who possesses visible agency, who is the visible dominant group, and who is visibly present are all markers of power. Illouz (2008) argues that storytelling feeds into individualistic enterprises, in which the stories that serve the self are prioritised. These stories are evident in survivorship bias, where a woman who is successful in a technological field may conclude that there is no sexism in tech culture, as she herself has prospered. Stories thus contribute to an understanding of legitimacy, of who can participate and who always has. The *story* is embroiled with norms, conceptions of what is natural, and thus what cannot be changed. This section aims to tell the story of how we came to understand technology as the purview of men.

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<sup>28</sup> Discourse (communication) is regulative in how it frames moral values, identities and norms. It communicates what is ordinary and what is not.

## **An Informal History of Exclusion**

Despite the efforts to remember women in computing, protagonists in the history of computer are “male” by default (Adam, 2004; Ensmenger, 2003; Hicks, 2017). The hacker, programmer, and developer are masculine, historically situated in stories of masculine prowess. I return to the language of “hacking” here to reflect on the origin of the masculine stereotype. In narrating the emergence of hacker culture, Jordan (2016) employs a Foucauldian (1991, [1971]) sense of genealogy to ascertain how the present balance of power was formed and became “natural”. This quest for an origin is ideologically saturated, as there is power in storytelling (Lakoff, 1980). Jordan (2016) constructs a narrative to account for the dearth of women in hacking, divided into four phrases: prehistory, golden age, diversification, and mainstreaming.

### ***Prehistory***

Jordan (2016) sees the core principles of the culture emerging in the *prehistory* of hacking, from the 1970s to 1990. These principles involved a tangible sense of cyberspace as a physical area, the discovering of technical manipulation techniques, and the emergence of a virtual community as computers first entered homes. There is much mixed imagery in the telling of hacking’s prehistory. But the mixing of metaphors reveals the centrality of masculinity. Accounts of gender conflict in the origins of this culture are permeated by masculine narratives. The primary form of categorisation used here is clerical. In *Computer Lib*, Nelson (1987) points to the Gnosticism of the computer priesthood, highlighting the clandestine nature of technical knowledge and insider status. In a manner comparable to all-male clerical organisations, Levy (2010, p. 63) refers to how women “did not take to hacking as a holy calling”. Moreover, Pittman (1975) compares creative programming to divine creation, stating “I can create something that will interact with me, as man interacts with God”. In this way, the creative programming of hacking is described as a calling, an obsession, and an end in itself infused with masculine devotion. Levy (2010, p. 63) charts how hackers in this period already accounted for the lack of women, and attributed the lack of gender diversity to “genetic” differences, as “cultural biases... do not explain the utter lack of women”

in physical and online spaces; even in the early stages, hackers were assuming that a lack of women in their field had biological, rather than cultural, explanations.

### ***Golden Age***

The *golden age* heralded the defining of the hacker identity in terms of a self-consciousness (Jordan, 2016). In *The New Hacker's Dictionary*, a lexicon of computer programming slang, Eric S. Raymond (1996) provides a definition of the hacker, as they putatively existed in Jordan's (2016) golden age; a hacker is a person who enjoys exploring and testing the capabilities of a programmable system. In contrast to creative hackers, those who do not invent are referred to pejoratively as "script kiddies".<sup>29</sup> The golden era also saw hacker culture increasingly articulate misogyny, with practices that further defined women as the outsider in a manner similar to "the frontline of warfare" (Jordan, 2009; Newton, 2001, p. 71). Eric S. Raymond's definition of a "Real Programmer" illustrates this point of masculine dominance.

*"Real Programmer n.*

*The archetypal "Real Programmer" likes to program on the bare metal and is very good at same ... thinks that HLLs are sissy and uses a debugger to edit his code because full-screen editors are for wimps. Real Programmers aren't satisfied with code that hasn't been bummed into a state of tenseness just short of rupture. [...] Real Programmers live on junk food and coffee, hang line-printer art on their walls, and terrify the crap out of other programmers -- because someday, somebody else might have to try to understand their code in order to change it."*

(Raymond, 1996, p. 56)

In this popular definition, masculinised language such as "sissy" and "wimps" is wrapped in sexually violent metaphors.<sup>30</sup> Tanczer (2016) argues that the androcentric nature of society leads

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<sup>29</sup> A person who uses existing computer scripts or codes to hack into computers, lacking the expertise to write their own.

<sup>30</sup> This definition is arguably intended sardonically. However, the focus on masculinity, competence and genius negates this intent. Study III explores the politics of irony in technology culture.

to women being perceived as being on the receiving, or passive, end of technology use, rather than holding a powerful creative position. Pritchard (1998) points to the existence of small communities of resistance to the masculine narrative, in which women focused on socialisation and building personal networks online, but the perception was still of a masculine-only community.

### ***Diversification***

The third stage saw the *diversification* of hacker culture post 2000. It is imperative to note that diversification, in Jordan's (2016) terms, does not refer to an increase in the heterogeneity of the hacker community's participants, but rather in its motivations. At the same time as the term "hacking" became more heavily associated with cybercrime, political motivations rose to prominence (Lessig, 2006). Often referred to as "hacktivism", political hacking involves mass action and the reinvention of civil disobedience for the digital age (Taylor & Jordan, 2004).<sup>31</sup> Tanczer (2015) argues that hacktivism is a cooperative alternative to hacking's regressive masculinity, which is defined by competition, mastery and domination. However, her research found that women still regard hacktivist spaces as a "hostile environment" where "there is a lot of misogyny... showing off and being macho" (2015, p. 1607).

In contrast to these more negative or isolationist connotations, in *The Hacker Ethic*, Himanen (2001) proposes that hacking is based on the values of passion, freedom, and creativity. For Eric S. Raymond (1996), hacking implies membership of a global online community, defined by an adherence to the ethic of information sharing and exploration. In *The Hacker Manifesto*, Wark (2004) also emphasises the creative efforts of hackers in fashioning the possibility for innovative social and technical developments. Wark (2004) discusses hacking with a Deleuzian (1984) lens

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<sup>31</sup> In this period there was an effort by those involved in the field to rebrand unauthorised access to a computer system as "cracking", however it didn't take off.

- desire as a productive force based in creativity, and a Nietzschean (1910) “will to power”, as a pleasurable force of appropriating what is outside oneself. In this sense, Levy (2010, p. 62) discusses how for two of the founders of the hacker community, Richard Greenblatt and Bill Gosper, “hacking had replaced sex in their lives”. Jordan and Taylor (2004) point to the obsessive, addictive, and pseudo-sexual aspects of the hacker mentality emerging in this era. The self-describing discourse of hackers obsessively fetishizes technological competences (See Eric S. Raymond’s definition of a “Real programmer”). In describing their enjoyment of absorption within self-enclosed systematic artefacts, Jordan and Taylor’s (2004) hackers narrate the “bliss”, “slow ecstasy”, and “drawn out parade of tenderness” of revelling in one’s technical ability. Similarly, Miller (1995) argues that the hacker narrates an inviting frontier of unclaimed territory, as inviting exploration is reminiscent of the ideal of chastity, making the taking of virginity sexually provocative. In keeping with this, there is relentless sexual harassment in hacking’s entry-level forums (Tancer, 2016). Franks (2011) and Mantilla (2015) see such gendered harassment continuing, perpetuated by anonymous forums and radicalised by techno-elitism. With such masculine domination of the discourse of hacking and fetishisation of the act, there is little room left for outward-looking social concerns of gender representation.

### ***Mainstreaming***

Modern hacking has emerged as a creative yet mundane act, diffusing into the mainstream from the mid-2000s (Briscoe & Mulligan, 2014; Jordan, 2016). From Jordan & Taylor’s (2004) “rebels with a cause”, hacktivists have developed commonplace infrastructures. Their tools remain widely used by ordinary programmers, including distributed licences to source code and the open source operating system Linux (Lessig, 2001). Such developments draw attention to hacking as foundational to the free software movement and creative programming (Lessig, 2001). As such, hacking became seen as not merely a realm for criminals and political activists, but as a “core principle of a new economy” (Jordan, 2016, p. 10), an “economy of creativity” (Lessig, 2001, p. 382).

In the process of mainstreaming, hacking has also accrued further ideological dimensions. Morozov (2013) points to the “folly of solutionism”, as intellectualists strive towards intervention and perfection in the doctrine of Silicon Valley. Simply put, solutionism contends that all problems are solvable and should be addressed with technology, as there are “lifehacks” or “shortcuts and tricks for making modern life easier and doing things better” (Pash & Trapani, 2011, p. 23).<sup>32</sup> This is akin to Weberian (1921) instrumentalist philosophy; the most efficient means by which to reach an end is the action that should be taken. Solutionism is seen as the reserve of “over-prolific alpha geeks” who develop solutions that allow technologies to be disseminated throughout society (Pash & Trapani, 2011, p. 27). Privilege here is located in the ability to deny the influence of situational factors and identity categories such as gender, race, and class on entrepreneurial success. The “geek” trope of being unpopular in school means that they are often blind to the advantages they have by virtue of their race and gender (Reagle, 2018). *The privilege of being oblivious to privilege*. The narrative consistently refers to the technological and entrepreneurial success of the white male, as geek culture refuses to acknowledge its own immense privilege.

In recounting the informal history of hacking I have shown how masculinity was embedded in technology in each stage of its development and evolution. From hobbyist culture to cybersecurity, male-by-default is entrenched in our understandings of technical skill. In the following section, I will look at how formal institutions arose alongside the fringe culture of hacking. I will show that in investing in the creative coding, institutions also invested in the masculinist narratives of technology, encoding gender power structures as they sought to control technological development.

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<sup>32</sup> A belief that every “problem” has a “solution” based in technology.

## A Formal History of Exclusion

This informal history of hacking shows the ways in which gender has permeated each chapter of its history. Concurrently, more formal institutions have also perpetuated the story that women lack a “natural” ability to hack. Here I look at how institutions perpetuated the story that men possess “natural” technological ability, contributing to women’s exclusion. In his historiography Ensmenger (2003, 2010) explores how alongside the development of the information industries, the professional role of the computer programmer evolved. By 1967, competition among companies for programmers was so high that it became the highest paid technological occupation in the USA (Ensmenger, 2003). Corporations sought to effectively integrate unreliable and incredibly expensive computers into their existing operations. This period from the late 1960s was dubbed *software crisis*, where due to an inability to hire enough qualified programmers, the quality of projects suffered (Ensmenger, 2010). Some projects even caused loss of life.<sup>33</sup> But as computer hardware became faster, cheaper, and more reliable the importance of software developers became more pronounced.

Ensmenger (2003) shows that despite their obvious importance to the history of computers, programmers have defied traditional occupational histories. Originally envisioned as little more than glorified administrative workers, their technical expertise meant that they assumed more power within organisations than their official role dictated. Ensmenger (2003, p. 155) paints the programmers as mediators “between the technical system (the computer) and its social environment (existing structures and practices)”. The character of the programmer thus plays an important role in shaping the perception of technology and its associated expertise. Programmers, somewhat unexpectedly, held powerful roles in institutions.

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<sup>33</sup> Some embedded systems used in radiotherapy machines failed so catastrophically that they administered lethal doses of radiation to patients. The most famous of these failures is the Therac-25 incident.

### *Invisible Technicians*

From the first electronic general purpose digital computer (Electronic Numerical Integrator and Computer – ENIAC) a clear division of labour in the programming process was set out. Outlined in the principal textbooks of programming until at least the late 1950s, programming was separated into high-level conceptual activities and the tedious but straightforward work of coding into machine readable format (Ensmenger, 2010). The planners of the programmes were largely scientists and thus overwhelmingly men. The coders were considered low status and almost universally women (Ensmenger, 2010). Manual computation was almost exclusively a feminine occupation. Ensmenger (2003, p. 156) highlights how the use of the term “coder” is significant, as it paints women as “transcribing the thoughts of others [...] merely operating the machinery designed by others”. Light (1999) shows that coders were quite literally the “invisible technicians”, never referred to individually in the press and cropped out of publicity photos. Yet, these coders would have to be intimately familiar with the mathematical analysis of the problem at hand, in order to debug their programmes and distinguish hardware and software errors (Ensmenger, 2010). ENIAC programmer Betty Jean Jennings is quoted by Ensmenger as stating:

*“Since we knew both the application and the machine [...] we learned to diagnose troubles as well as, if not better than, the engineers”*

(Ensmenger, 2003, p.158)

The recording of women’s role as “coders” does more to reflect the expectations of societal norms of gender roles, rather than how it worked in practice. In fact, Adele Goldstine wrote the original technical description of the ENIAC (Light, 1999).

Women’s invisibility is not limited to technicians involved in the development of computers, but also extends to academic contexts, such as the Macy Conferences (1946-1953). The aim of these conferences was the development of the field of cybernetics; the study of technology and computers from a range of academic perspectives, including anthropology. In recording the history of the development of cybernetics at the Macy Conferences, Hayles (1999) looks to the

figure of Janet Freed, assistant to the conference programme. Although Freed constructed the system in which the Macy Conferences operated for two decades, her status as a woman did not allow her contribution to be made. She is “glimpsed largely in the speech of others” (Hayles, 1999, p. 82). Akin to the coders, women are “embedded in context”, rendered invisible through eyes that refused to see them as participants in such technical, intellectual, and masculine spaces (Hayles, 1999, p. 83). The generalisation of cybernetics to a theory of society would later be made by Talcott Parsons, forming the foundations of much scholarship on the sociology of technology. Women have thus been historically excluded in the development of the technical and study of the technological.

### ***Born, Not Made***

Returning to the story of computers, the limitations of first-generation hardware often demanded that programmers develop creative solutions and “work-arounds” (Ensmenger, 2003). Memory devices had limited capacity, coders had to develop craft knowledge to enable their programmes to function in the available space. It was during this period in the 1960s that the stereotype of the computer programmer possessing uniquely creative ability emerged. “Coding” was not regarded as mechanical as it was once presumed to be, and was thus no longer a fit for women (Ensmenger, 2003; Hicks, 2019). As a result, primarily men were recruited in order to meet the need for computer programmers.

The “creative” stereotype influenced hiring practices, as programmers were hired based on assumptions of intellectual gifts and aptitude, rather than business knowledge (Ensmenger, 2003). The identification of these individuals was informed by stereotypes of (“male”) chess masters or virtuoso musicians. A publication of the *Selection of EDP Personnel* recommended companies look for “those who like intellectual challenge rather than interpersonal relations” (Ensmenger,

2001, 2010).<sup>34</sup> This conception of the “natural” programmer was supported by a series of aptitude tests and personality profiles (such as the Cannon-Perry test) developed by hiring experts (Chang, 2019). Despite considerable methodological flaws (including being based on a sample of twelve), a widely cited IBM study became the new common wisdom (Chang, 2019; Ensmenger, 2010). The study contended that an excellent programmer was twenty-six times more effective than their average colleague (Ensmenger, 2010). Skilled programmers were thus thought to be irreplaceable, as their characteristics were aligned with masculine traits (independence, boldness), and they received enormous remuneration. The same personality traits that were indicative of innate ability and genius could also be seen as antisocial and subversive if found in a woman (Chang, 2019). Society views antisocial men and women differently. In women it is typically pitied or rejected, whereas in men it carries associations of genius, a characterisation of a “lone wolf” that is valorised in figures such as Beethoven, Einstein, and Tesla (Chang, 2019). Programming became an innate ability, an art form fit for erratic geniuses (Ensmenger, 2010). This indispensable creative was painted as unmanageable, possessing levels of autonomy that did not extend to other professionals.

As computers became central to business practices, corporations struggled with how to fit computer programmers into the managerial structure, given their ambiguous status and emphasis on creativity (Ensmenger, 2010). Programmers in this period were aware of their own ambiguity, working to establish academic certifications of computer science in a bid for professional status (Ensmenger, 2001). Riley (2017) argues that STEM education is assessed in masculine terms, exemplified by the focus on “rigor”. Informed by hacking narratives, a masculine eroticism was embedded in the “clean, hard, fast” values of STEM disciplines (Riley, 2017). This language was coupled with an understanding of scientific knowledge as complete, coherent, and verifiable;

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<sup>34</sup> EDP stands for Electronic Data Processing.

devoid of value-meaning. As a “science”, computing became embroiled in the associations of structured knowledge. Overtones of objectivity means that flexibility and diversity in the curriculum are a threat to the “rigorous” nature of STEM (Blickenstaff, 2005; Riley, 2017). Riley (2017) shows how standards for academic curriculums reinforce gender, race and class hierarchies, maintaining the invisibility of repressed groups. The qualification of rigour or “academic standards” includes objectivity, math-intensiveness, empiricism/positivism, and reductionism (which is particularly evident in modelling) (Riley, 2017, pp. 256–257). The notion of academic objectivity facilitates a narrative of meritocracy, whilst perpetuating hierarchies (Haraway, 1988). Hence, the academic certification of computer science resulted in formal avenues of computing education being associated with the masculine values and language of informal hacking.

As computer science gained certification, management literature retaliated by reinforcing the notion of programmers as self-interested, narrow technicians, rather than working in the profit-making interests of the larger company (Ensmenger, 2001). This conception of the programmer was reinforced by aptitude tests and personality profiles (of questionable validity), which associated programmers with youthful inexperience, and “addictive” natures, as “people close to the machine can lose all perspective” (Ensmenger, 2003, p. 170). As COBOL programming language was introduced, it was marketed as so simple that even a woman could do it, in IBM’s “Meet Susie Meyer” advertisements.<sup>35</sup> If a woman could do it, then so could just about everyone (Ensmenger, 2010).<sup>36</sup> In Britain, women were a hidden engine of growth in technology from the 1940s to the 1960s. Obscured in a language of efficiency, organisational efforts were made to paint programming as glorified administrative labour (Hicks, 2019). As computing experienced

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<sup>35</sup> COBOL was favoured by companies over FORTRAN as it was easier for nontechnical management to understand. It translated mathematical formula into what resembled natural, spoken language.

<sup>36</sup> Adding to the condescension of the “Meet Susie Meyer” advertisement, COBOL was invented by Grace Hooper, American Computer Scientist and US Navy Rear Admiral.

a gender role-reversal (becoming masculine in the late-1960s) labour shortages grew as the large, technically trained, workforce of women was ignored. Shortages matured into structural problems and such gender discrimination caused the nation's largest computer user - the civil service and public sector - to make decisions that were devastating for the British computing industry (Hicks, 2019). Britain ignored the women who were already trained on these machines, in favour of men who lacked experience and practical knowledge. Gender norms were ultimately prized above industrial prosperity. These associations of computers with feminine stereotypes implicitly frame the way individuals interpret the behaviour of others, particularly in regards to “natural” ability (Scarborough & Risman, 2017). The programming occupation was *deskilled* in its association with femininity.

### ***Coding Femininity***

Not only do these narratives of technology and stories of the culture fail to account for women’s absence, but the lack of women’s representation also leads to the misrepresentation of feminine identity. This in turn, makes it difficult for women to represent themselves with authenticity, and deters them from participating in the culture (Light, 2011). In programming forums, the overrepresentation of information generated from a masculine perspective leads to a submissive and pre-coded, pre-defined role for women users. Cooper argues that the association of computer culture and technological work with masculinity is;

*“glorified in depictions of Silicon Valley life [in which] men compete in cubicles to see who can work more hours, who can cut the best code, and who can be most creative and innovative.”*

(Cooper, 2000, pp. 381-382)

Massanari (2015b) and Cooper (2000) argue that connotations of prestige and glorification emerge from “revenge fantasies”. “Revenge of the Nerds” is a phenomenon that refers to the founders of Silicon Valley moving from their youthful socially marginalised position to become rich and powerful through technological prowess and entrepreneurship (Cooper, 2000). Even

when the image of hackers was “generally uncool ... nerds and geeks”, the entrepreneurial culture they are a part of was riddled with discrimination (Neff et al., 2005). This is a masculinised story of those who rise to success in the technological industry. Massanari (2015b) sees this trajectory that valorises the white male as the basis of the technological industry. The geek became a prime site of capital investment, typed for entrepreneurial success.

### ***Brotopia, Brogrammers, and Boys Clubs***

There are multiple characterisations of masculine identity in computer culture. A significant contributing factor is the widespread use in the 1960s of personality profiles that favoured masculine traits in hiring programmers. These profiles built on the stereotype, and contributed to the reign of the nerd as a self-perpetuating prophecy (Chang, 2019). As Ensmenger summarises;

*“[The] industry selected for anti-social and mathematically inclined males, and therefore antisocial mathematically inclined males were over represented in the programmer population. This in turn reinforced the perception that programmers ought to be antisocial and mathematically inclined (and therefore male), and so on ad infinitum”*

(Ensmenger, 2010, p. 79)

From this self-perpetuating stereotype emerged what Kendall (1998, 2002) framed as *geek masculinity*, in which technological mastery forms the basis of masculine esteem and status. For its coherence, geek masculinity requires the maintenance of gender stereotypes about male technological skill and female ineptitude. The machismo of male exclusivity and control of technology has been evident in geek spaces and informal culture, from video game arcades in the 1980s to online forums in the 1990s (Kendall, 1998; Salter, 2017). The geek emerged out of the characterisation of early programmers as socially awkward, brilliant loners (Ensmenger, 2010). Its resistance to hypermasculine indicators such as athleticism and heterosexual prowess means that geek masculinity contains contradictory constructions as victimised outsider that also maintains power and dominance through control and assertion of technological power (Salter, 2017).

Kendall (2002) theorised geek masculinity as simultaneously resistant to and complicit in gender inequality, since even in its rejection of typical masculine hegemony it paints the feminine as subordinate. However, technical skill has become a widely recognised route to wealth and celebrity, exemplified by Bill Gates or Steve Jobs. Jobs was a different type of tech figure to those celebrated previously. His marketing skills, leadership style, and willingness to take risks compensated for his relatively limited technical skillset; his cofounder Steve Wozniak (an archetypal hacker) was responsible for most of Apple's early technical innovation (Chang, 2019). Much of the stigmatisation of geeks has been replaced with a fervour for the economic value of technological enterprise (Salter, 2017). In the climate of the dot-com bubble and the wake of the charisma of Steve Jobs, bravado was what attracted investment to "young tech geniuses" (Chang, 2019). This masculine audacity extended to the daily practices of running companies, encompassing the customs of tech companies in the 1990s of drinking, gambling, and team meetings at strip clubs. Young companies in this period were still using personality tests and brainteasers in order to find programmers (Chang, 2019). It wasn't until 2013 that Google stopped using such quizzes.<sup>37</sup>

From 2012, entrepreneurial hacker and geek fantasies have been recast with "a competitive frat house flavour", exhibiting the hypermasculinity commonly associated with the culture of college fraternities and moving away from "uncool" hackers of the 2000s into the mainstream (Dusenbery & Pasulka, 2012; Neff et al., 2005, p. 314). This new stereotype is coined the "brogrammer" (Hicks, 2013). The evolution of geek masculinity to brogramming points to how discourses and misogynistic actions are evidence of a replicating pattern in computational development. Technologies are fundamentally about power, and misogynist attitudes are manifested in reality

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<sup>37</sup> Google were notorious for their quizzes because they made them publically available. Feeding into the meritocracy myth, the idea was that if you could solve the puzzle you could work for Google.

and products.<sup>38</sup> Hicks (2013) sees programmers as seeking to monopolise power through their conceptions of an “alpha male effect” in environments that encourage technological ends and further the aims of an elite. As technical ability has become increasingly prized, programmers are seen to compensate for relatively limited technical skill with overt performances of hypermasculinity, such as heteronormative sexualisation (Raja, 2012). In a *Mother Jones* article, Raja (2012) narrates examples of the masculine toxicity of programmers. She (2012) recalls a talk by Matt Van Horn, a young social media executive in which he referenced pursuing a job at Digg (a social bookmarking site and early competitor of Reddit), by sending the cofounders “bikini shots” from a “nudie calendar” he’d put together with photographs of fellow students posing in their swimsuits. Van Horn is emblematic of the culture: he got the job at Digg and went on to be reasonably successful. Such instances demonstrate how the technology industry became a boy’s club, as the lucrative outcomes of technology melded hegemonic masculinity with the geek stereotype. Authoring yet another masculine stereotype in technology, women were cast as outsiders by ability and heterosexuality.

## **The Warrior and The Wife**

As a category made real by social performance, gender can not be understood as something natural, nor as something consciously assumed by an individual selecting from an array of identities (Hicks, 2019). Instead, as argued earlier, gender is a social structure beyond an aggregated series of actions and institutional practices. As a focus of analysis it lays bare the assumed or cultural heterosexuality of women (heteronormativity), involving the expectation that they would rather be wives than follow any career or artistic passion (Hicks, 2019). In early computing companies, Hicks (2017) highlights “retirement parties” for the few women who

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<sup>38</sup> There are many notable instances of such hetero-masculine behaviour, usually justified through employing a measure of humour. For example, at the TechCrunch Disrupt 2013 conference the fictional mobile app “Titstare” was pitched. The app was intended to be satirical, based on images of men staring at women and their breasts (Raja, 2012).

worked there, following on the announcement that they were to be married. She also points to a supposedly empowering 1960s novel titled *Anne in Electronics*, where the woman protagonist navigates the male-dominated computing field by graciously allowing her male peers to take credit for her work (Hicks, 2019, pp. 143–144). Anne takes particular joy in letting a man who she is romantically involved with take credit for her solving of a significant problem in the development of jet engines. The novel’s message, Hicks (2019) reiterates, is that a woman can be successful in a male-dominated profession, if she is prepared to work hard and take on a submissive role.

In addition to being narrated by hackers as an outsider, and even the enemy, Adam (2003) proposes that the role of women in hacking has been further marginalised by scholarly works. Levy’s (2010) book on hacker culture begins with a “Who’s Who”. The list references fifty-two men, ten computers, and three women. All the women are discussed in terms of being a wife, permitted to enter the physical spaces of hackers by heteronormativity, despite their own hacker credentials. In reflecting on the history of hacking, Adam (2003) asks how the rhetoric of equality and open meritocracy arose in the first place. Pekka Himanen’s book *The Hacker Ethic* is proposed as a source of such a narrative, placing little emphasis on actants (Coleman, 2015; Himanen, 2001). Adam (2005) holds that material barriers to women’s entry into hacking are rarely noted, such as the long hours and late nights of hackathons, which are juxtaposed to narratives of domesticity and childcare (Pe-Than & Nolte, 2019).<sup>39</sup> By being characterised as wives, women are seen as incompatible with computer culture.

One of the best-known names in open-source software, Eric S. Raymond (2015), dismisses those who critique the masculine dominance of programming as Social Justice Warriors (SJWs) and

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<sup>39</sup> I contributed to *The 2nd Workshop on Hacking and Making at Time-Bounded Events* along with Pe-Than & Nolte at CHI, 2018 and drafted the section on gender inclusivity.

the “enemy” of the hacker’s “cult of meritocracy”. SJWs are comparable to Ahmed’s (2010) feminist killjoy, where the feminist who is challenging the “fantasy” of gender equality is seen by others to infringe on their happiness and thus faces social sanction. This negative portrayal of feminists can be attributed to a so-called postfeminist climate, where feminism is increasingly seen as irrelevant, as equality has been achieved (McRobbie, 2009). In programming culture, however, claims to a meritocracy actively encourage bias. The in-group feels that simply by virtue of their membership of a meritocratic organisation, informal and formal, they do not need to reflect broader social diversity. The smartest people are already in the metaphorical room. Instead, Raymond attributes the disparity of gender representation to one key reason:

*“young women in computing-related majors show a tendency to tend to bail out that rises directly with their comprehension of what their working life is actually going to be like.*

*Biology is directly implicated here. Women have short fertile periods, and even if they don’t consciously intend to have children their instincts tell them they don’t have the option young men do to piss away years hunting mammoths that aren’t there.”*

(Raymond, 2010)

The commentary of figures such as Raymond is not inconsequential. As co-founder of the Open Source Initiative, he is well known in formal and informal avenues of computing. When voiced by such prominent individuals, these statements act as proof that computer culture is hostile to women, actively dismissing any claims to the contrary. Whereas SJWs can be taken to refer to any individual with socially progressive ideas surrounding identity politics, online it is a term that is more commonly used pejoratively. Its negative use gained prominence during the Gamergate controversy, with Massanari (2015b) highlighting it as an epitome of toxicity in technocultures (referring to cultures associated with technology).<sup>40</sup> An SJW is seen as motivated by personal

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<sup>40</sup> Concerns issues of sexism and progressivism in video game culture, stemming from a harassment campaign of women in the industry beginning in August 2014, nicknamed GamerGate.

validation rather than political conviction. In providing a voice counter to the view of hacking as a meritocracy, a feminist voice calling for more women in computing can be perceived as a moralising project or imposition. Such impositions are a necessity, showing that sexism does not exist only in the writings of Raymond and Damore, but is intrinsic to the formation of computer culture. In Ahmed's (2010) terms, the feminist project to dispel the myth of equality is one of "killing joy".

## **Alternatives & Resistance**

What underscores the discussion of history and technology is that technological change is inevitable. As outlined, Moore's law has a *trajectory* that mimics a natural law, a path that lays out the way ahead. Silicon Valley's mantra of solutionism is based on a (white and male) pro-innovation bias. For those who inhabit the Valley change is inevitable, and society should adopt innovations without allowing for social alterations, refusing to adapt for those who are excluded (Morozov, 2013). Godwin and Vinck (2017) outline four assumptions behind the goodness of technological innovation: (1) it is attractive, embracing the cultural value of creativity; (2) it is the product of planning and experimentation; (3) it is created through rational decision making, and (4) it takes place in the research and development sector. Godwin and Vinck (2017) show that this is a problematic narrative of innovation that does not take into account resistance, scepticism, failures, and unwanted consequences. In the history of technology, innovation is attributed not just to business ventures, but to hackers as "heroes of the computer revolution" (Haigh & Priestley, 2015; Levy, 2010). Mackenzie and Wajcman (2006) highlight how much of the romanticism associated with the development of technology is due to the interaction between anti-corporation counterculture and masculine hobbyist culture.<sup>41</sup> Pro-innovation discourses have

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<sup>41</sup> Famously, Steve Jobs and Steve Wozniak (the founders of Apple) started out in *phreaking*, the culture of unauthorised exploration of telephone communications systems. Through a blue box that mimicked dial tones, individuals were able to gain free access to the telephone network. Phreaking is generally

become intertwined with narratives of destructions, epitomised in Facebook founder Mark Zuckerberg's now famous motto "move fast and break things" (Levy, 2010). The notions of hype and novelty that have seeded in history of technology have emphasised the technicalities rather than the social implications. Godwin and Vinck (2017) reflect that much academic scholarship in technology studies is implicitly pro-innovation, reinforcing hype, novelty, and biases. A focus on the materialities of technology and progress as equivalent to natural laws can distract researchers from those who remain excluded.

In terms of the formal avenues of computing, the technology industry is supposedly operating in a more enlightened age than the 1960s, where men and women are equals in the workplace. Yet, a survey of over 200 women with at least 10 years' experience in technology found that 60% of women report unwanted sexual advances, and 90% have witnessed sexist behaviour (Madansky, 2018). As a result, 55% of women have left a job because of personal mistreatment or because they felt that their workplace was a generally toxic environment for women (Madansky, 2018). In informal avenues of technology cultures the imbalance of social power is equally pervasive (Dunbar-Hester, 2019). The belief of these communities in open meritocracy means that the conviction that "if people aren't there it's because they don't want to be" is perpetuated (Dunbar-Hester, 2019). In this climate of exclusion, even with pro-innovation bias, the benefits of diversity are largely ignored.

Research points to how gender-balanced teams are more productive on a collaborative level (Song et al., 2015). Moreover, women's participation in-group assignments raises the performance levels of other members of the group, even when gender is not disclosed. Song et al. (2015) speculate that the reason for such improvement is that women act more cooperatively. Terrell et

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argued to lead the way for computer hacking, in terms of creative but authorised access to computer systems.

al.'s (2017) study of gender effects in proposed changes to a software project's code, documentation, or other resources found that women's contributions are accepted more often than men's if their identity is unknown. However, when gender is made salient, women's contributions are 15% less likely to be accepted (Terrell et al., 2017). Women's participation in computing culture and professions has plummeted in recent years. For instance, in 2013, only 26% of computing professionals were female - down considerably from 35% in 1990 (Corbett & Hill, 2015). This decline in participation is unique to computing, with other STEM fields seeing a moderate increase in the same period (Corbett & Hill, 2015). In Study I, I will explore the interplay of stereotyping and technical knowledge in anonymous forums. Assessing and increasing the gender balance in hacking can serve to benefit creative coding cultures.

### ***Markets Versus Diversity***

It is important to be reflexive in asserting the benefits of diversity in terms of profit. Dunbar-Hester (2019, p. 233) highlights how the prominence of market-based rationales for technological development means that profit-seeking logics are "quite easily affixed to diversity advocacy, and other articulations take more effort". Dunbar-Hester (2019, p. 234) goes on to argue that workplace diversity and improved products reflect a "limited basis for confronting social power" in technological development. For marginalised groups the expansion of market potentials is not the aim of emancipatory politics, but is the easiest way to motivate corporate interests (Dunbar-Hester, 2019). Superficial promotional listing of the *diverse people* who make an impact in technology celebrates diversity without specifying what exactly its benefits are. Diversity here is essentialised as a demographic characteristic possessed on an individual level. This focus on the individualised level distracts attention from less palatable assertions of structural inequality (Dunbar-Hester, 2019). Thus, whilst the history of technology has often been driven by profit seeking and pro-innovation biases, diversity should not be merely an extension of these capitalist logics.

## *Hackathons and Hackerspaces*

Hackathons emerged out of informal hacking practices, as meet-ups for those involved in the online manifestations of technological culture – a chance to meet and compete “in real life”. They are 12-36 hour-long events in which programmers collaborate intensively on software projects, largely organised in the form of a competition. The first use of the term “hackathon” was in 1999, when OpenBSD held a cryptographic developments event in Canada, to avoid the export regulations of cryptographic software from the United States (OpenBSD, 2020). Framed as sites of innovation and invention, the creative potential of hackathons was realised by venture capitalists as a way to quickly develop new technologies. From the mid-2000s they became significantly more widespread and were the birthplace of several major companies.<sup>42</sup> Technology giants have strong traditions of internal hackathons to develop new features, such as the prototyping of Facebook’s “Like” button in 2012, which was rolled out across the platform within two weeks. This is the logic behind the time limit; to force participants to distil the concepts behind their projects into actionable solutions (Cruz & Thornham, 2016). Since hackathons became commonplace for tech giants, start-ups, and charities alike, they have become formalised, more organised and more lucrative. Corporate hackathons are open calls for participation and often boast large prizes. For instance, in 2014 the first prize for HackGT was \$50,000 investment in the project developed, as well as \$10,000 cash, and \$60,000 Azure credit (Microsoft’s cloud computing service). Even university (college) hackathons commonly have cash prizes of at least \$4,000, as well as including bundles of devices and other sweeteners. Hackathons are a convergence of the informal and formal history of computing discussed earlier in this chapter.

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<sup>42</sup> For example, GroupMe began as a project at a hackathon at the TechCrunch Disrupt 2010 conference. In 2011 it was acquired by Skype for \$85 million.

They are a refusal of work-day norms in favour of geek hedonism, with devotion to a singular project refusing to rest until it is completed.<sup>43</sup>

Hackathons are a manifestation of Bechky's (2006) *temporary organisations*, organised around structural role systems which are negotiated in place. Akin to sporting leagues, university (college) hackathon teams will attend multiple events in a league, maintaining continuity across different projects and competitions. Hackathons are fundamental to the culture of creative coding in hacking. Coleman (2010, p. 49) argues that online interaction or "networked hacking" should not be seen to displace physical interaction, rather, the "two modes powerfully reinforce each other". Hackathons are ritualistic and "ingrained in the ethos of coding" (Leckart, 2012, p.109 cited Jones et al., 2015, p. 325). Jones (2015) proposes that they are not merely opportunities for technical work, but express ideological tenets such as valorisation of individual competences even within the team setting. Hackathons are emotionally charged, as interpersonal relationships manifest themselves and the prosaic nature of the hackers' social world is ritually embodied. Irani (2015) posits that in hackathons technical practices became ways of remaking culture. She argues that they produce an entrepreneurial citizenship, oriented towards "Silicon Valley for models of social change" (Irani, 2015). This high-velocity practice favours quick and forceful action, solutionism with no time for unintended consequences.

### ***Hackathons and Gender***

Women have founded projects that reimagine the physical spaces of hacking. Stemming from the ideology of and discussion about *The Geek Feminism Wiki* (2008), hackerspaces emerged as a physicality in which femininity in hacking was seen as normative and necessary. A hackerspace is an arena in which individuals with a common interest in computers or technology can socialise

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<sup>43</sup> Work day norms such as a 09:00 to 17:00 day.

and collaborate, operating like an informal hackathon (Dunbar-Hester, 2019).<sup>44</sup> Hackerspaces have spread quickly across the UK and USA from 2010, influenced by the dominant German-based model in their understandings of openness based on interest, rather than requiring a pre-proven ability, unlike the *Hacker Ethic* (Damiani et al., 2018). In the last decade, several feminist hackerspaces have emerged, such as the “Hacker Gals” in Michigan (established in 2014). These informal spaces of technology can serve as sites of visible diversification in creative coding. However, in her study into diversity in open-technology culture in the USA, Dunbar-Hester (2019, p.60) highlights the “failed promise of hackerspaces” as they are “usually white, male, and heterosexist”. The *promise* of feminine spaces was incompatible with technological knowledge. She demonstrates that the ethos of hackers is to “debug” the culture; making small changes and adjustments to what is already there (Dunbar-Hester, 2019). However, systemic discrimination is a “feature” of hacker culture, not a “bug”.<sup>45</sup> Small scale methods of inclusion (such as women only events) come up short for issues of unequal social and economic power. Distributing “diversity” in technical production is not equal to generating justice (Dunbar-Hester, 2019). Like the wider masculine hacker discourse, hackerspaces carried the hacker’s fundamental and enthusiastic belief of a technological meritocracy.

Like hackerspaces, hackathons are physical spaces in which a hacker’s identity as a woman is made salient and is *visible*. Women also organise in these spaces, often developing informal procedures to encourage female participation (Coleman, 2010). In hackathons individuals are formed into teams that contribute to a shared project. As text and speech can be considered ideologically situated in everydayness, code at hackathons becomes similarly ordinary.

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<sup>44</sup> “Hackerspaces” come from “makerspaces”, a collaborative work for making and learning that uses high tech to no tech tools (Damiani et al., 2018)

<sup>45</sup> This is a reference to a trite expression within computer programming. “It’s not a bug, it’s a feature” is a maxim used by software developers when they try to convince a user that a flaw in their program is actually what it’s supposed to be doing. The joke is that by recording a *bug* (error) as a *feature* (part) of the overall project, it is no longer an overlooked mistake.

Mackenzie (2005) argues for a performative analysis of code itself, extending a speech-based notion of code as instruction to include the mediated practises of programming, configuring, and running a computational project. Here, code is an “objectification of a linguistic praxis” (Mackenzie, 2005, p. 76), understood not just in terms of the explicitly meaning ascribed to it but as self-reflexive, mediated by the individuals, interactions, and culture that created it. As Latour (1999) contends, the object created in coding has its own agency and is a product of the ideological spaces in which it was conceived. Thus, the intervention of gender in the labour of coding is vital to the analysis of practice in creative coding and is incorporated into Study III of the project through participant observation of hackathons.

Visibility in hackerspaces contributes to the defining of femininity in corporeal terms, as they are attended in person.<sup>46</sup> It is not as simple to hide one’s identity at a hackathon as it is in an online space. In technology culture the presence of women is acknowledged (and visible) only when they present their bodies (Tanczer, 2016).<sup>47</sup> Thus, it would be problematic to see feminist hackerspaces and women-only events as clear-cut resistance. Women-only hackathons and hackerspaces are characterised by the absence of androgyny or embodied masculinity (Dunbar-Hester, 2019; Toupin, 2014). In this way, masculinity’s cultural privilege in relation to the feminine other is reinforced, and the social hierarchy of hacking as a male space is recreated. In response, Toupin (2014) recognises that a woman-only space is not an end in itself, but aims to solidify a feminist hacker culture. Although women-only spaces do provide an arena for women’s engagement in creative coding, the gendered divisions and emphasis on physical visibility reaffirm the narrative of hacking as a masculine practice; it is male by default, and thus feminine

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<sup>46</sup> In slang that is common to online forums, the shorthand for this is “irl” in “in real life”

<sup>47</sup> The conception that an individual can only be believed to be female upon showing a feminine body is a well-known “rule” of online anonymous forums, often expressed in the adage “Tits or GTFO” (get the fuck out).

spaces need to be explicitly created. Here, women can find solidarity through shared marginalisation.

## **Conclusion: How did we get here?**

Storytelling shows us how we got here. Genealogy shows us that the quest for diversity in technology and its creative culture is ideologically saturated and historically situated. Tracing genealogy to Nietzsche's definition (2006 [1887], p. 35), forgetfulness is not just inertness or inactivity "but rather an active ability to suppress", in which memory acts as a doorkeeper and guardian to action. In the Introduction, I showed how visibility is political, as "vision is always a Question of the power to see" (Haraway, 1988, p. 585). Women have been forgotten, unseen and unaccounted for in the history of technology. Paradoxically, a few notable figures have risen to visibility in tokenised processes of remembering. In charting the history of hacking and programming, many works of scholarship recreate the inequality of the representation they seek to Question by narrating women as incompetent. The heteronormative masculine insider's power constructs the feminine as incompetent and juvenile (Butler, 1990). This is epitomised in the declaration:

*"Girl hackers are as rare as Linux code in a Windows factory."*

(Lynch as cited in Taylor & Jordan, 2004, p. 129)

This citation and its humorous tone should not be taken as apolitical, as it illustrates an in-joke and in-group in a simple test of technical understanding. Since 2016 a Linux subsystem has been a Windows 10 feature that can be run by any user (e.g. Ubuntu). Linux code is no longer rare in Windows, and women should no longer be rare as creative programmers, hackers, and developers.

As shown in Jordan's (2016) genealogy and the accounts of Hicks (2017) and Ensmenger (2010), the history of hacking is informed by the ideology of computing that gave rise to the flagships of technology. The historiography outlined is the typical narrative, proposing a lack of women at each stage of the culture's development. This project aims to deconstruct these masculinist

narratives that define the absence of women at the origin (Derrida, 1967). Rather, I propose that gendered conceptions of the hacker lead to the “forgetting” and overlooking of women’s involvement, leading to presumptions that all creative coders are male and masculine. Tokenising the history of technology serves to render women invisible in historical and contemporary narratives, which undermines the significance of their innovation. By contrast, the history of creative coding as a process that considers the diversity and historical nature of social experience (Hall & Gay, 1997) allows us to understand discourse and identity in context. Through historically contextualising how an in-group has emerged, a space can be opened for cultural interruption.

## Section II: The Gender Code

Stereotypes are fundamentally about relations of power. In *The Nature of Prejudice*, Allport (1954) argued that even simple prejudice such as antilocution, if left unchecked, can develop into extreme forms.<sup>48</sup> Prejudice is defined as “antipathy based upon a faulty and inflexible generalization [that] may be felt or expressed toward a group ... or a member of that group” (Allport, 1954, p. 9). From this perspective, discrimination is a spontaneous expression of prejudice, and the engine that drives it is a group-based irrational hostility (Dovidio, Glick, & Rudman, 2005). Hostility refers to an *opposition* that is fuelled by categorical and parochial beliefs that are rigidly ignorant (Glick & Fiske, 2001). The hostility is then discharged without restraint. In Chapter I, Section I, I outlined Risman’s (2009, 2012) thesis of gender social structure. Here, I use this theoretical foundation to show that stereotypes are the result of larger cultural processes, and in turn stereotypes dictate interactions on a micro, individual level

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<sup>48</sup> Antilocution is negative verbal comments directed against a person or community that are not addressed directly to the target, involving an in-group ostracising an out-group on a biased basis.

(Scarborough & Risman, 2017). Allport's (1954) original text "misses the ordinariness of gender prejudice", but since its publication a vast body of literature has since emerged on sexism and stereotypes in social psychology (Dovidio et al., 2005, p. 107). The overarching conclusion of gender stereotyping research is that for women to enter male-dominated positions and fields, it is necessary for them to disconfirm gender stereotypes – to act more like men. Building on the scholarship of Tanczer (2015), Levy (2010) Jordan and Taylor (2004), Section I showed that women are deterred from entering programming due to the male dominance, misogyny, and hostility found in creative coding culture. Even prior to participating, perceptions of the male insider and hostility may prevent entry and obstruct feelings of belonging, thereby creating a gendered barrier to women's participation.

Women are underrepresented in anonymous forums (Brooke, 2019a; Tanczer, 2016). This is on a continuum with their lack of representation in more formal avenues of learning. These conceptions are supported by bodies such as Quantcast (2016), who found that women accounted for a maximum 10% of the traffic on programming forums in the US. The male dominance here is quantifiably obvious, yet there is little exploration of where this inequality of representation stems from. Women have been shown to observe ("lurk") on programming forums and similar sites, put off by masculine discourse (Ford et al., 2016), or they are made to feel that "programming is not for them" before even reaching these sites (Master et al., 2016).<sup>49</sup> Data and research that chart this process as a narrative experience are lacking. Rather, research investigates points in time, focusing on already established communities or education networks.

The purpose here is to delve into current understandings of women's exclusion from technical fields. I will examine the content of gender-based stereotypes and the reasoning that leads to their

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<sup>49</sup> Lurking is the practise of observing an online community, learning their conventions, before participating. The premise is that a person must be familiar with the norms of interaction before taking part.

continued existence both on and off platforms. Here, I am defining platforms as multisided digital frameworks that shape the terms on which participants interact with one another. I consider a range of literature on a variety of platforms in order to emphasize the need to move away from a platform-centric approach to understanding stereotyping and online discrimination. According to GlobalWebIndex (2019), the average person has between 7 – 8 social media accounts, meaning that examining social interaction in an isolated platform is unrepresentative of the lived experience of users. Research across STEM, formal, and informal avenues of computational culture shows a pervasive stereotype: women cannot write code.

### **I am who I think you think I am.**

The term *stereotype* has been used up to this point in a general sense, but it is useful to provide a specific definition as I introduce social psychology literature. A stereotype refers to an over-generalised belief about a category of people, despite variations on the individual level, which often results in prejudicial treatment. From a structural perspective, stereotypes are relational and their content is dictated by belonging to a high or low status group (Cuddy et al., 2008; Fiske et al., 1999). As proposed by Glick, Fiske, and Cuddy (2008), the Stereotype Content Model postulates that high status social groups are considered competent. The hypothesis of this model is that stereotypes possess two dimensions: (1) social groups are *warm* if there is not in-group competition for the same resources; (2) they are considered *competent* if they are high in status, such as being economically successful. The model thus supports the argument that a lack of in-group competition predicts perceived warmth, and status predicts perceptions of competence. The intersection of these dimensions is shown in Table 2 below.

*Table 2 Stereotype Content Model*

		Competence	
		<i>Low</i>	<i>High</i>
Warmth	<i>Low</i>	Paternalistic Stereotype Low status, non-competitive <u>Types:</u> Housewives, elderly people, disabled people	Admiration Stereotype High status, non-competitive <u>Types:</u> In-groups, close allies
	<i>High</i>	Contemptuous Stereotype Low status, competitive <u>Types:</u> Welfare recipients, impoverished	Envious Stereotype High status, competitive <u>Types:</u> Feminists, wealthy

With foundations in the works of Adorno (1950), research by Cuddy et al. (2008) Fiske et al. (1999) and Spencer et al. (1999) has shown that those who perceived the social world in terms of a hierarchy are more likely than others to hold prejudices towards lower status groups. Stereotypes serve to promote system-justification in this manner through confirmation biases. Lower status groups with little mobility are heavily associated with a lack of competence and thus their low status position is justified. Those who protest such hierarchy, such as feminists, are subject to an envious stereotype and are resented. This reductionism has been the foundation of systematic discrimination. The Stereotype Content Model thus shows how dominant groups maintain power, through associations of competence with high status, fuelling a myth of meritocracy.

Stereotyping is a formula of small-scale intervention used to govern collective behaviour. In the terms of Deleuze and Guattari (1989), it is a *micro-politics*, that is, it is a form of political regulation contributing to the formation of desire, belief, inclination, and judgement in individual subjects. The conjecture is that power is exercised on the level of individuals, and the everyday techniques that form perceptions, desires and judgements of individuals as they are embedded in their worlds (Deleuze & Guattari, 1989). As an example, Deleuze and Guattari (1989) use

patriarchy to show that reference to women as a “minority” is politically saturated and sensitive to relations of power. They further note that in this case, the “majority” is the dominant group, not the numerically larger. Discrete objects (man-woman) only appear so because there is a vested and pragmatic interest in demarcating them as such in a given context, which is mirrored in and enforced by language (Bakhtin, 2017). Here, gendered language is shown to be a short hand approximation of assemblages, of *becoming* man/woman (Deleuze & Guattari, 1989). Gendered words are regimes of descriptive texts that demarcate fields of interconnected particles and assemblages. Adorno (1950) and his co-authors also highlight how a demarcated, rigid categorical thinking is a central ingredient in prejudice. This form of categorical thinking was systematically explored by Allport (1954), who held that people possess a natural tendency toward the categorisation of phenomena. Since attributes such as gender exist on a continuum, social labels such as “male” or “female” are never more than approximations. Rather, these attributes merely represent useful linguistic conventions.

### ***Male and Female; Us and Them***

When performed correctly, gender appears natural, but it is compulsory and many societal norms act to police the social appearance of gender. As a process, gender is “a set of repeated acts within a highly rigid regulatory frame” (Butler, 1990, p. 25). Building on and extending Butler’s argument, Risman (2004; 2013) understands gender as a social structure, based on the conception of *natural* sex categories. Gender here has three dimensions of consequence:

*“(1) at the individual level, for the development of gendered selves; (2) during interaction as men and women face different cultural expectations even when they fill the identical structural positions; and (3) in institutional domains where both cultural logics and explicit regulations regarding resource distribution and material goods are gender specific.”*

(Risman & Davis, 2013, p. 744)

Stereotypical characteristics attributed to men and women in a social context influence the classification of gender roles as masculine or feminine; for example, scientists are men because

men are rational and analytical. To illustrate this point, studies conducted by Cuddy et al. (2015) show that within a given social context, male stereotypes align more closely with core cultural values than do female stereotypes. In a series of cross-cultural studies, they found that the socially desirable traits relevant to a particular context are associated with men and undesirable traits are associated with women (Cuddy et al., 2015). Despite the utility of categories in everyday life and in socially understanding others, the false isolation of people from each other or their social context can be devastating. A dogmatic adherence to categorical thinking tends to produce a distortion in perception. Typically, such distortions take the form of minimising differences within a social group (*assimilation*) and exaggerating differences between group categories (*contrast*) (Cuddy et al., 2015). If these differences are consistent with legitimised and widely accepted stereotypes, the distortion of perception may be highly resistant to change. Complementary to assimilation is the “out-group homogeneity effect”, meaning that the out-group is seen as more alike than in-group members (Simon, 1992). Out-group members, as a result, are at risk of being fungible and interchangeable, a key ingredient in stereotyping.<sup>50</sup>

Sex roles were operationalised and quantified in the 1970s in the Bem Sex Role Inventory (otherwise referred to as Psychological Androgyny), and since then Donnelly and Twenge (2017) conducted a cross-temporal meta-analysis of masculine and feminine traits that Bem identified. Bem’s (1974) inventory measures an individual’s identification with traditionally masculine and feminine qualities, such as affection, shyness, and tenderness for femininity, and leadership, aggression, and assertiveness for masculinity. Recent studies to validate the contents of the inventory have found that the overall picture is that the stereotypes persist over time, despite relatively radical social changes that have occurred since the mid-1970s (Donnelly & Twenge, 2017; Prentice & Carranza, 2002). Research into stereotypes has largely focused on socially

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<sup>50</sup> Fungibility is the property that the object possesses can be mutually substituted with objects of the same or similar type (Kuper et al., 2012).

desirable traits, and not the characteristics that are undesirable and sanctioned. Prentice and Carranza (2002) show that traits differ in their desirability for men and women respectively. Gendered behaviour is not equally desirable or undesirable but rather there is an expected level of conformity. When a violation of a typed identity is noticed, reactions depend critically on the nature of the trait involved. Violations that involve gender-intensified prescriptions or proscriptions often lead to punishment. Women who show signs of being controlling, or men who appear to be naïve and gullible are subject to social sanction.<sup>51</sup> In fact, Prentice and Carranza (2002) note that the harshest treatment goes to those who are perceived to defy gender-intensified barriers. This violation is severe, as it typically involves both the defying of gender barriers and a failure to manifest desirable traits. Many examples of the punishment of women in masculine roles fall into this category, including that of the woman as programmer.

### ***Statistics or Stereotypes?***

The identification of an in-group can be aided by a rationality that is dictated by existing members of a group founded on a base rate and statistical inferences. One such inference is Bayesian decision theory, a statistical system that attempts to quantify a trade-off between various decisions, making use of probabilities and costs (Cao et al., 2018).<sup>52</sup> An agent operating in this system uses Bayesian statistics (informed by *prior* assumptions on the distribution of a population) to estimate an expected value of its actions, and updates expectations based on new information.<sup>53</sup> From this perspective, any prediction represents assumed prior knowledge – that is, I rarely know any information exactly, instead I often only have some beliefs about the information I want to use to make a decision (Cao et al., 2018). Cao et al. (2018) examine

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<sup>51</sup> A gender-intensified prescription is one where deviation from the role is met with a strong reaction. For example, a man may face strong social sanction for being highly emotional rather than for not being good at maths. Whilst both challenge what is expected of men, we are more tolerant of those who are bad at maths than of those who express feminine emotions. This is distinct from *hyper-gender* characteristics or the exaggeration of gender stereotypes, such as aggression in men.

<sup>52</sup> A base rate is a prior probability, unconditional on feature or immediate evidence.

<sup>53</sup> This “agent” is typically referred to as a Bayesian estimator.

rationality in the context of gendered assumptions for medical professionals, and judgments made on the rationality of others. In the case of my research, if I use a statistic cited earlier, that 82% of computer science graduates were men and 18% were not men, then the base rate of men who are computer science graduates is simply 82%. Given this context, one could ask a Question in the following form: “A man writes code. A woman writes code. Who is more likely to be a computer science graduate?” The Bayesian Answer is that a man is more likely to be a computer science graduate because of two premises: (1) computer scientists are more likely to be men, and (2) not everyone who writes code is a computer scientist. The first premise is a well-known base rate, and its neglect is a much-cited logical error, known as base rate fallacy (Cao et al., 2018). Premise 2 is questionable if only computer science graduates write code, but many learn to code through informal networks.

Much categorical thinking is based on the representativeness heuristic, that is making judgments based on the similarity of an object or person to an existing stereotype of a group (Cao et al., 2018; Kahneman & Tversky, 1972). This heuristic would also predict that a man is more likely to be a computer science graduate than a woman, conditional on both individuals writing code, because a man is prototypical of technical professions. As a representativeness heuristic specifies only a direction, Bayesian analysis specifies a precise magnitude by which a man is more likely to be a computer scientist graduate (Cao et al., 2018; Kahneman & Tversky, 1972). An alternative Answer to the Question of who is most likely to be a computer science graduate is founded in a Rawlsian (1971) moral imperative to make equal judgments of those who behave identically. Bias here can be deliberate or latent; it can be intentional discrimination, or an implicit prejudice. Because both the man and the woman write code, both should be viewed equally, as computer science graduates. This egalitarian ideal is embedded in universities and the hiring practices of most technical institutions and companies. Yet much research shows that this aspiration is rarely realised. Biernat and Kobrynowicz (1997) find that women are required to meet higher thresholds than men when demonstrating competence, as women are evaluated consistently with negative

stereotypes in technical fields. Judging that the man is more likely than the woman to be a computer science graduate when both individuals write code can be another double standard. The code of equal treatment is harshly challenged by stereotypical understandings in everyday life. Gendered expectations are therefore visible in the interactional and cultural context of technology.

In the social psychology framework of decision making, Cao, Kleiman-Weiner, & Banaji (2018) highlight how the moral imperative of egalitarianism is often at odds with the imperative to consider priors based on group membership. From this standpoint, the appropriateness of relying on statistical imperatives is incredibly contentious when making decisions on judgments of individuals from different social groups whose behaviour is identical (Cao et al., 2018). In their study, participants were told that a man had performed surgery and a woman had performed surgery, after which they were asked who was most likely to be a doctor: (a) the man, (b) the woman, or (c) both equally likely. The particularly interesting finding of the study by Cao et al. (2018) is that individuals criticised the morality and intellect of another person who made the same Bayesian judgment they did – i.e. that all doctors are male. This reproach holds even if the individual made the same judgment based on the same rationality. A statistical basis for decision making in others is seen as repugnant. Cao et al. (2018) propose a solution to the inconsistency and hypocrisy they observed: a blatant sexist and a feminist statistician would come to the same conclusion in terms of gendered assumptions for vastly different reasons. Cao et al. (2018) proposed that the inconsistency of moral judgment apparent in the study can be resolved if one considers that the base rate, a priori, is that someone who sees men as more likely to be doctors than women is more likely to be sexist than a statistician. By condemning those who consider a man more likely to be a doctor than a woman, the study by Cao et al. (2018) shows that participants express a desire for equal judgments, a position that is undermined by their own judgment that a man is more likely to be a doctor than a woman.

The examination of the representativeness heuristic (Kahneman & Tversky, 1972) and Bayesian decision theory (Cao et al., 2018) shows that statistics of representation are not apolitical. In fact,

a priori knowledge of group membership can influence perceptions of those who operate in technical cultures online and offline. Perceptions of competence are framed by a statistical understanding of who is *most likely* to be capable, based on stereotypes rather than individual ability.<sup>54</sup> Knowledge of a lack of women in creative coding can perpetuate the absence and strengthen stereotypes, even when we are critical of this judgment in others. Although rationality may be justified in terms of cold, hard statistics and Bayesian probabilities, it can result in judgments that are prejudicial, discriminatory, and sexist. A reliance on statistically-based assumptions compounds inequalities and perpetuates stereotypes. These numbers do not represent objectivity, rather they inform thresholds of what proportion of women is considered acceptable.

### ***A Just World***

Looking past a statistical and quantifiable framing of absence, prejudice is also linked to the way the in-group and out-group account for each other's behaviour. Such explanations, or *causal attributions*, are sources but also symptoms of prejudice and discrimination (Burgess & Borgida, 1999; Nier et al., 2013). If a young woman fails mathematics and this is attributed solely to dispositional factors, such as lack of ability, then prejudice towards women is likely to continue. However, if her failure is attributed instead to poor teaching, prejudice may not come into play. Regarding prejudice and the resulting discrimination, there are three attributions that are often used to make causal judgments about the behaviour of out-group members. In *just-world attributions* the ideology dictates that individuals essentially get what they deserve; the impoverished are lazy, and the best and brightest succeed in meritocratic system (Burgess & Borgida, 1999). The geek revenge fantasies in Section I are one such example. These fantasies are perpetuated by survivorship bias, where those that failed are overlooked – usually because they are less visible. The bias is fuelled by overly optimistic beliefs because the failures are

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<sup>54</sup> In reference to the Stereotype Content Model discussed earlier in the chapter.

ignored (Terrell et al., 2017). This dogma downplays the role of situational factors and argues that the problem of social injustice lies not in society, but with its victims.

In addition to the just-world belief, a second more general tendency exists to attribute behaviour to dispositional causes, internal or even genetically determined (Pettigrew, 1979). In this *fundamental attribution error*, even when behaviour is undeniably caused by situational factors, an audience will generally refer to dispositional explanations (Burgess & Borgida, 1999). Taking this one step further is *ultimate attribution error*, which is when in-group members attribute negative out-group behaviour to dispositional causes. At the same time, positive out-group behaviour is attributed to: (1) a fluke or exceptional case, (2) luck or special advantage, (3) high motivation and effort, or (4) situational factors (Cheryan et al., 2009). This double standard makes it incredibly difficult or near impossible for an out-group member to expressly challenge and overcome stereotypes and prejudice. Positive actions are explained away, and negative actions are used against the low status groups to legitimise their position. Therefore, domination of identity categories is justified by the association with competence, maintaining established hierarchies. Stereotypes are a belief that can powerfully affect social perceptions and behaviour.

## **Description and Prescription**

The components of stereotypes are responsible for various forms of sex discrimination, through distinct psychological mechanisms. Burgess and Borgida (1999) argue that the prescriptive and descriptive components of the “female” stereotype lead to differing forms of discrimination. Stereotypes are descriptive, containing beliefs about how a social group *typically* acts, as well as prescriptive, in terms of beliefs about how a social group *should* act (Burgess & Borgida, 1999; Walsh, Hickey, & Duffy, 1999). They are *descriptive* in the sense that they are beliefs about the attitudes, roles and behaviours that characterise men and women. Gender stereotypes are highly prescriptive. The qualities that they assign to women and men are not just seen as desirable, but they are also often obligatory. The stereotype of women as emotionally intelligent and caring is

matched by a social prescription that they should be so. The belief that men are strong and wilful is matched, again, by the social prescription. Such gender stereotypes act to justify and perpetuate the status quo and dominance of masculinity (Burgess & Borgida, 1999; Butler, 1990; Cheryan et al., 2009; Glick & Fiske, 2011; Russell & Trigg, 2004). Violations of typed characteristics and gendered expectations are met with sanctioning, hostility, and even violence.<sup>55</sup> The prescription of stereotypes is a reinforcement of power structures, which can be mediated by attention (Fiske, 1993). As stereotyping exerts control, it maintains and justifies the status quo. The socially powerful or in-group can be motivated by their own self-concept, having the luxury of paying attention only to the positive aspects of their stereotype, as they are minimally affected by the associated adverse traits (Fiske, 1993). Burgess (1999) points to how men are more likely to discriminate on the basis of gender stereotypes than women. Though a powerful group can pay little heed to negative stereotypes and the out-group are at their mercy, stereotypes are largely inflexible and persist over significant stretches of time, even when the larger social context can seem to change dramatically.

Gender-based descriptions of identity result in stereotypes and discrimination through a disparate impact, where women are perceived in traditional female roles and are thus deemed inappropriate for stereotypically male occupations. Burgess (1999) points to how the discrimination may be unintentional on an individual basis, but the stereotype serves to structure the flow of information in daily life. The *prescriptive* component is also built on beliefs surrounding the attributes to which men and women are expected to conform. The disparate treatment results in the devaluing of women, who are subjected to a hostile environment if they violate prescriptions about how women should behave (Burgess & Borgida, 1999). Here, discrimination is motivated by hostility

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<sup>55</sup> For example, there are particularly high levels of violence against the transgender and gender non-conforming community. Anti-transgender stigma, denial of opportunity and increased risk factors compound to create a culture of violence (HRCF, 2020).

and gender prejudice, as stereotypes serve to maintain power inequalities in society. Individuating information has no bearing on discrimination, as women's success is coloured by their social context. That is, an individual *woman* can like Star Trek or be gifted at mathematics, but this is not seen to challenge the overall categorisation that *women* don't like sci-fi or are bad at mathematics as a group. They become the exception that proves the existence of the rule. Deviation from a socially constructed gendered norm is allowed on a discrete basis. Stereotypes are a fundamental contributor to sex-based discrimination and form a key component of analysis of gender inequalities.

### ***Women like white knights***

If the rigid categorical thinking of stereotypes can lead to prejudice, from a Marxist standpoint they can also be connected with *false consciousness*. In the work of notable thinkers such as Gramsci and Althusser, false consciousness refers to the creation of social norms and values by ruling classes to naturalise a cultural hegemony and dominance by a particular social group (Dovidio, Glick, & Rudman, 2005). In more recent research, the concept has been adopted as a way of accounting for how groups accept negative stereotypes about themselves. In this context, false consciousness is defined as the holding of beliefs that are contrary to one's own group interest and that contribute to the maintenance of a disadvantaged position (Dovidio et al., 2005). For instance, women may themselves hold the belief that they are less capable of mathematics or rational thought than men, and therefore think that their lower position and lack of progress and representation in the field are unavoidable or deserved. Drawing on the concept of false consciousness, Jost & Banaji (1994) postulate that stereotyping serves a system justification function. Stereotypes that serve to justify an existing state of affairs will operate at the expense of or to the detriment of an individual or collective interest. However, an individual can internalise and accept the stereotype as explaining their status.

Building on Marxist conceptions of system justification, Glick and Fiske (1996) look to the implicit features of the stereotype content model in order to differentiate between the forms of

discrimination and sexism that the components of the female stereotype lead to.<sup>56</sup> They (1996) explore the interrelated components of sexism as *hostile*, involving negative feelings towards women. Sexism is also *benevolent*, seen as a chivalrous ideology that offers protection and affection to women who adopt conventional gender roles and stereotypical behaviour (Glick & Fiske, 1996). Three factors make up the Ambivalent Sexism Inventory (ASI): (1) paternalism, in terms of masculine dominance and protection; (2) gender differentiation; and (3) heterosexuality, in which women are sex-gatekeepers and objects of desire. Exploring the concept in greater depth, hostile sexism fits Allport's (1954) classic definition of prejudice as antipathy based on generalisation. The concept of *benevolent* sexism is slightly more complex, referencing a set of interrelated attitudes towards women that are sexist in terms of viewing women stereotypically in restrictive roles that are subjectively positive in feeling or tone for the perceiver (Glick & Fiske, 1996). In this form, the behaviours elicited are categorised as pro-social or intimacy seeking. The origins of this sexism lie in traditional male dominance, wherein the benevolence lies in intention, not in receipt or effect. Both concepts of sexism share the belief that women are "weaker" (Glick & Fiske, 2001). These associations with "weakness" in typing women foster prejudice and discrimination, as a social group (i.e. women) is treated as inferior due to their group membership that classifies them as being intellectually inferior. Following the ASI (1996), Glick and Fiske developed the Ambivalence towards Men Inventory (AMI) (2001). Again, the hostile and benevolent subscales of the AMI are based on conventional attitudes towards men that have opposing *valences*. The contents of the hostile measures of sexism are illustrated in Table 3.

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<sup>56</sup> Both Ambivalent Sexism Inventories (ASI, AMI) are built into Study I.

Table 3 ASI and AMI: Hostile Stereotypes

The Ambivalent Sexism Inventory	The Ambivalence Toward Men Inventory
<ul style="list-style-type: none"> <li>– Women exaggerate problems at work</li> <li>– Women are too easily offended</li> <li>– Most women interpret innocent remarks as sexist</li> <li>– When women loose fairly, they claim discrimination</li> <li>– Women seek special favours under guise of equality</li> <li>– Feminists are not making reasonable demands</li> <li>– Feminists are seeking more power than men</li> <li>– Women seek power by gaining control over men</li> <li>– Women tease men sexually</li> <li>– Once a man commits, she puts him on a tight lead</li> <li>– Women fail to appreciate everything that men do for them</li> </ul>	<p>Resentment of Paternalism</p> <ul style="list-style-type: none"> <li>– Men will always fight for greater control in society</li> <li>– Even sensitive men want traditional relationships</li> <li>– Men pay lip service to equality, but can't handle it</li> </ul> <p>Compensatory Gender Differentiation</p> <ul style="list-style-type: none"> <li>– Most men are really like children</li> <li>– Men would be lost without women to guide them</li> <li>– Men act like babies when they are sick</li> </ul> <p>Heterosexual Hostility</p> <ul style="list-style-type: none"> <li>– When in positions of power, men sexually harass women</li> <li>– Men have no morals in what they will do to get sex</li> <li>– When men “help” women it is to prove they are better</li> <li>– Men usually try to dominate conversations with women</li> </ul>

Unsurprisingly, Glick and Fiske (1996; 1999; 2011) found the ASI and AMI scales to be strongly correlated, that is, if someone holds strong stereotypes about women they most likely also hold strong stereotypes about men. This correlation can be explored with reference to Goffman’s (1961) *role sets*; the complement and assemblage of social relationships which an individual is involved in because they occupy a particular social role. Building on Goffman (1961), Merton (1961) developed the *status set*. A role set refers to the relevant audiences of a particular performance and a status set refers to a collection of social statuses that an individual holds. We can apply these networks of relationships to gender-based roles. For instance, let us take the masculine stereotype and desirable trait of the “white knight”; a physically and emotionally strong man who is chivalrous and noble. This stereotype and its associated character traits make little sense without the fair, helpless, damsel in distress. Here, through a heterosexual matrix (Butler,

1990), the white knight and damsel in distress are complementary characters from fairy tales that we are all very familiar with, but they illustrate tropes and desirable gender role sets that we still expect; men are strong and agentic, whereas women are passive. In white knighting behaviour, one may use benevolent intentions to produce (intentionally or unintentionally) a relation of dominance. This is where Merton's (1961) associated *status sets* are particularly important, as the role of white knight is nonsensical unless there is an understanding that there is an associated social status to legitimise the role. As Hogan (2018) argues in the example of a doctor and nurse, you can't just act like a nurse, you must have the associated status and legitimacy to go with it. In this sense, by performing one stereotypical role, one is reproducing not only that role, but the role relation. The rejection of the assistance offered by the white knight is a slight, for those who do not see how the interaction reproduces hierarchies. Reagle (2016) argues that "mansplaining" is a central tenet of geek culture, as an act of gendered knowing and white knighting.<sup>57</sup> Gender performance does not merely affect the individual level but also serves to replicate power structures: a gender performance subjugates and dominates. Implicit in these role sets is compulsory heterosexuality, where gender expresses sex. Thus, stereotypes, even if not as refined as the white knight in the ASI and AMI, exist as complementary sets with complementary male and female characters, and their continued existence is an expression of the legitimacy that is collectively ascribed to them.

### ***Ambivalent Sexism in STEM***

In looking to the implications of hostile and benevolent sexism in STEM, Kuchynka et al. (2018) see hostile sexism in terms of the overtly negative, angry attitudes and behaviour toward women who are in masculine domains or who push for social change. In the same context, benevolent sexism is affectively positive but is still patronising and condescending, encouraging women to

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<sup>57</sup> This concept is explored in more depth in Study III. In general, white knighting is when a man comes to the aid of a woman (needed or not) expecting gratitude or even sexual favours in return.

embrace traditional gender roles. In traditional educational environments, such as the university classroom, Kuchynka et al. (2018) propose that increasing institutional pressure and raising awareness of discrimination may hamper more overt, hostile expressions of sexism. There is research that shows that institutional intolerance of gender prejudice can affect internal biases (Kuchynka et al., 2018). Even though women in STEM are in a non-traditional environment, the potential social and legal sanctions may constrict manifestations of sexism to its more benevolent forms. Kuchynka's (2018) study found that women in STEM university courses reported experiencing higher levels of protective paternalism and gender differentiation (benevolent sexism) than hostility. Their (2018) research also found that hostile sexism has less effect on those who already strongly identify with a STEM subject and can be considered part of an in-group. It was not clear in their study what the consequences of hostile sexism were, as this was arguably the non-normative form of sexism in universities. The implication of such research is that hostile sexism may be more evident and overtly expressed in anonymous forums where regulatory powers and institutional values hold little sway.

### ***Women are bad at maths***

A popular theory in social psychology, *stereotype threat* refers to being at risk of confirming, as a self-characteristic, a salient (typically negative) stereotype about one's social group (Steele & Aronson, 1995). The conditions that generally produce stereotype threat are ones in which the highlighted stereotype impacts the self through association with a relevant social category. When one's self is viewed in terms of a salient group membership, performances can be undermined because of concerns about confirming negative stereotypes of one's group. Originally developed by Steele and Aronson (2000) to examine the effect of emphasising the impact of race on academic achievement, stereotype threat effects have been shown in a wide range of social groups. Gender-based examples include the conception that women are bad at maths (Spencer et al., 1999; Walsh et al., 1999) or that men are less socially sensitive than women (Koenig & Eagly, 2005). The susceptibility to the threat is referred to as "stereotype vulnerability" (Aronson et al.,

2002). There are several factors that play a role in vulnerability, namely group membership, domain identification, group identification, internal locus of control, personality, and stereotype knowledge (Spencer et al., 1999). Salient identities can become threatened when relevant stereotypes are invoked in how one performs in an environment. It induces what is described in Mertonian terms as a *self-fulfilling prophecy*: a false definition of the situation (e.g. women aren't good at maths) evokes new behaviour, which makes the original false conception come true. Merton (1948, p. 195) points to the “specious validity [...] perpetuating a reign of error” as the prophet cites the course of events as proof that she was right from the offset (e.g. I failed that maths test because I am a woman and women are bad at maths). Therefore, stereotypes are not only harmful in the way others perceive an individual or a group but can be internalised to the extent of providing a confirmation bias.

Examining stereotype threat and its implications in context, Adams et al. (2006) show how even the belief that they are in the presence of an instructor who is sexist harms women's performances when completing a task. Prentice and Carranza (2002) point to how, even in a professional and academic context, women are held to higher (contextually irrelevant) standards of feminine niceness than their male peers. However, they are not held to (contextually relevant) standards of agency and intellectual achievement (Prentice & Carranza, 2002), the origins of which were discussed in Section I. In universities, showing high levels of intelligence, competence and rationality is seen as good, and desirable in the context. But, if women do not show qualities of intelligence then it is not so bad – not as severe, by any measure, as if academic men fail to demonstrate high levels of these qualities (Prentice & Carranza, 2002). The disparate expectations constitute discrimination.

In contexts such as universities and professional settings in which achievement is paramount, the latitude given to women on achievement-related traits is not a kindness or favour. To borrow a phrase used by George W. Bush to describe the treatment of ethnic minority students in the classroom, it is “the soft bigotry of low expectations” (as quoted in Prentice & Carranza, 2002, p.

280). Therefore, stereotype threat refers to the “threat” that one may conform to the negative stereotypes surrounding one’s groups, which in turn becomes a self-fulfilling prophecy (Aronson et al., 2002; Spencer et al., 1999). Using the concept of stereotype threat to explain disparities in achievement has attracted criticism for involving an additional mechanism that can be explained by established theories. However, many theories proposed as alternatives are largely biologically reductive, similarly reminiscent of natural laws, such as Yerkes–Dodson law, which charts the relationship between mental arousal and performance.<sup>58</sup> Nonetheless, the point of this discussion is not to debate stereotype threat, but rather to use stereotypes as a reasonable lens for analysis to account for the dearth of women in creative coding.

### ***Women do not like Star Trek***

An alternative approach to stereotype threat that is relevant to this study is *ambient belonging*, proposed by Cheryan et al. (2009). Ambient belonging is generally the feeling of fitting into an environment, specifically referring to the material objects and structural (layout) components, as well as the people seen to be occupying the space. Here, there is another type of identity threat to consider besides the fear of being negatively stereotyped or being devalued in a domain because of one’s identity, and that is the threat of entering an environment and feeling like one simply does not and will not belong there (Master et al., 2016). Cheryan et al. (2009), whose study focusses on women in computer science, propose that a lack of ambient belonging can preclude women from ever developing an interest in domains associated with those environments (Cheryan et al., 2009; Master et al., 2016). In the first study they ran, they found that women’s interest in computer science varies across physical environments that can be considered stereotypical, non-stereotypical, and a baseline, whereas men’s does not. According to the study, exposing women

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<sup>58</sup> More explicitly, the “law” is the relationship found between mental arousal and performance: performance increases with mental arousal but only to a limit. When levels of arousal or stimulation become too high, performance decreases. We reference this law merely to outline alternative theories, not to endorse a purely biologically deterministic approach.

to stereotypical computer science objects (such as Star Trek posters and video games) actively deters women from participating, as they serve as a reminder that it is a male-dominated field.<sup>59</sup> Cheryan et al. (2009) went as far as testing whether the findings held up in an all-female environment and found that even if a technological environment is entirely populated by women, stereotypical objects associated with masculinity in computer science will put off around 82% of women, whereas they have no effect on men. The results of their study show that the stereotypes of computer science environments are heavily associated with masculinity, even when exclusively populated by women. The point is that the stereotypical nature of the environment communicates to them that they do not belong there. The more masculinity populates an environment, the more it signals to women that they do not belong there, even if they can see a majority female population. Although the presence of stereotypes and stereotypical objects does not attract men, it is important that it does not repel them. Masculinity is the default presence, so an apparent increase in its salience is unrelated to men's choice of computer science and technological spaces. As the strength of the stereotype increases and the more an environment is associated with that stereotype, the less women feel that they belong and want to take part. It is worth noting that Smeding's (2012) study into the implicit gender stereotypes in STEM showed that women in these technical fields hold weaker gender stereotypes and implicit biases than men in female-associated subjects. In an example reminiscent of the feminine "coders" of the 1950s-60 (Ensmenger, 2003), Google was recently sued by a number of its employees as it was categorising women who worked for them as "front-end" (i.e. UI design) developers without justification. This in turn blocked their access to higher pay grades and faster promotion avenues, while also being unrepresentative of the actual work they were doing (Vedres & Vasarhelyi, 2019). Cheryan et al.

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<sup>59</sup> Star Trek has been praised for its social commentary, including steps towards gender neutrality in costumes since the Next Generation. This claim to feminism is problematic. In the Original series there are heavily sexualised Orion slave girls, who in Next Generation are revealed to actually be the enslavers – using their pheromones to entrap men. This aside, the undeniable association with geek masculinity is the focus of enquiry here, not a debate on the gender politics of the franchise.

(2009) conclude that their research indicates that changing a stereotype in arenas like computer science and web development can encourage more women to express interest in and enter the field, and can even diversify the range of masculinity by appealing to men who favour non-stereotypical environments.

I propose that ambient belonging translates online into the form of the affordances of a platform. Affordance refers to the properties of an online environment that permit and facilitate social actions, as platforms shape the terms on which participants interact with one another. Schwartz and Neff (2019) show that a user's gender alters how they perceive a space and thus the possibilities for action. Coining the term *gendered affordance*, they illustrate how users are "afforded different actions based on cultural repertoires and social institutional factors" (Schwartz & Neff, 2019, p. 2418). The social structure of gender is reproduced in how users interact with a platform, as cultural repertoires normalise the submissive role of women. Marwick (2013) points to how the norms and values of programmers are built into the platforms they produce. She (2013) argues that ("authentic") self-presentation on platforms is a strategic application of business logics. These forms of acceptable self-expression are those deemed tolerable to young, white, middle class men (Marwick, 2013). As ambient belonging is signalled through physical objects that facilitate fitting into an environment, gendered affordances of anonymity online can solidify the perception of a masculine majority. Social structures dictate that belonging in technical spaces is a bestowed on men only, and the potentiality of legitimate participation is not afforded to women.

Looking at anonymity as a technological affordance, Hogan (2013) describes three classes of pseudonyms and their associated uses: (1) *functional*, where pseudonyms denote a specific social or technical function; (2) *situational*, where an external motivating force mandates the masking

of identity; or (3) *personal*, where an internal prerogative to adopt a persona makes them useful.<sup>60</sup> On Twitter, for example, Hogan (2013) shows that pseudonyms serve a functional purpose, where the microblogging format restricts and affords the number of characters available for handle (username denoted by “@”) and message. He additionally cites historical examples of how pseudonyms were used to publish work so as to avoid discrimination based on ethnicity or gender, such as the earlier publications of the Brontë sisters or George Eliot (née Mary Anne Evans). The use of these anonymous frameworks online may mean that one allows oneself to be assumed as male in order to follow the social conventions of a platform (Tanczer, 2016). In such gender work, Kitzie (2018) points to how the degree to which a person can keep a desired element of their identity unknown can be useful for communities who are often stigmatised such as LGTBQA+ individuals. Kitzie’s (2018) research highlighted how totally anonymous spaces, such as 4chan’s LGTBQA+ board, can be problematic as non-hegemonic discourses can be disrupted by trolls and stigmatising behaviour. As such, on the trans women board on 4chan, the feature of being able to log into the platform and create a username, which is not used by most members, becomes an affordance to reclaim a space and provide a contextual measure of authenticity. This example illustrates how the affordances of anonymity should be distinguished from its functional uses. Consistency in pseudonymity is a matter of confidentiality. Overall, Cheryan et al.’s (2009) concept of ambient belonging can be applied to the platform in terms of the affordances of anonymous spaces.

## **Typing in Computer Mediated Communication**

In traditional sociology, Goffman (1956) demonstrated that in face-to-face communication individuals use verbal and nonverbal languages in an effort to present themselves to others in a

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<sup>60</sup> Here I use Hogan’s (2013) definition of anonymity as a state (implying the absence of identity markers) and pseudonyms are a practice used to facilitate content creation. *Pseudonymity*, then, is an anonymous state which can be returned to through the continuous use of an account with a pseudonym.

desired manner, and this phenomenon is called impression management. Hogan (2013) states that the social sciences have been indifferent to debates of authenticity in “real name” (e.g. Facebook) versus anonymous spaces. Instead, research has followed in the tradition of Goffman (1956), in looking at the *aspects* of identity performed in different spaces and on different platforms. Considering this trend, it is thus reasonable to consider that the affordances and contexts of a platform may shape the manner in which identity is communicated.

In text-based Computer-Mediated Communication (CMC), the modification of impression is typographic, limited to language and contextual information. In the early theories of CMC, arguments based on social presence theory claimed that the fewer non-verbal cues you have in an interaction, the less social presence or connection you feel. Without this personal communication and presence, it was proposed that communication becomes more task orientated, even more hostile and self-absorbed (Lamerichs & te Molder, 2003). For these earlier researchers, the lack of audio or visual cues in CMC would be perceived as impersonal and there would be less social or emotional content exchanged (Kiesler et al., 1984). Contrary to social presence theory, Walther’s (1996) Hyperpersonal Communication Model proposed that CMC can exceed face-to-face interaction, affording communicative advantages over more traditional dyadic relationships. The model illustrates the unique affordances of CMC, as individuals can deliberate over how they represent themselves to others, how others interpret them, and how interactions can create a reciprocal spiral (Walther, 1996). Compared to face-to-face communication, text online affords greater ability to develop and edit self-presentation, enabling a formulated presentation of one’s self to others. *Disentrained channels*, such as asynchronous communication on boards or forums, give individuals a way to manage their relationship within groups more efficiently than in personal communication. Rather, Walther (1996) proposes that group members can enjoy a more “democratic” atmosphere in CMC than in face-to-face communication, as voices are equally valued. This feeling can be amplified by anonymity, as members of a group can feel more freedom to verbalise, without the pressure of high-status members.

An alternative model that is focused upon identity is the social identity model of deindividuation effects (SIDE). The model suggests that anonymity changes the relative salience of personal versus social identity, and therefore it can have a profound effect on both individual and collective group behaviour. *Saliency* in online communication refers to how visible a person's identity categories are, such as gender, race, or nationality. The SIDE model builds on the conception of anonymity in deindividuation theory, which saw antinormative behaviour as being facilitated by individuals acting in groups and no longer seeing themselves as individuals. In applying this framework to CMC, Reicher, Spears, & Postmes (1995) developed SIDE, suggesting that when social identities are salient, such as during in-group/out-group comparisons, this can lead to switching to a group level of self-categorization in which self and others are seen in terms of their group identities.<sup>61</sup> The effect of immersion and anonymity does not produce a loss of self as proposed by deindividuation theory. Rather, relative salience of personal and social identities shifts, and as the group identity becomes the core of the self, perceptions of the out-group become more stereotypical. Self-perception also shifts, as the self and other in-group members also become interchangeable, and the individual self-stereotypes are seen in terms of group attributes. However, this does not imply a loss of rationality or disinhibition – rather, the in-group standards dictate the regulatory framework of behaviour. It is also important to note that this is not deterministic, as anonymity does not automatically affect the salience of social identities. An individual can be identified in a manner that promotes a stronger social categorisation. This is particularly potent when social categories are potentially meaningful and visually identifiable, such as gender.

Several CMC studies have noted the prominence of stereotyped perception in online forums. Like any other area of social interaction, the Internet is “sex-typed” and full of stereotyping and sexism

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<sup>61</sup> This is also referred to in social psychology research as “depersonalisation”.

(Drakett et al., 2018; Fox et al., 2015). Sociolinguistic variation is visible here, as a community develops patterns of expression, and as the variation becomes conventional knowledge it becomes a stereotypical attribute (Needle & Pierrehumbert, 2018). A speaker can communicate an array of social information concurrently with a message, representing a system of speakers and listeners, with their associated attributes, e.g. coolness, hostility, sensitivity (Needle & Pierrehumbert, 2018). In addition to this linguistic approach, communication studies have supported a gender-in-context approach, in which context has a strong influence on gendered differences: by “knowing” the gender of an individual one is communicating with, one can generate expectations and prototypical behaviour, especially if there is not a pre-existing relationship or history of interaction.

As interactions are depersonalised online, Postmes, Spears, and Lea (2011) argue that categorisation of social attributes becomes fundamental to sense-making. Significantly, the influence of stereotypes increases in anonymous online communication. For instance, Postmes and Spears (2002) found that the activation of gender stereotypes in a context of anonymous CMC resulted in an increase in prototypical male or female behaviour, such as the tendency for women to ask more questions in interaction and to be less dominant than men.

*“The inability to individuate group members not only increases the stereotypicality of impression formation but also of behaviour”*

(Postmes & Spears, 2002, p. 1080)

Research by Guegan, Moliner, & Milland (2016) showed that in a dyadic model (interaction between two people), anonymity and visibility in CMC have more effect on identity reorganisation in line with a male stereotype than a female stereotype. Their study found that the anonymity of the CMC had a greater impact on the perceptions of a member of the dominant group (men) than on perceptions of a lower status group (women), when gender is known. Visibility and anonymity was manipulated through names (provided v. withheld) and the presence or absence of a webcam, to accompany the text-based communication they were investigating.

Guegan, Moliner, & Milland (2016) conclude that when anonymity affects interaction, this is mediated by gendered power imbalances. The SIDE model shows that the perceived stereotypicality and homogeneity of dominated and of dominant groups are reinforced during anonymous CMC.

Criticisms have been voiced against the SIDE model, particularly regarding its limited conception of identity and the social nature of CMC. SIDE's conception of identity is mechanistic, considered as "already there" – only decreasing or increasing in salience. Moreover, identity is viewed as an individual level phenomenon, rather than a collective and shared process. Finally, the model defines norms in terms of the regulation of an agent's behaviour, as opposed to resources for performing a range of social action (Lamerichs & te Molder, 2003). An alternative approach may see certain norms as internalised, but the breaking of normative or expected behaviour needs to be accounted for as a use of resources (Lamerichs & te Molder, 2003). In seeing text and talk as a social practice, language is no longer considered as an abstract system of reference. As an alternative to SIDE, a discursive approach (first touched on in Section I) focuses on what participants *do* with language, such as greeting, acknowledging responsibility, or presenting an argument as factual. Discourse is thus a domain of action, rather than the output of a cognitive process. In proposing a discursive approach to CMC, Lamerichs & te Molder (2003) demonstrate that SIDE does not represent a truly social approach, as its cognitive focus draw attention away from talk as action. "talk" cannot be separated from interaction, and thus is relational and performative. From a methodological perspective, the discursive model emphasises the need to observe talk in a discursive and rhetorical context, as the formation of identity is an active and dynamic process. Lamerichs & te Molder (2003) are proponents of a discursive approach in which text and talk are treated as social practices. Therefore, when considering CMC, the literature highlights a need for the inclusion of an understanding of talk as action, rather than as the result of a cognitive process, and this recognition will be incorporated in the analysis of Study II.

### *Computer-Mediated Communication & Gendered Discourse*

Gender has also been shown to be a significant arbitrator of interaction in CMC. As outlined, early scholarship heralded affordances of CMC as liberating, proposing that anonymity can subjugate gender hierarchies (Allen, 1995). However, recent research has shown that anonymity serves to homogenise participants in online forums as belonging to a singular group: college educated, white, male (Brooke, 2019a). From an (offline) sociolinguistic perspective, Lakoff (1973) first proposed that men and women differ in how they use words. Needle and Pierrehumbert (2018, p. 3) argue that “for gendered social meanings to exist, gender differences in observed usage must be present”, with the qualification that this is not bilateral, and that difference does not imply meaning. Rather, to ascertain if gendered differences carry meaning one must look at the interrelated layers of context (Needle & Pierrehumbert, 2018), such as what it means for a woman to be a speaker in any given scenario.

Identity struggles are visible in discourse. Wenger & Lave (1991) propose that researchers of collective identity should focus on communities of practice (CoP) in which members are drawn together by a common interest or that are created deliberately with the goal of gaining knowledge in a certain field. This conception has since been extended to include virtual communities of practice (VCoP), to show the expansion of this anthropological phenomenon online. Building on CoP, Bucholtz (1999) contends that communities of practice are a more accurate representation of the negotiation of identities in flux, rather than fixed categories of gender essentialism. In her study, Bucholtz (1999) illustrates how self-identifying “nerd” young women negotiate levels of their feminine identity with masculine nerd associations. In such local contexts, central and peripheral members’ identities are a contested domain of positive practices (who is better at being a nerd?), and control of identity via negative exclusionary practices (who counts as a nerd?). As such, Bucholtz (1999) argues that an ethnographically-based methodology is fundamental to understanding the gendered social meaning that is attributed to practices by individuals and communities. Moreover, the representation of identity in speech should be conceptualised in

terms of communities of practice rather than communities of speech, as identity and the bestowing of agency cannot be segregated from culture.

In applying the sociolinguistic framing of gender and local context to Lamerichs & te Molder's (2003) discursive model of CMC, feminist linguists have pointed to how normative discourse can represent gendered power structures and the male-centric nature of language, such as the use of "guys" as a collective (Tanczer, 2016). As the physical markers of gender are invisible in pseudonymity, male-centricity is amplified to male-by-default in these environments, perpetuating and stabilising feminine stereotypes (Tanczer, 2015). This communication process cultivates femininity of technological incompetence and juvenile girlness (Nic Giolla Easpaig & Humphrey, 2016; Shifman & Lemish, 2011). Contrary to assumptions of disembodiment in these spaces, the feminine body is discursively constructed, and cannot be separated from the linguistic acts that name it "girl" (Butler, 1993). Butler's (1993, p. 177) *girling* is a social process of naming to allocate norms of sexual identity to a subject. By referencing a juvenile status that is often sexualised, such discourse regulates power relations. The girl is required to conform to sexual norms as her identity is conceived as an object for the pleasure of a male viewer, indeed, an object of Mulvey's (1989) male gaze. In naming *women* as *girls*, they are outsiders and made juvenile.

The discourse of male-by-default is pervasive across pseudonymous spaces. The male gaze predominates on 4chan and Reddit, both of which have earned a reputation for misogyny (Milner, 2013; Phillips, 2015). They are prone to gender antagonism, with explicit identification as female often being met with hostile argument, when outside of female-identifying spaces (Milner, 2016). Massanari (2015a) shows that the male gaze on Reddit discursively excludes women and people of colour, marginalising many voices. She defines such social practices as *toxic technocultures*, which are "toxic cultures that are enabled by and propagated through sociotechnical networks" (Massanari, 2015b, p. 333). The male gaze dismisses women as fungible, a sexual object that may be mutually substituted with similarly typed objects (Levmore & Nussbaum, 2019). The process of recreating this stereotype of the objectifiable woman constitutes what Nakamura (2013)

denotes as a *cybertype*, reflecting how the Internet shapes and reshapes perceptions of identity. Although Nakamura's (2013) focus is primarily on race, she identifies how depictions of gender online can impact the way gender is thought about, in a two-way causal relationship between online and offline society. She argues that historic power relations are crucial to the defining of cybertypes, often determined by stereotypes that exist offline, but that the defining attributes of the offline stereotype are amplified as the characteristics are translated online (Nakamura, 2013). Building on the literature on communication, the next section examines gender specifically in creative coding culture online.

## **Gender in Programming Forums**

In looking at barriers to women's participation on the popular programming forum Stack Overflow (SO), Ford et al. (2016) found that impersonal interactions were the main factor that discouraged women from contributing. The women ( $n = 22$ ) interviewed for the study cited three features of CMC on the platform that deterred them from contributing: (1) pseudonymity was seen to encourage blunt (direct) and argumentative responses on posts; (2) invisibility of women leads to the site feeling like a "boy's club" full of "bro humour" (Ford et al., 2016, p. 6); (3) large communities are intimidating, and not possible in the same way offline. Using this example, the affordances of CMC are evidently more beneficial to an in-group, and attributes that might work for a majority group can be barriers for identifying with a community. Building on this, Ford et al. (2017, p. 1) conducted a second study where they developed the concept of *peer parity*: having similar individuals to compare oneself to in a space. The study (Ford et. al., 2017) found that the presence of female-identifying usernames on a thread increased the likelihood that a woman would engage actively with the SO community.

In a similar project, Vedres and Vasarhelyi (2019) found that on the open source development platform GitHub, "disadvantage is a function of gendered behaviour". *Femaleness* was qualified by variables such as professional ties, level of activity (push/pull requests), and areas of

specialisation (Vedres & Vasarhelyi, 2019). The study argues that measures of reputation (“success” – as starred repositories) and survival (“time account active”) on the platform were adversely affected by femaleness rather than by categorical discrimination. They found that not only was this true for women, but men and users with unidentifiable gender are also likely to suffer for exhibiting behaviour that demonstrates “femaleness”. The findings of Vedres and Vasarhelyi (2018) are counter to dominant threads in the literature, as they find that it is feminine behaviour that adversely effects one’s status, not just listing as female on a profile. However, as is typical of computational gender classification studies, the behavioural aspect is built from an extrapolation of categorical gender. That is, the features that are defined as femaleness are built from behaviour associated with a female (categorically defined) account. Thus, the causality of gendered performance versus identification is unclear, and generally not supported by critical studies. Nevertheless, that study shows that the default masculinity is ratified through behaviour that generates contextual success, rather than by the overt presence of men.

### ***Communication and Contextual Success***

An emergent theme in research into CoP in STEM and VCoP is the qualification of “success”. The ways in which achievement is understood, and the specific measurements of ability that a culture prizes, can drastically affect who is able to be visible, who is allowed to succeed and on what terms. Shorey et al. (2020) point to how failure is a fundamental part of programming, of debugging, and ultimately building things. But for those with negative beliefs about their abilities, these initial failures are proof to themselves that they cannot do it.<sup>62</sup> Shorey et al. (2020) show that social processes and collaborative problem solving are important factors in allowing people to overcome these deep set beliefs. They show that “participatory debugging”, socialising to solve problems, is crucial to challenging stereotypes and fostering an interest in “computational

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<sup>62</sup> Predominantly women in this research context, but this extends to all groups who face the “bigotry of low expectations” (Prentice & Carranza, 2002).

thinking” (Shorey et al., 2020). Instances of failure are part of programming, but the qualification of success also plays an importance role.

Platforms that value the aggregation of large audiences and that use voting and reputation-based systems as moderation efforts are the most likely to host gendered toxicity in Massanari’s (2015a) toxic technocultures, and she points to how herding effects dictate what rises to prominence. Similarly, in the study of gender and disadvantage on GitHub, Vedres & Vasarhelyi (2018) qualify success as starred repositories, when many other factors can be considered. For example, in the context of GitHub, women’s pull requests are more likely to be accepted than men’s (Terrell et al., 2017), even if their repositories are less likely to be starred (Vedres & Vasarhelyi, 2019). The qualification of success as merely survival in a community over a period of time is also somewhat problematic if features of hostility, affirmation bias, and sexism are not taken into account.

In STEM classrooms, women’s lack of confidence in their ability has proven to be a detrimental factor in success across multiple studies (Kuchynka et al., 2018; Master et al., 2016). A study by Fisher and Cox (2006) proposes that the women’s lack of confidence in programming is detrimental in high profile programming contests, and proposes how alternative qualifications of success should be considered. However, such assertions are not necessarily beneficial to women’s representation and propositions of equal ability. In a recent ACM article, Frieze and Quesenberry (2019) show how Carnegie Mellon University (CMU) has achieved a nearly 50-50 split in gender representation in their Computer Science programme since 2002. They argue that the “curriculum should not be made pink” and that it is the culture of learning in programming that is the problem (Frieze & Quesenberry, 2019). In fact, conceptions that women need a gendered curriculum can perpetuate a gender divide. In the case study of CMU, the stereotypes that fed biases were challenged as they led to negative consequences for women in computing, and for the field itself. Visibility is crucial here. A study by Mishkin (2019) shows that *relatedness* is the principal factor in motivating young women to learn to code and increasing confidence in ability. Whilst self-

determination theory prizes competence and autonomy as drivers in one's learning, Mishkin's (2019) research showed that relatedness and *someone like me* is a motivating factor that should not be underestimated. This study aligns with the findings of Ford et al. (2017) and Vedres & Vasarhelyi (2019), who observe women's homophily online and shows a continuation of the phenomenon. Despite the fact that Vedres and Vasarhelyi (2018) view women's homophily as a negative predictor of success, I believe this is in part due to their qualification of success as starred repositories and I am critical of this assertion of causality.<sup>63</sup> Overall, the qualification of success in online and offline spaces should be approached with caution, and measures of success should incorporate an understanding of the culture of the platform, rather than being a simple numerical indicator to be taken at face value. Quantified measures of reputation and the framing of success may just show the salience and status of masculinity.

## **Conclusion: The Gender Code**

To perform critical research, it is important to be aware of the limits of what one can claim. The literature has led to a focus on hostile forms of sexism, which research has shown to be highly prevalent in computational culture. Seeing sexism, however, is political. Though benevolent sexism is more heavily institutionalised, hostility appears to be more prominent online in spaces where there is arguably less social reprisal. While this concept of sexism is necessary to operationalise the research for this project, it does mean that some of the subtleties of benevolent prejudice may be masked. Thus, the claims that I can make surrounding sexism do not directly reference the equally destructive benevolent form. Moreover, there is a noticeable lack of further intersectional matters in this project, such as considerations of cross-cultural names or other manifestations of white privilege. Anonymous forums have been shown to propagate racist

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<sup>63</sup> It is worth introducing the point here that success ought to be partly defined by those who seek it, not just the affordances that are easiest to extract. Measures of success in a masculine dominated platform will be masculine by default. Rather, researchers should consider working with minority and suppressed groups to define what they consider a success, in a given context.

outlooks and identities, and this study examines the essential aspects of in-group/out-group relations. It is my hope that much of this research can be viewed as transferable across the study of exclusion in technical spaces. That said, the social grouping of identities is historically situated and studies should also include this cultural context. I support any endeavour to add intersectional nuance to my findings.

The discrimination against women in creative coding fosters a view of technological skill as incompatible with femininity (Miltner, 2019; Wajcman, 2006). As such, the narrative of gendered difference in coding not only provides an explanation for women's lack of representation in computing, but also enables us to identify a potential cause. As technologies become omnipresent and computing devices are embedded in everyday objects, the values they are programmed with need to be critically assessed. Who codes matters - there are serious ramifications when only a narrow section of society builds widely used technologies. For example, Noble (2018) shows that Google search algorithms become racist and sexist when they reflect the biases and values of the people who create them. Gillespie (2018), Hicks (2019), Neff (2016), Ensmenger (2010) and others argue that there are clear consequences that come with discriminatory structures, and not just for those who are discriminated against. The creators of code inscribe politics into algorithms, assembling lines of code to a purpose, logic, and functional specification (Blass & Gurevich, 2003; Gillespie, 2014; Kowalski, 1979). As Ullrich argues:

*“Algorithms are imbued with the values of their makers, values that move outward into the wider, nontechnical world [...]. It matters greatly, then, who writes the code.”*

(Ullrich 2002, p. 1; 2017)

The literature explored here largely contributes to a reinstatement of a gendered binary in technology. This project presents an exploration of gender and technology, ultimately revealing how gender prejudice is encoded into computational culture. The virtues of technology are immense, yet in restricting participation we run the risk of hardcoding prejudice and discrimination into the development of everyday technologies.

# CHAPTER II

## STUDY I: PERCEPTIONS OF GENDER AND HOSTILITY

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*“Growing up, I slowly had this process of realizing that all the things around me that people had told me were just the natural way things were, the way things always would be, they weren’t natural at all.*

*They were things that could be changed, and they were things that, more importantly, were wrong and should change, and once I realized that, there was really no going back.”*

- Aaron Swartz<sup>64</sup>

In Chapter I, Section I, I outlined how we got here – how the assumed masculinity of computers and technology cultures is historically situated. Section II then aligned this situated narrative in stereotype and Computer Mediated Communication (CMC) literature. Stereotyping attributes social inequalities and power imbalances to individual level characteristics, rather than to larger social structures (Nier et al., 2013; Risman & Davis, 2013). This study shows the effect of perceived masculine dominance of entry-level programming forums, and how hostile gender-based stereotypes can create a barrier to women entering creative coding cultures.<sup>65</sup> Drawing on the classifications of Glick and Fiske (1996) in the Ambivalent Sexism Inventory (ASI) and Ambivalence Towards Men Inventory (AMI), this study will examine hostility and gender-based

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<sup>64</sup> Aaron Swartz was a computer programmer, political activist and hacktivist. He was involved in many free-software projects, including the web feed format RSS, Markdown publishing format, the Creative Commons and he was co-founder of Reddit.

<sup>65</sup> *Perceived* is used to refer to users’ assumptions and impressions of a platform.

stereotypes, creating the foundation for subsequent studies. In Chapter III, Study II explores gender salience and its consequences for established programming forums, whereas Study III examines how gender mediates ritualised coding events at hackathons. The direction of the investigation into gender salience and mediation is led by the forms of stereotyping analysed in this Study. The research questions outlined below are formulated in the exploratory framework of “weak theory”, as characterised by Sedgwick (2013) and Stewart (2008), which will be discussed in depth in the Methods section. The questions that I ask here are:

**RQ1:** Does the gender majority of a platform affect perceptions of hostility?

- a) Does a person’s gender affect the assumed gender majority?

*H<sub>1</sub>: Increase in perceived masculine dominance will lead to an increase in hostility*

**RQ2:** Do gender-based stereotypes affect perceptions of hostility?

- a) Does feminine stereotyping effect perceptions of hostility?
- b) Does masculine stereotyping effect perceptions of hostility?
- c) Is there a difference across platforms?

*H<sub>2</sub>: An increase in ASI and AMI will lead to an increase in hostility.*

**RQ3:** What are the gendered assumptions of technical knowledge in anonymous spaces?

- a) Are there gendered assumptions in seeking technical help?
- b) Are there gendered assumptions in offering technical help?
- c) Are the gendered assumptions different in technical help offering and technical help seeking?

*H<sub>3</sub>: An increase in ASI and AMI will mean that a user seeking technical help will be seen as feminine.*

*H<sub>4</sub>: An increase in ASI and AMI will mean that a user offering technical help will be seen as masculine.*

The term “assumption” is used here to refer to perceptions of gender roles in technical and coding cultures. The affordances of anonymity can lead to perceptions being accepted as a certainty, without proof or verification. Likewise, I am careful to examine my framing of “gender” here, and to avoid isolating the experiences of femininity from the complete gender value system. In this way the research design does not frame femininity as a deviation from masculinity and it

thereby rejects the position that men's perception is the baseline standard against which women can be compared.

The formulation of research questions reflects non-directional hypothesis, meaning that the outcome predicted is open and results can go in either direction. There is a persistent tension in the literature, which concludes that women's lack of participation in anonymous spaces is due to: (1) the affordances of platforms; (2) the group associated with the spaces; (3) an individual's own biases. While the existing scholarship points to stereotypes having an effect on women's participation and perceptions of hostility, it is difficult to decide whether the stereotype of men as technologically competent or women as incompetent is the main contributing factor or whether, as I argue, gender functions as a role set. Moreover, most of the work on stereotypes occurs in more traditional settings such as university classrooms or places of employment, so it is difficult to predict the effect of text-only anonymous online interaction on the strength of the stereotypes of gender and programming. As such, I take an exploratory approach to the research design of this study. I posit that stronger gender-based stereotypes will increase the perceived hostility of a platform.

## **Section I: Introduction and Methods**

This first Study provides a quantitative contribution to an examination of gender in online spaces, informing the direction of enquiry for Study II and Study III. I explore whether perceptions of hostility are consistent across platforms. Here, platforms are defined as multisided digital frameworks that shape the terms on which participants interact with one another. Acknowledging that there are sub-communities within a site, I asked users about the platform as a whole to focus on their situated, individual, assumptions. In presenting Study I, this Section outlines research

design, and the subsequent Section delves into the findings and results. Overall, this Study serves to explore perceptions of stereotypes, gender, and hostility in learning to programme, prior to engaging with entry-level forums.

## **Method**

The research design of this Study is focused around a survey. In designing the survey, categorical and scale (VAS) questions have been used to examine perceptions of gender and hostility in regard to requesting and offering technological help on Python programming on Twitter, Reddit, and 4chan.<sup>66</sup> Python is a language that continues to grow in popularity in online discussion forums, surpassing PHP in 2017 and C# in 2018 (Stack Overflow, 2018).<sup>67</sup> These platforms were chosen as they have varying levels of anonymity and are more public-facing than other social networking sites, such as Facebook. They are associated with technology culture, and are seen as spaces where it is normative to leverage knowledge and ask questions outside of one's personal network, without the technical associations, hostility, and in-knowledge of Stack Overflow.

Questions on gendered stereotypes have been drawn from the hostile sexism elements of the Ambivalent Sexism Inventory (ASI) (1996) and the Ambivalence Towards Men Inventory (AMI) (1999) as developed by Glick & Fiske. The inclusion of the hostile-only element was supported by the work of Kuchynka et al. (2018) and Cheryan et al. (2009), whose work indicates that hostility and hostile sexism are likely to be problematic in online anonymous spaces without formally institutionalised norms of behaviour. The framing of hostility here is not explicitly gendered. Rather, respondents were simply asked for a rating of hostility of a platform as a whole, prior to being asked about gender and gender balance – to control for order effects. The respondents were recruited through CrowdFlower, a crowdsourcing platform. As CrowdFlower

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<sup>66</sup> See Appendix I for examples of how technical help seeking and offering were represented on each platform.

<sup>67</sup> The analysis itself, however, was done in R.

is used for data processing, the survey was designed through Qualtrics to allow for the inclusion of questions in the form of multiple-choice, sliders, and matrix tables. Before commencing the survey, participants are required to pass a screen by correctly identifying at least two of the three platforms targeted for the study.<sup>68</sup> When a respondent failed the screen, demographic information was collected to allow for comparison between knowledge of a platform and demographics, such as gender, education, and age. Ethical approval was granted in February 2017.<sup>69</sup>

The ability of Qualtrics to manipulate the flow of questions facilitated a two-level compensation framework. Those who attempted the survey, but failed the screen, were compensated \$0.10 to encourage participants, whereas those who completed the entire survey were remunerated \$1.00. This differentiation in payment was achieved through confirmation codes and the employing of a regular expression that validated survey completion, as per CrowdFlower (2017) guidelines. The payment figure was calculated based on the conventional payment for a six-minute survey and is in line with the USA living wage, as mandated in the ethical approval process. Moreover, disproportionately high levels of compensation can put a study at risk, resulting in incentive effects, which leads to low quality data (Walliman, 2011). The compensation amount also allows for statistical power within the design of the research. Using G\*Power, I performed a MANOVA F-test, and a priori power analysis to compute required sample size; given  $\alpha$ , power, and effect size. Based on  $\alpha = 0.05$  and three predictor variables (platform, gender majority, response hostility), I determined that a minimum sample size of 148 respondents was required (Faul et al., 2009).<sup>70</sup> Overall, 274 respondents passed the screen.

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<sup>68</sup> I did not control for the level of familiarity (i.e. if a respondent was an avid user or not) as the focus of this study is assumption and perception across platforms. In this way, the users are completing the survey based on their own assumptions and level of familiarity.

<sup>69</sup> CUREC Ethical Approval Number: SSH OII C1A 17 002.

<sup>70</sup> In calculating a minimum sample size, statistical power is conventionally set at 0.8. That is, an 80% probability of detecting an effect.

In assessing the limitations of surveys, random and systematic measurement errors are the primary concern. Random error is the result of any factor that randomly affects the measurement of a specific variable across the sample (Neuman, 2014). In determining the appropriate sample size through G\*Power, random error was accounted for. Opposed to the “noise” of random error, systematic error is caused by any factors that methodically affect measurement of the variable across the sample, also considered to be a bias in measurement. One way this was addressed by running the survey in two pilot modes of 25 respondents at a one-week interval, which showed no significant bias between the samples or variables. Moreover, as recommended by Crowdfunder (2017), contributors were ranked at Level 3, as these are the “most trusted workers”, which means they possess “a near perfect overall accuracy”. Respondents were English-speaking, and were residents in the USA or UK. Furthermore, the use of the ASI and AMI scales facilitates the ability to examine the gender-based hostility of participants. Overall, concerns surrounding the statistical power, measurement errors, and biases of respondents have been considered and addressed.

This is not to say that the research design is without its limitations. The basic questions and statements developed as examples for the survey are not creative coding in terms of the developing or repurposing of code in innovative manners, but they reflect the necessary steps prior to such imaginings. These questions are a precursor to imaginative programming. As an explanatory metaphor, painters must first consider the shapes and forms that make up their subject to render them in a skilful artistic manner. Moreover, the survey’s focus is specifically on technical knowledge in the form of Python programming language and does not consider knowledge in terms of physical computers, servers, and hardware. The choice to exclude these material types of knowledge (e.g. building a computer) was made since the focus of this project is creative coding cultures.<sup>71</sup> I also did not ask respondents if they could code as this would

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<sup>71</sup> The gender dimensions of software/hardware are discussed in depth in Study III.

actively introduce stereotype threat into the study. Hence, the drawbacks of the selected analysis have been considered and accounted for within the scope of the project.

### ***Users and Platforms***

When learning new skills in an online setting, women are more likely than men to leverage their social networks (Kramarae, 2001). That is, overall, women's learning style often benefits from a social and inclusive environment (Burgess, 2009; Tisdell, 1995). The focus of the analysis in this chapter is the point in time at which a person asks the *how?* and *where?* of learning to code. As women will often utilise social capital in learning a new skill, the points of study are three social networking sites. My research looks across three platforms that are often associated with online geek culture but are not programming forums: Twitter, Reddit, and 4chan. These three sites were chosen due to the study's focus on perceptions of gender in anonymous creative coding cultures, as it is normative in each instance to have a profile without an easily identifiable gender. Each platform affords anonymity, allowing users to leverage knowledge outside of their personal network or established affiliations. This focus excludes by default sites such as Facebook and LinkedIn where real names are actively encouraged, and deviation is sanctioned socially and formally by the platform.

In terms of the specific platforms chosen, 22% of Americans are Twitter users (335 million average monthly users) with 42% of these using the at least once a day. In strong contrast to Stack Overflow, the majority of Twitter users are women (Pew Research Centre, 2019). The second platform, Reddit, is a lot more heavily associated with online geek culture than Twitter (Massanari, 2015b). Unlike the micro-blogging format of Twitter, Reddit is a social news aggregation and discussion forum. With 330 million users, it is not too dissimilar in size to Twitter (Pew Research Center, 2019). Reddit's user base is 53% male identifying, as stated by their

Demographic (RedditHelp, 2017), and it is normative to operate under a pseudonym.<sup>72</sup> Finally, 4chan is the least popular of the platforms with 22 million monthly visitors, and an estimated 70% male user base (Milner, 2013). The inclusion of these three platforms thus provides a diverse typology of social networking sites, across varying levels of anonymity and male dominance. In this way I aim to move beyond a platform-centric approach to research and increase the ecological validity of the findings. The aim of this project is to identify, across these social networking sites the common of perceptions and assumptions of learning to code.

## **Description of Variables**

As the survey design included multiple platforms, multiple measures were taken for each participant in the survey. To take part in the survey, each participant was required to pass the screen that involved correctly identifying a minimum of two of the three platforms (Twitter, Reddit, 4chan). This means that there are at least two observations for each respondent. Thus, the number of participants in the survey is 274, but the number of observations is 717. Prior to outlining the results of the regressions, this section will detail and describe the predictor and response variables used in an analysis, providing the theoretical context for their inclusion in the initial stages of the stepwise procedures.

### ***Demographics***

671 individuals attempted the survey, with 274 passing the screen. Of the 671 respondents who attempted, 394 (59%) identified as men, 275 (38%) identified as women, 3 identified as non-binary or chose “other”. Of the 274 who passed the screen 91 (33%) were women, 183 (67%) were men, and 1 (0.3%) were non-binary. Though in the wider project gender is understood beyond binary terms, this study presents gender as a male-female as a matter of pragmatism, without conflating negative assumptions of gender with programming specific cultures. The

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<sup>72</sup> Throughout this study “male” refers to “male identifying”, and “female” to “female identifying”.

distribution in the age of participants can be found in Table 4. This age distribution is consistent between identified genders with statistically insignificant variation found using a parametric t-test.

*Table 4 Age of Participants*

<b>Age</b>	<b>Men</b>	<b>Women</b>	<b>Total</b>	<b>Failed the Screen</b>
	<b>%</b>	<b>%</b>	<b>%</b>	<b>%</b>
18-24	49	33	43	21
25-34	39	40	39	37
35-44	9	15	11	20
45-54	2	7	3	18
55-64	1	6	3	4

Focusing on the highest level of education generally achieved by those who passed the screen, 31% had a 4-year degree (the highest percentage), 22% were high school graduates, and 20% had some college education. The complete results are listed in Table 5.

*Table 5 Highest Level of Education*

<b>Level of Education</b>	<b>Passed the Screen</b>			<b>Failed the Screen</b>		
	<b>%</b>			<b>%</b>		
	<i>Men</i>	<i>Women</i>	<i>Total</i>	<i>Men</i>	<i>Women</i>	<i>Total</i>
Less than high school	1	2	1	2	4	4
High school graduate	25	17	22	12	21	16
Some college	16	28	20	22	19	21
2-year degree	14	10	13	6	16	11
4-year degree	33	28	31	33	19	27
Professional degree	10	12	11	25	21	24
Doctorate	1	2	1	2	0	1

## ***Feature Scaling***

The range of the predictor and response variables was standardised (0-1 range) to facilitate interpretation.<sup>73</sup> The primary benefit of feature scaling is that it standardises  $\beta$ . This allows me to compare the relative strength of the effect of each predictor variable to the response variable. The shorthand description of each variable is contained in Table 6.

***Table 6 Variable Description and Scales***

<b>Variable</b>	<b>Description</b>
<i>ASI</i>	Rating of 0-1, with 1 as the highest measure of hostile sexism. Score reflects a measure of sexism towards women that is taken from the hostility measures of the Ambivalent Sexism Inventory developed by Glick and Fiske (1992).
<i>AMI</i>	Rating of 0-1, with 1 as the highest measure of hostile sexism. Score reflects a measure of ambivalence towards men that is taken from the hostility measures of the Ambivalence Towards Men Inventory developed by Glick and Fiske (1999).
<i>Platform</i>	Platform that the respondent completed the screen for. Each respondent completed the survey for at least two platforms. The options were Twitter, Reddit, and 4chan.
<i>GenderBalance</i>	Respondents' rating of the visible gender balance of the platform. From 0: Totally female dominated, to 1: totally male.
<i>Hostility</i>	Rating of 0-1 of the unfriendliness of a platform, where 0 is incredibly friendly and 1 is completely hostile.
<i>GenderHelpSeeking</i>	Binary classification of the presumed gender of a user who created a post that is seeking technical knowledge, such as assistance with beginning programming in Python. 0: Female 1: Male.
<i>GenderHelpOffering</i>	Binary classification of the presumed gender of a user who created a post that is offering technical knowledge, such as posting tutorial videos that they have produced themselves. 0: Female 1: Male.

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<sup>73</sup> Features were standardised by scaling to unit variance. Not information was lost in scaling.

Gender-based prejudices were included through the Ambivalence Sexism Inventory (ASI) and the Ambivalence Towards Men Inventory (AMI). The statements from each inventory were presented with a Likert scale of Agree to Disagree. For instance, the ASI hostile measure included the statements: “Most women interpret innocent remarks as sexist” and “When women lose fairly, they claim discrimination”, and the AMI included: “Men pay lip service to equality, but can’t handle it” and “Men usually try to dominate conversations with women” (Glick & Fiske, 1999). The Likert scores were then combined into two measures of sexism, scaled to a 0-1 range.

### ***Platform-Specific Features***

As defined in Chapter I, platform refers to a web-based social operating system that leverages social connectivity to distribute applications. On platforms, the ways in which technology structures interaction introduces distinct affordances that alter how users engage with and are shaped by online environments (Papacharissi, 2010). These affordances introduce new possibilities for interaction and new dynamics that shape participation (Papacharissi, 2010). An affordance of programming spaces that is a focus of this study is anonymity, which facilitates social practices that are not socially acceptable in the doctrine of the real name Internet (Hogan, 2013). The research design thus represents an opportunity to ask about perceptions without making presumptions about identity markers. For each platform (Twitter, Reddit, 4chan) participants are asked for their perceptions on the gender balance, hostility, and presumed gender of a user who is asking for or offering technical help in Python programming.

The *GenderBalance* variable refers to a visibility index constructed from two measures of gender dominance, where 0 reflects an all-female population and 1 all-male, as perceived by the respondent. This variable was included because, as shown in ambient belonging, a perception of unequal gender balance and male domination acts to put women off entering creative coding cultures, increasing the likelihood of a space being socially read as hostile. Secondly, *Hostility* refers to a rating of the perceived hostility of a platform. This variable was included in research

by Cheryan et al. (2009) and Kuchynka et al. (2018) and indicates that perceptions of hostility have an adverse effect on women's willingness to enter technical spaces.

*GenderHelpSeeking* and *GenderHelpOffering* were included to account for gender-based perceptions on requesting advice on where and how to learn Python, as well as the sharing of user-created resources. I wrote the posts that users were shown, based on the content that is common in each of the platforms. I specifically avoided directly technical questions, and instead focused on linking to content a user would have created ("Check out my YouTube tutorials on getting started with Python! [Url]") or a general declaration of a lack of knowledge ("I'm worried it's too late for me to get started with python, can anyone recommend an easy course for beginners?"). Participants were shown one of two possible posts for each measure, a sample of which can be found in Appendix I. The literature leads to the hypothesis that offering technical knowledge will be seen as a masculine activity, while asking for basic advice on how to learn Python will be less clearly gendered. I hypothesise that sexism will be the strongest predictor of perceived gender in asking for and offering technical knowledge in Python, as a higher ASI/AMI score indicates a more stable belief in stereotypes (Glick & Fiske, 1996, 2001). I predict that hostile sexism in the form of the *ASI* and *AMI* will be significant predictors in all models.

## **Exploratory Stepwise Regression**

The purpose of preliminary research is to clarify the exact nature of the research subject. Exploratory research does not intend to offer conclusive solutions, rather it intends to *define* the research problem. Modelling is a central process of such research. In statistical terms the purpose of models is to infer the relationship between two or more variables. They are a combination of inferences based on collected data and understanding of a population to predict information in an idealised form. Regression asks how well a response variable (depicted as  $y$ ) can be estimated

from predictor variables ( $x_1, x_2, \dots, x_k$ ).<sup>74</sup> In using such models in Social Science researchers need to pay specific attention to the limits of explanation, both in terms of statistical power, but also in terms of theoretical generalisability.

In modelling, exploratory multiple regression can be used to Answer “weak theory” research questions, where several variables have potential value in explaining variability in a dependent variable.<sup>75</sup> The theory is “weak” as the nature of intercorrelation confuses more stable predictors of what the casual relationship might be (See Stewart, 2008). This study is such an exploration of weak theory, as it aims to clarify the nature of the relationship between gender, hostility and technical knowledge. Stepwise methods are particularly appropriate for this form of inquiry. Based in theoretical considerations, a stepwise approach provides information that can be used to understand the relationship between variables (Hastie et al., 2017). Such models use a measure of automation to choose the most appropriate features from a set of explanatory variables, based on a pre-specified statistical criterion. With this focus on exploration, stepwise models aid in the development of theory that then leads to confirmatory research. In this study I will first (Model 1) explore the gendered dimensions of assumed hostility of platforms. In Models 2 and 3 I will investigate how perceptions of gender and hostility lead to stereotypicality in attributes of technical knowledge. The exploration of gendered barriers to women’s inclusion in coding cultures set out here will be refined in Study II and III of this project.

### ***Direction***

In stepwise regression a direction needs to be specified, that is an approach to simplicity that is forward, backward, or both. In *forward* direction, the initial (minimum) model contains only the

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<sup>74</sup> Moreover, as models seek to add clarification to a phenomenon they can also obscure key identity categories, a process which is explained in more detail in Study II.

<sup>75</sup> In Sedgewick’s (2013) terms, a theory is “weak” if it is open to changing and is localised and reparative. Weak theory has direct implications for external validity as it seeks flexibility, rather than a doctrine of succinct explanation.

constant ( $\beta_0$ ) and then other predictors are added based on increasing amounts of variance a model can explain. The *backward* method is the opposite: all predictors are added to the model, and an assessment is made as to whether the explanatory power of the model increases with the removal of certain variables. As the name implies, *both* is a combination of forward and backwards directions: a predictor is added, and then it is assessed whether removing any of the predictors in the model leads to an increase in the explanation of variance.

In this study I used a combination of backward elimination and forward selection, as my aim was to construct a parsimonious model, that is, a model that accomplished the desired level of explanation with as few predictor variables as possible. As with “the law of briefness”, I aimed for optimum parsimony and minimal parameters to model each phenomenon sufficiently. I chose to combine these approaches to stepwise regression as just using forward selection can result in suppressor effects, which happen when a predictor has an effect, but only when another variable is held constant. Forward selection is more likely than backwards elimination to exclude predictors involved in suppressor effects. As such, forward selection is more prone to Type II errors.

### ***Exploring the Procedure***

In the combination of forward selection and backward elimination approach to stepwise regression used here, I first started with no predictors in the model, and at each step a predictor was entered or removed. The first step of the procedure is to define the significance level for deciding when to enter ( $\alpha_E$ ) and remove ( $\alpha_R$ ) a predictor in the stepwise model.  $\alpha_E$  and  $\alpha_R$  are typically greater than the usual  $\alpha = 0.05$  so that it is not too difficult to enter or remove predictors from the model. In the case of my model,  $\alpha_E$  and  $\alpha_R$  were set at the Bonferroni point of 0.15. Following the specification of significance, predictors are added or removed based on the partial  $F$ -tests ( $t$ -tests for the slope parameters). There are three stages to the progressive model that are laid out below.

### Figure 2 Stepwise Algorithm

#### Step I:

Each of the one-predictor models is fitted – regress  $y$  on  $x_1, \dots$ , and regress  $y$  on  $x_{p-1}$ . For  $x_j$ , when  $p < \alpha_E$ ,  $x_j$  with the smallest associated  $p$  is included in the model. If no predictor has a  $p < \alpha_E$  then the model formulation stops with no significant predictors found in the candidate list.

#### Step II:

Suppose  $x_1$  has the smallest  $p < \alpha_E$ : this is the first predictor added to the model. Note that the population  $y$ -intercept ( $\beta_0$ ) and random error term ( $\varepsilon$ ) are also included. If no other predictor has a  $p < \alpha_E$ , then the one-predictor model is the final model.

Then, each of the two-predictor models must include  $x_1$  – regress  $y$  on  $x_1$  and  $x_2, \dots$ , regress  $y$  on  $x_1$  and  $x_{p-1}$ . For  $x_j$ , when  $p < \alpha_E$ ,  $x_j$  with the smallest associated  $p$  is added to the model. Suppose  $x_2$  fits this criterion, it is added to the model.

Since  $x_1$  was the first predictor in the model, we test to see if the inclusion of  $x_2$  has affected the significance of  $x_1$  – check  $p$  for testing  $\beta_1 = 0$ . If  $p$  for  $\beta_1 = 0$  is  $> \alpha_R$  then  $x_1$  is removed from the model.

#### Step III:

Suppose both  $x_1$  and  $x_2$  are included in the two-predictor model and remain there, the three-predictor model must include  $x_1$  and  $x_2$  – regress  $y$  on  $x_1, x_2$ , and  $x_3, \dots$ , regress  $y$  on  $x_1, x_2$ , and  $x_{p-1}$ . Of those predictors whose  $p < \alpha_E$ , the predictor with the smallest  $p$  is added to the model. If no predictor  $p < \alpha_E$ , the formulation is stopped, and the two-predictor model is the final model.

But suppose instead  $x_3$  had  $p < \alpha_E$  and was entered into the model. Since  $x_1$  and  $x_2$  were the initial predictors in the model, it is assessed whether the inclusion of  $x_3$  affected the significance of  $x_1$  and  $x_2$  predictors – check  $p$  for testing  $\beta_1 = 0$  and  $\beta_2 = 0$ . If  $p$  for either  $\beta_1 = 0$  or  $\beta_2 = 0$  is now  $> \alpha_R$  then the associated predictor is removed from the model.

This progressive model enhancement procedure is continued until the inclusion of an additional predictor variable does not yield  $p < \alpha_E$ . Model selection was checked using the *Akaike information criterion* (AIC) as an estimator of out-of-sample prediction error (Hastie et al., 2017). Given multiple models, AIC estimates the relative quality of a model in comparison to the others, providing a means of model selection.

### Logistic Approaches

In the following Section (II), Model 1 is characterised as a linear regression, and Models 2 & 3 are logistic. In logit models,  $y$  is descriptively categorical. In this case  $y$  is a binary response coded 0 or 1. The response variables for these models are *GenderHelpSeeking* and *GenderHelpOffering*,

which are the presumed *Gender* (0: female, 1: male) of a user requesting and providing technical knowledge on each platform of study. With such data I model the probability that  $y = 1$ , under the assumption that the outcomes of  $y$  are independent given these probabilities using a Logit model. This model is an alternative to linear regression since it is not ideal to fit the continuous linear regression model,  $X\beta + \varepsilon$ , to data  $y$  that takes on the values 0 and 1. Logit models are formally defined as models where the log-odds of the probability of an event ( $y = 1$ ) is a linear function of the predictors. In the context of logistic regression, each exponentiated coefficient ( $\exp(\beta)$ ) is the ratio of the odds for successive values of the associated covariate, when all else is held equal. In a linear regression  $\beta_1$  gives the average change of  $y$  associated with a one-unit increase in  $x$ , in a logit model increasing  $x$  by one unit changes the log-odds by  $\beta_1$ . In this method, I look for estimates of the coefficients so that the predicted probability  $\hat{p}(x_i)$  of  $\hat{y}$  for each datapoint corresponds as closely as possible to the observed value of  $y$ . As an exploratory approach, stepwise selection was used in multiple logistic regression to identify the prognostic factors in gender in technical help seeking and offering. As with my linear model (Model 1),  $\alpha_E$  and  $\alpha_R$  were set at 0.15.<sup>76</sup>

### ***Assumptions & Evaluations***

Based on the ordinary least squares (OLS) algorithm, multivariate linear regression as in Model 1 makes four key assumptions: (1) a linear relationship between  $x_1, x_2, \dots, x_k$ ; (2) multivariate normality – the residuals are normally distributed; (3) no multicollinearity -  $x_1, x_2, \dots, x_k$  are not highly correlated with one another; and (4) homoscedasticity – the variance of  $\varepsilon$  is similar across all values of  $y$ . Prior to initiating the stepwise procedure for each of the three models, scatterplots indicated a linear relationship in each instance. Using Cook's distance, no problematic outliers were detected. Second, using a Q-Q-Plot, the errors between observed and predicted values were

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<sup>76</sup> AIC corresponds to using a p-value of 0.1573.

seen to be normally distributed. Third, multiple linear regression assumes that there is statistical independence between the predictor variables. All coefficients had a magnitude below 0.80 and the VIF is reported for each model. VIF indicates the degree to which the variances in the regression estimates are increased due to multicollinearity. No problematic factors were detected even with a conservative threshold of 5.0. A conservative benchmark was used as there was a concern that ASI and AMI may produce some warnings of multicollinearity. Nevertheless, the two inventories are measuring two divergent stereotypes and thus were not considered a composite index. Finally, following the construction of the model, homoscedasticity was confirmed with the studentized Breusch-Pagan test ( $p < 0.05$ ).

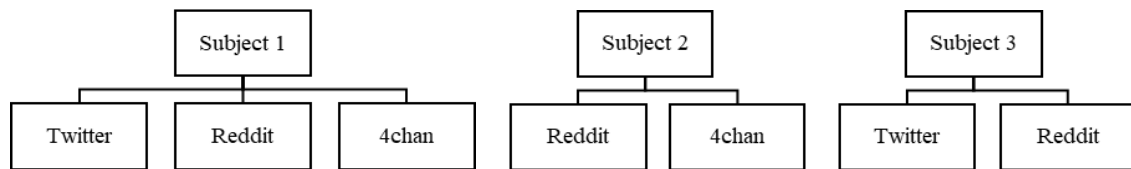
As it is not based on the OLS method, logistic regression does not make the key assumptions of linear and general linear models. However, observations must be independent of each other and multicollinearity must not be present among predictor variables. As with Model 1, Models 2 and 3 evidence no problematic multicollinearity nor any concerns with *VIFs*. Moreover, logit assumes the linearity of response variables and log-odds, although this does not require predictor and response variables to be related linearly. Thus, the assumptions of OLS and logit regression were accounted for to provide a stable and correctly specified model.

To evaluate the model and negate statistics that can be affected by overfitting it is not advised in stepwise regression to rely on the F-statistic, significance, or multiple R, but rather to assess the model against a set of data that was not used to construct it in the first place, using the technique of out-of-sample validation. This validation is a method of measuring prediction error in machine learning and other statistical techniques that avoids the need for independent validation datasets. This technique is also used in Study II and is discussed further in Chapter III, Section I. Following an evaluation of the fitting of Models 1, 2, & 3, in the analysis I report on how well the model is predicting  $y$  on a “new” set of data. I produced probabilities in the form of  $\Pr(y = 1/X)$ . The decision boundary was set at 0.5. If  $\Pr(y = 1 / x) > 0.5$ , that  $y = 1$ , otherwise  $y = 0$ . A common technique to avoid a reliance on a manual split of the data is  $k$ -fold cross validation, in which  $n$  is

randomly partitioned into  $k$  equal sized subsamples. A singular subsample is used as the validation data for testing the model and  $k - 1$  are used as training data. The advantage of this method is that the  $k$  results are averaged to produce a singular estimation, as all observations are used for both training and validation and each observation is used for validation exactly once. In stepwise methods, Tabachnick and Fidell (2007) propose data splitting and cross validation as mandatory for assessing model accuracy and generalisability. Using the caret package (Kuhn et al., 2012), 10-fold cross validation was used to obtain the statistics reported for the model.

### ***Random Effects***

As each subject has observations within multiple platforms, nesting is a property of the experimental design – not the model. Here I have platforms nested within subjects. The crucial point here is that between each subject, the platforms have the same identifier, even though they are distinct if they are nested. Reddit appears in the data available for Subjects 1, 2, and 3, but Twitter appears in Subject 1 and 3, but not 2 (See Figure 3).



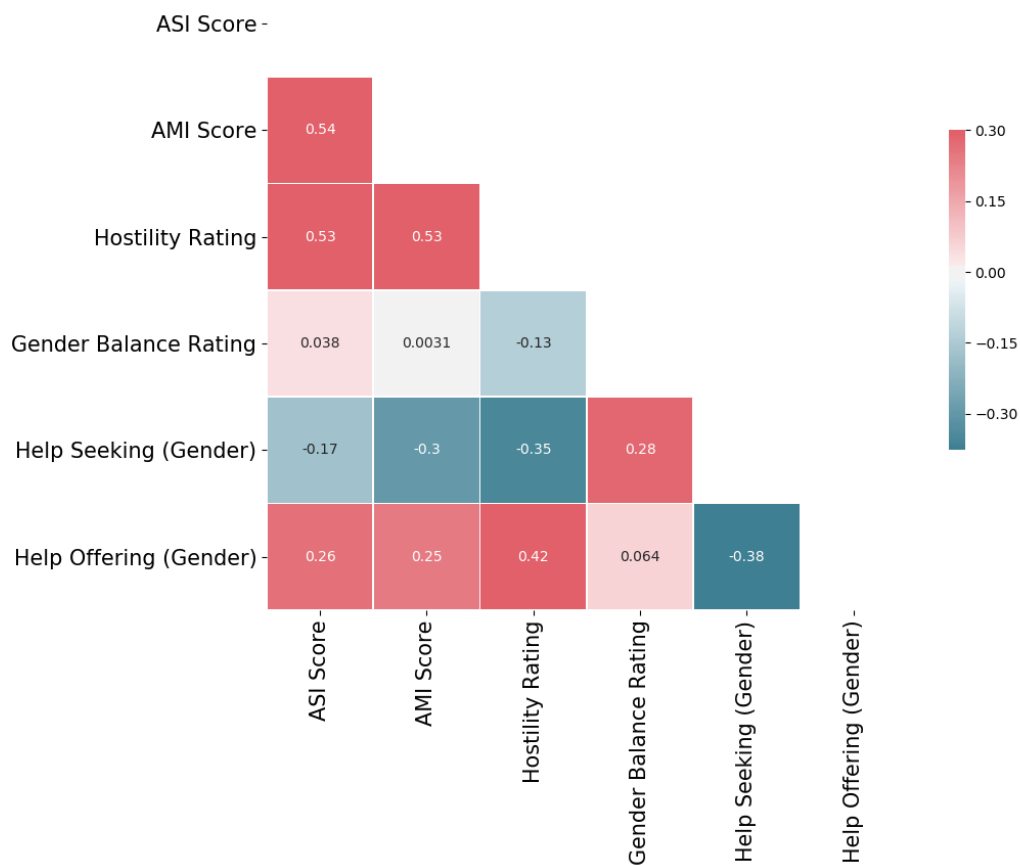
***Figure 3 Nested Random Effects***

Rather than just being a factor of the experimental design, the nesting of the random effects reflects how I expect the platform to be different for each subject. Building on feminist theories of situated knowledge, I expect the embodiment of gender and social identity to affect an individual’s perception of *Hostility* and *GenderBalance* etc. on each *Platform*. This builds on the work of Haraway (1988, 2006), who argues that one’s perceptions are shaped by prevailing power structures, and that interpretation of experiences is informed by awareness of one’s social position. That is, if Subject 3 is a woman, and they see Twitter as female-dominated and Reddit as male-dominated, I hypothesise that their own gender and associated perceptions will impact

the response variable. Moreover, the existence of such differences across platforms is supported by theories of identity in impression management in online anonymous spaces (Walton & Rice, 2013; Hogan, 2013; Turkle, 2017). Taking account of this theoretical framework and the transparency of model development, the findings of the models are outlined in Section II.

## Section II: Testing Assumptions and Perceptions

Employing the data gathered from the survey, I aim to examine which factors are most likely to influence perceptions of hostility and perceived gender in technical help seeking (*GenderHelpSeeking*) and offering (*GenderHelpOffering*) on platforms. The first response



predictor is platform *Hostility*, which is then incorporated as a predictor variable into gender in technical help seeking and offering. Figure 4 is a depiction of the correlations (Pearson's product-moment) between all of the variables.

*Figure 4 Heat Map Correlation Matrix of Candidate Variables*

Many of the correlations are in the mid to low-strength range, and the presence of these relationships is not surprising. The strongest correlation (0.54) is between the two measures of sexism (*AMI*, *ASI*), which was expected as these sexist stereotypes operate in role sets (Merton, 1961). Looking to platform *Hostility*, the correlations support my hypothesis that an increase in an indicator of sexism increases the perceived *Hostility* of a space, with a  $\beta$  of 0.53 for *ASI* and *AMI*. Gender in *Help Seeking* and *Help Offering* are correlated with *ASI* and *AMI*. This indicates an association with gender roles. First, *ASI* and *AMI* and negatively correlated with gender in *Help Seeking*. This means that as the rating of sexism increases, the likelihood of a user seeking technical help being seen as a man decreases. For gender in *Help Offering* this relationship is reversed, as *ASI* and *AMI* ratings increase a user offering technical assistance is more likely to be seen as male. This indicates that the stronger belief in gender roles a person has, the more likely they are to see seeking technical knowledge as feminine and displaying technical knowledge is masculine. I will examine this relationship will further in Models 2 and 3 later in this Chapter. The remaining correlations, though weak, are statistically significant and thus worthy of further investigation and indicate that collinearity is unlikely to be problematic.<sup>77</sup>

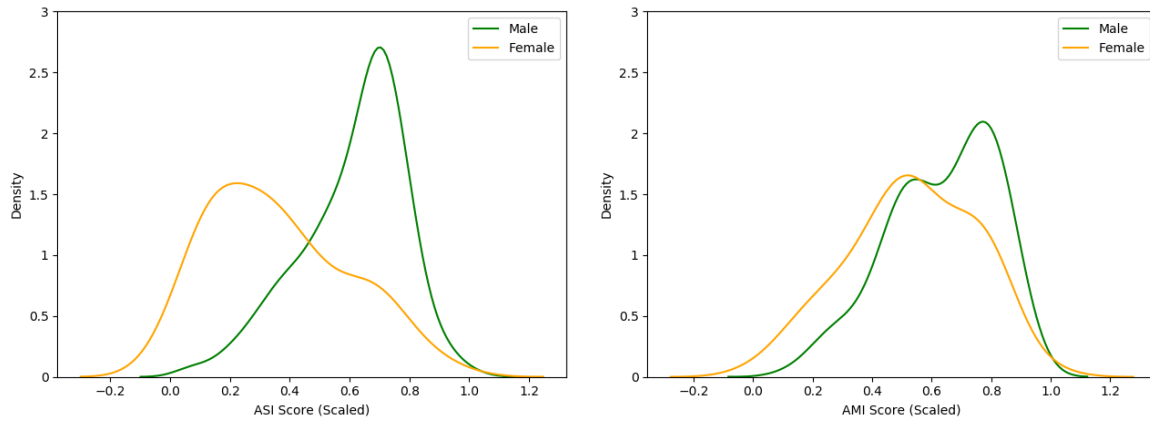
## **Ambivalent Sexism Inventories**

Prior to modelling, I will discuss the distribution of gender-based prejudices in the sample, as measured through the *ASI* and *AMI*. A kernel density estimation (KDE) of these variables by

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<sup>77</sup> I also examined the VIF on the condition indices to determine if the level of collinearity was problematic, and found that it was not.

gender is shown in Figure 5. On each graph, 0 indicates no hostile sexism/hostility towards men and 1 indicates severe (scale maximum) hostile sexism.<sup>78</sup>



**Figure 5 Kernel Density Estimation for ASI and AMI (Scaled, 0-1) by Gender**

The differences between the ASI and the AMI between genders were found to be statistically significant, using the Hausman Test for independence. ASI and AMI scores were averaged (Table 7) from the Likert scales and were only collected for those who passed the screen.

**Table 7 Ambivalent Sexism Inventory Hostility Score (0 to 1)<sup>79</sup>**

	Mean	Median	Std.
<b>Male</b>	0.62	0.67	0.17
<b>Female</b>	0.37	0.33	0.23
<b>Overall</b>	0.54	0.62	0.22

In terms of hostile sexism, the median for those who identified as male is 0.67 and for women is 0.33, which shows that men are rated as more strongly hostile sexist in the measures of the ASI than women, as hypothesised. The skew for men is a -0.79, and for women is 0.36, meaning that there is departure from symmetry. For men the distribution is negatively skewed, demonstrating that the majority of men are rated as towards the upper boundary of the sexism scale. In

<sup>78</sup> Glick & Fiske’s (1996) ASI explicitly refers to hostile sexism as hostility against women, hence the inclusion of the hostile measures of the AMI in this study.

<sup>79</sup> “Overall” includes all gender categories and is unweighted by gender.

comparison, the distribution for women is positively skewed, reflecting comparatively lower levels of hostile sexism. Overall, men have higher levels of hostile sexism than women, supporting the findings of Glick and Fiske (1996).

*Table 8 Ambivalent Towards Men Inventory Hostility Score (0 to 1)*

	<b>Mean</b>	<b>Median</b>	<b>Std.</b>
<b>Male</b>	0.65	0.70	0.18
<b>Female</b>	0.54	0.54	0.22
<b>Overall</b>	0.62	0.64	0.20

Looking at the hostility measure in AMI (Table 8), there is significantly less divergence between men and women than in the ASI. The mean value of AMI for women is 0.54 and for men is 0.65. While this is similar to the ASI result, with men displaying higher levels of hostile gender-based prejudice than women, the contrast is less pronounced. The skew for both women and men is -0.30 and -0.62 respectively, meaning that both distributions are negatively skewed towards the upper limit of the AMI scale. This shows that whilst sexist views towards men are common across genders, men still possess higher hostile sexism towards men than women do.

## **Model 1: Modelling Perceptions of Hostility**

In the first model I am examining which factors lead to perceptions of hostility, creating a gendered barrier to entry in anonymous platforms (Adams et al., 2006; Levy, 2010; Tanczer, 2015). Moreover, multivariate analysis allows us to control for the effect of other variables (Miles & Shelvin, 2001). In the case of my model, I can examine the influence of ambivalent sexism towards men and women one at a time, relative to a standardised measure of the *GenderBalance* of a platform. This allows me to examine the relative influence of sexism towards men and women on perceived *Hostility*, controlling for the perceived *GenderBalance* of a platform. The inclusion of the gender of a participant as a candidate predictor variable was informed by the Stereotype Content Model, as discussed in Chapter I, Section II. The theory emphasises that there are heavy in-group biases within a culture, particularly in regard to gendered characteristics (Cuddy et al., 2015). This leads to a hypothesis that if a participant is a woman who sees the platform as majority

female, she will perceive the platform to be less hostile (“warmer”). Model 1 was constructed using most likely variables to predict platform hostility, as ascertained from the literature. The candidate predictor variables ( $x_{ji}$ ) were *AMI*, *ASI*, *Platform*, *Education*, *Age*, *Gender*, *GenderBalance* to predict *Hostility*.

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_7 x_{7i} + \varepsilon_i$$

**Equation 1 Model 1: Candidate Predictor Variables**

Where  $\beta_0$  is the intercept,  $\varepsilon_i$  is the error term (residuals), and  $\beta_1 \dots \beta_3$  are slopes against the interdependent variables  $x_1 \dots x_3$ . The inclusion of the candidate variables was informed by the literature, which pointed to a given platform’s affordances, demographic factors, and normative expectations as likely predictors (Kuchynka et al., 2018; Master et al., 2016; Spencer et al., 1999). In fine-tuning the model, nested random effects were included to control for dependence due to repeated measures or ordered effects.<sup>80</sup> In addition, an approach informed by theoretical considerations indicated that it is one’s own gender that directs one’s gendered sociability (Cuddy et al., 2015), and the model depicted above was tested against one which included *Gender* as an interaction term on *GenderBalance*. I aimed to test the hypothesis that the relationship between the *GenderBalance* of a platform and its perceived *Hostility* would differ according to whether the respondent was male or female. I theorised that if a respondent was a woman and she saw a platform as male dominated, she would be more likely to see the platform as more hostile. As the models were nested, this test assessed whether the addition of the interaction term resulted in a statistically significant reduction in the residual sum of squares compared to the initial model.<sup>81</sup>

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<sup>80</sup> Fixed effects are constant across individuals, and random effects vary.

<sup>81</sup> For instance, Model A is nested in Model B if the parameters in Model A are a subset of the parameters in Model B.

Notably, the addition of an interaction term of *Gender* on *GenderBalance* made no statistically significant difference and was dropped from the model.

Following the variable selection procedure and appropriate fine tuning where *Subject* over *Platform* was manually added as a random effect  $\gamma$  on the intercept  $\beta_0$ , Model 1 can be characterised as follows:

$$y_i = (\beta_0 + \gamma) + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \varepsilon_i$$

**Equation 2 Model 1: Predicting Hostility**

$y_i$  is the  $i$ th observation of the dependent variable *Hostility*,  $x_{1i}$  is the  $i$ th observation of *AMI*,  $x_{2i}$  is *ASI*, and  $x_{3i}$  is *GenderBalance*. As before,  $\varepsilon_i$  is the error term. Table 9 summaries Model 1. Note that Conditional  $R^2$  is used as it accounts for test error in a training/test split and the inclusion of random effects.

**Table 9 Forward selection OLS predicting perceptions of the hostility of the platforms**

	$\beta$	SE	VIF
<b>Intercept</b>	-0.018	0.05	-
<b>AMI</b>	0.42***	0.06	1.47
<b>ASI</b>	0.38***	0.06	1.89
<b>GenderBalance</b>	0.18***	0.07	1.03
<hr/>			
<b>Conditional R<sup>2</sup></b>	0.38		
<b>N</b>	717		

Note: VIF = Variance inflation Factor

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

Table 9 shows that out of the candidate predictors the only significant predictors of the perceived hostility of a platform are *AMI*, *ASI*, and *GenderBalance*. The selection process has identified features that were either redundant or irrelevant, hence can be removed without incurring much loss of information (Bermingham et al., 2015). The variables that have been removed in automatic selection are demographic indicators: *Age*, *Education*, and most interestingly *Gender*. *Platform*

(i.e. Twitter, Reddit, 4chan) has also been dropped. Each coefficient (Pearson's product-movement) represents the additional effect of adding that variable to the model, if the effects of all other variables in the model are already accounted for. As the regression coefficients are standardised, I can state that the strongest predictor is *AMI*  $\beta = 0.42$ . This means that accounting for all other predictor variables, one-unit increase in the standard deviation (SD) of Ambivalent Sexism (*AMI*) towards men results in 0.42 increase in the perceived hostility of a platform.<sup>82</sup> This is stronger than *ASI*  $\beta = 0.33$ , meaning that a unit increase in sexism towards women results in a 0.33 unit increase in perceived platform *Hostility*, holding all other variables equal.

The final variable selected for inclusion in the model was *GenderBalance*  $\beta = 0.18$ . Accounting for all other variables, a unit movement towards male dominance of a platform results in a 0.18 increase in perceived *Hostility*. The conditional  $R^2$  indicates that 38% of the variances is explained.<sup>83</sup> Overall, Model 1 illustrates that for my dataset the strongest predictor of perceived *Hostility* is sexism towards men, followed by sexism towards women (*ASI*), and *GenderBalance* of a platform. In addition to the features selected, the dropping of respondent *Gender* as an insignificant predictor and interaction term deserves to be further examined and situated within the literature.

## **Model 2: Modelling Perceptions of Gender in Technical Help Seeking**

The response variable of Model 2 is the expected gender of a user in seeking technical help, such as asking where they can find Python tutorials, and if Python is “more useful” than JavaScript. As gender in technical help seeking (*GenderHelpSeeking*) was binomial (0: female, 1: male), the

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<sup>82</sup> The coefficients are the predicted change in the target per unit change in the input. As the coefficients are normalised, they now reflect change in the target per normalized unit (0.1) allowing for easier interpretation of relative feature importance.

<sup>83</sup> Even with this strong effect size the conditional  $R^2$  is likely to be conservative, due to the out-of-sample testing used to cross-validate my model. According to Cohen's (1992) convention, and the perception-based nature of my research design, my model has a strong effect size.

model is built using logistic regression. Once the model was fitted, I can then back-transform the estimated regression coefficients in R off a log scale so that I can interpret the condition effects of  $x_i$ . The candidate predictors were: *Platform*, *Gender*, *Education*, *Age*, *GenderBalance*, *Hostility*, *ASI*, and *AMI*. The full model was:

$$\text{Ln}\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_8 x + \varepsilon_i$$

**Equation 3 Model 2: Candidate Predictor Variables**

Following the variable selection procedure and addition of the nested random effect  $\gamma$ , *Subject* over *Platform* was added as a random effect  $\gamma$  on the intercept  $\beta_0$ . Model 2 can be characterised as follows:

$$\text{Ln}\left(\frac{p_i}{1-p_i}\right) = (\beta_0 + \gamma) + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_5 x_{5i} + \varepsilon_i$$

Where:

$$p_i = \text{Pr}(y_i = 1 | x_i)$$

**Equation 4 Model 2: Gender in Technical Help Seeking**

Here,  $y_i$  is *GenderHelpSeeking*, and the independent variables are *Gender*, *GenderBalance*, *Hostility*, *AMI*, *ASI*, while  $\varepsilon_i$  is the error term. As discussed in the methods section, the coefficients ( $\beta_j$ ) are estimated using the maximum likelihood method. Table 10 shows the coefficient estimates for a logit model that predicts the assumed gender of a user seeking technical help. Each exponentiation of  $\beta_j$  is the change in log-odds in the multiplicative scale for a unit increase in the corresponding predictor variable, holding other variables at certain value. The classification rate or predictive probability of success (PPOS) is reported as an alternative to  $R^2$ , which is generally

not applicable to logit models.<sup>84</sup> PPOS is the probability of observing a success in the future based on existing data. In this context “success” refers to correctly predicting (classifying) the value of  $y$  given  $x_1, x_2, \dots, x_k$ . In order to evaluate the accuracy of the predictive classification, I can compare the PPOS with the *null accuracy*, that is, the maximum accuracy that can be achieved by always predicting the most frequent class, thus the minimum accuracy of my model. The null accuracy of Model 2 is 0.49. Therefore, my model improves the predictive ability by 0.22, a satisfactory improvement (Miles & Shelvin, 2001), indicating a suitable level of model accuracy.

*Table 10 Model 2: Predicting gender in technical help seeking*

	$\beta$	$exp(\beta)$	SE	VIF
<b>Intercept</b>	4.82	123.83	0.56	-
<b>Gender: Male</b>	0.49*	1.63	0.25	1.49
<b>GenderBalance</b>	-0.30***	0.74	0.07	1.08
<b>Hostility</b>	-1.07**	0.34	0.38	1.27
<b>ASI</b>	-1.60**	0.20	0.61	1.97
<b>AMI</b>	-2.53***	0.08	0.61	1.46
<b>PPOS</b>	0.71			
<b>N</b>	717			

*Note: VIF = Variance inflation Factor*

*\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .*

The  $p$  associated with the predictor variables is exceedingly small, as to be expected with stepwise methods, indicating that each of the variables apart from *Education* and *Age* are strongly associated with *GenderHelpSeeking*. For the predictor *Gender*, with all other variables being equal, if the respondent is male this means that there is a 0.49 increase in the log-odds of perceiving a “help seeker” as male. Looking at the odds ratio,  $exp(0.49) = 1.63$ , the odds for a male seeing a help seeker as male are 63% higher than odds for females seeing a help seeker as male. As the coefficients are standardised, this shows that the gender of the respondent is the

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<sup>84</sup> The model estimates from a logistic regression are maximum likelihood estimates arrived at through an iterative process. They are not calculated to minimize variance, so the OLS approach to goodness-of-fit (i.e.  $R^2$ ) does not apply.

strongest factor in determining the presumed gender of a user seeking technical help. The log-odds for the remaining variables indicate a negative relationship for each of them. This means that, holding all other variables equal, believing a platform is more female-dominated makes it less likely that the gender seeking technical help will be predicted as male. Additionally, perceiving a platform as *Hostile* corresponds with lower odds of seeing the help seeker as male. For both sexism measures (*ASI*, *AMI*), the greater the rating, ceteris paribus, the lower the odds that the help seeker (*GenderHelpSeeking*) will be perceived as male. Extrapolating from this, a user seeking technical help is most likely to be perceived as a woman if a space is seen as female dominated and hostile, through a lens of stereotypicality.

### **Model 3: Modelling Perceptions of Gender in Technical Help Offering**

The response variable of Model 3 is the expected gender of a user in offering technical help (*GenderHelpOffering*), such as posting links to Python tutorial videos they have created. As gender in technical help offering was coded as a binary variable (0: Female, 1: Male), the model is built via logistic regression, in the same manner as Model 2. The candidate predictors were; *Platform*, *Gender*, *Education*, *Age*, *GenderBalance*, *Hostility*, *ASI*, and *AMI*. Note that gender in help seeking is not considered a predictor variable.

The full model prior to the stepwise procedure can be characterised as:

$$\text{Ln}\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1x_{1i} + \beta_2x_{2i} + \dots + \beta_8x_{8i} + \varepsilon_i$$

*Equation 5 Model 3: Candidate Predictor Variables*

Following the variable selection procedure and addition of nest random effects as in Model 2, Model 3 can be characterised as:

$$\text{Ln}\left(\frac{p_i}{1-p_i}\right) = (\beta_0 + \gamma) + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i$$

Where:

$$p_i = \text{Pr}(y_i = 1 | x_i)$$

**Equation 6 Model 3: Gender in Technical Help Offering**

Here,  $y_i$  is *GenderHelpOffering*, and the predictor variables are *Gender*, *GenderBalance*, and *Hostility*. Looking at the variables that were excluded in the stepwise process, it is particularly interesting that this is the only model in which the measures of hostile sexism (*ASI*, *AMI*) are extraneous. Rather, the significantly contributing variables are related to gendered assumptions. Table 11 shows the coefficient estimates and the odds ratio for the logit model. The PPOS represents a satisfactory improvement on the null accuracy (0.64).

**Table 11 Model 3: Predicting gender in technical help offering**

	$\beta$	$\exp(\beta)$	SE	VIF
<b>Intercept</b>	-0.05	0.95	0.45	-
<b>Gender: Male</b>	0.62*	1.86	0.26	1.14
<b>GenderBalance</b>	0.18*	1.19	0.09	1.11
<b>Hostility</b>	0.96*	2.62	0.41	1.09
<b>PPOS</b>	0.85			
<b>N</b>	717			

Note: VIF = Variance inflation Factor

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

The associated  $p$  with each of the predictor variables is small, meaning that they have a significant impact on *GenderHelpOffering*, which is to be expected in a theoretically informed stepwise approach as is the case in Model 2. The fitted model says that, holding all other variables at a fixed value, the odds of a man perceiving a user offering technical help as male over the odds of a woman perceiving the user as male is  $\exp(0.62) = 1.86$ . In terms of percentage change, I can

say the odds for men are 86% higher than the odds for women. Moving to look at the impression of the *GenderBalance*, holding *Gender* and *Hostility* at a fixed value, I will see a 19% increase in the odds that a user offering technical help is male with each increase in the male-ness of the *GenderBalance* on a platform as  $\exp(0.18) = 1.19$ . Finally, given a fixed value for *Gender* and *GenderBalance*, I see a 162% increase in the odds that a user offering technical help is male given a one-unit (0.2) increase in perceived *Hostility* as  $\exp(0.96) = 2.62$ . The overall picture here is that the odds that a user offering technical knowledge on a platform is perceived as male will increase if the perceiver is male. There is additional sizeable increase in the user being perceived as male as the perceived *Hostility* of a platform increases. Thus, the model shows that respondent *Gender*, *GenderBalance*, and *Hostility* are the significant predictors of perceived gender in *Help Offering*.

## **Gender and Hostility in Technical Assistance**

These three models reflect a narrative; a representation of a linear collection of experiences that contextualise the decision whether to enter creative coding communities. A substantial body of work discussed in the literature review shows that an assessment of a forum's hostility intervenes in the willingness to participate (Cheryan et al., 2009; Ford et al., 2017; Vedres & Vasarhelyi, 2018). As such, I conducted this study to determine what gender characteristics affect hostility, and how this then contributes to perceptions of gender in technical help seeking and offering. The overarching assumption here is that a user is unlikely to ask for help in a space they see to be toxic and hostile (Massanari, 2015a; Master et al., 2016; Walsh et al., 1999). Once satisfactorily educated in technical disciplines and techniques, an individual may then seek to aid others, to include them in the technical culture and to be competent themselves.<sup>85</sup> This tendency towards collaboration, collective knowledge, and co-operative problem solving is a defining feature of

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<sup>85</sup> In terms of self-confidence and self-assessment, an external validator or qualification is not required here.

creative coding culture (Coleman, 2015; Himanen, 2001; Jordan, 2016). I conclude that stereotypes are the strongest predictor of assumed hostility, rather than the gender of the perceiver. Study I thus provides a foundation for Study II and Study III.

### ***Platforms, Stereotypes, and Hostility***

The feature selection procedure excluded respondent *Gender* as an insignificant predictor in Model 1. The omission of participant *Gender* in predicting *Hostility* is contrary to a hypothesis informed by the literature surveyed. Building on the outlined work of Glick & Fiske (1996, 1999), Cuddy et al. (2015), and Cheryan et al. (2009), I expected *Gender* to be a strong predictor of *Hostility* as women associate male dominated and masculine technical spaces with hostility. Though it was the weakest predictor in Model 1, *GenderBalance* was still significant. With all others being equal, a unit increase in masculine dominance of a platform resulted in 0.18 increase in *Hostility*. This suggests that an increase in the male dominance of a platform increases perceived hostility for men as well as women.

Many studies of women's exclusion in spaces of anonymous creative coding exclude men, but my study shows that not accounting for perceptions of an in-group may lead to false conclusions. It is shown that for men too, an increase in perceived male dominance (*GenderBalance*) of a space increases the likelihood that it is socially read as hostile. This was unexpected, as work by Cheryan (2009) showed that increasing the stereotypically masculine presence of a physical space had no effect on men (Ambient Belonging as discussed in Chapter I, Section II). The role of stereotypicality in embodied technical spaces will be clarified in Study III. Moreover, in manually fine-tuning Model 1, the inclusion of respondent *Gender* as an interaction term on *GenderBalance* was also found to be insignificant. The absence of an interaction between these two variables, verified with a *t*-test, adds dimension to the hypothesis of peer parity proposed by Ford et al. (2017) and the homophily of Vedres and Vasarhelyi (2019). Like Tanczer (2015), Ford et al.'s (2017) methodology was interview-based, where women participants discussed visibility in terms of masculine discourse rather than "female" presence. In these studies, outlined in detail in

Chapter I, interviewees cited a discursive “boys club” of “bro humour” that defined the space as male-by-default and this, rather than the gender of users of the platform, created a barrier to women’s participation. The men interviewed by Tanczer (2015) and Ford et al. (2017) were oblivious to the effect of gendered domination of a space. In other words, the absence of possessed *Gender* shows that seeing a platform as dominated by *someone like me* in terms of simple numbers does not impact the *Hostility* of a platform. Rather, increases in masculine hegemony lead to an increase in perceived *Hostility*, regardless of the gender of the perceiver.

In addition to *GenderBalance*, both measures of sexism (*ASI*, *AMI*) were strong predictors (*AMI*  $\beta = 0.42$ ; *ASI*  $\beta = 0.38$ ) of perceived hostility of a platform. The inventories that were included in the study were the hostile measures of sexism, so it was hypothesised that they would at least be significant. It was not, however, predicted that the measures of sexism would be stronger than *GenderBalance* or respondent *Gender*. For masculine and feminine hostile stereotypes, the inventories account for attitudes that reflect: (1) paternalism, (2) compensatory gender differentiation, and (3) hostile heterosexuality (Glick & Fiske, 1996, 1999). Overall, the higher a score of sexism the higher the fidelity to gender-based stereotypes. Model 1 illustrates that for both men and women the stronger the belief in gender stereotypes the more likely it is that a platform will be viewed as *Hostile*, holding all other variables equal. This is a continuation of original definitions of prejudice and the ordinariness of sexism (Allport, 1954; Dovidio et al., 2005). As I look to the relative strength of the sexism measures, a unit increase of *AMI* results in 0.09 of an increase in perceived hostility above *ASI*. In abstract terms, this leads to a conclusion that a belief in a male stereotype is a mildly stronger predictor of *Hostility* of a platform than a female stereotype. Building on the work of Glick and Fiske (1996; 1999), I theorise that this comparative difference is due to male stereotypes being more strongly associated with seeking domination and desiring traditional gender roles (paternalism), thus more outwardly hostile than female stereotypes. Overall, the contributions to knowledge here are three-fold. Firstly, a movement away from a platform-centric understanding of anonymous spaces is supported by a

lack of significance of the variable in the analysis. Secondly, an increase in the perceived masculine dominance of a platform (*GenderBalance*) results in an increase in *Hostility* for men as well as women. Finally, with the caveat of *ceteris paribus*, I find that it is the fidelity to stereotypes that is the strongest predictor of hostility, and not possessed and descriptive gender.

Across Models 1, 2, and 3, *Platform* was found to be an insignificant predictor of perceived *Hostility* of a platform and the assumed gender of a user asking for (*GenderHelpOffering*) or seeking technical assistance (*GenderHelpSeeking*). Moreover, the bivariate analysis found that platform was *not a significant predictor for any of the models*. This supported my methodological choice of a cross-platform approach, moving away from a platform centricity that attributes sexism to the unique cultures of a space, rather than focussing on affordances of anonymity. In the context of my study, this supports the conception that it is the visibility of users in pseudonymity that contributes to perceptions of a platform and its culture (Hogan, 2013; Kwon et al., 2014). It is worth noting that the study design did involve the inclusion of *Platform* as a nested random effect in all models to account for identity in multiplicity and impression management, without platform-based determinism.

## **Stereotypes and Technical Knowledge**

The remaining models examined presumptions of gender in technical knowledge seeking and offering. For Model 2 it was unclear from established literature if attempts to engage with and enter creative coding cultures would be assumed to be masculine or feminine. Nonetheless, the literature surveyed led to the presumption that users offering technical help would be more likely to be typed as male, as the offering of technical knowledge and overt displays of competence are seen as a masculine behaviour (Ensmenger, 2010; Master et al., 2016). Platform *Hostility* (Model 1 response variable) was included as a candidate predictor variable in both cases, as the literature led to the hypothesis that hostility contributes to the defining of the in-group of the technologically competent, supporting the literature summarised in Chapter I, Sections I and II (Adams et al.,

2006; Cheryan et al., 2009; Cuddy et al., 2008). Therefore, the candidate predictors were informed by the previous studies, and the robust natures of the coefficients allow for a comparative analysis in the logit models.

### ***Gender in Technical Help Seeking***

In Model 2, the significant predictors were respondent *Gender*, *GenderBalance*, *Hostility*, *ASI* and *AMI*. The candidate variables that were dropped during feature selection were *Education*, *Age*, and *Platform*. Following a refinement of Model 2, platform was included as a nested random effect on subject. I see the conclusions of this model as unclear, except in indicating that there is a causal relationship between gender and assumptions of a user in technical help seeking. The model, in broad strokes, shows that in a female dominated space that is read as hostile it is most likely that a user seeking technical help will be seen as female. Moreover, it also shows that sexism (towards men and women, *AMI* and *ASI*) is a strong predictor that a user seeking technical help (*GenderHelpSeeking*) will be seen as female. Though the female platform domination leading to a female user can be attributed to a Bayesian conclusion (Chapter I, Section II), it was unexpected that an increase in hostility and sexism indicators would lead to a decrease in the likelihood that a user seeking technical help would be seen as male. Here, the significant model is a finding. It shows the relevance of a gendered approach to understanding gender in technical help seeking, whilst demonstrating a potential misstep in forming and operationalising the variables in this instance. Rather, it may be valuable to view technical help seeking in a more ecologically sensitive and contextual framework. Such debates in operationalisation are the point of undertaking this exploratory work. I shall look to avoid viewing the seeking and offering of technical help in isolation, but will rather include responses in contextual pairs in Study II (discussed in Chapter III, Section I). This is in line with the discourse in context approach to CMC championed by Lamerichs & te Molder (2003). Moreover, the coefficients of the model are significant, and thus while the picture of causality is unclear, the influence of predictor variables should not be discounted.

The model shows that men are 63% more likely than women to see a user asking for technical help (*GenderHelpSeeking*) as a man. This predictor shows that men perceive that a man is much more likely to enter creative coding cultures than a woman, which asserts a masculine stereotype of a male programmer. The complex gendered nature of modelling who is seeking technical help is evident here. Nonetheless, the models show that across the platforms studied, men are more likely than women to attribute seeking technical knowledge to a man then a woman. Like Model 1, this reflects a measure of in-group bias, as a user's gender is the strongest determinant. Perceiving a platform as more woman-dominated in population (*GenderBalance*) and low in *Hostility*, leads to seeing the user as more likely to be a woman (*GenderHelpSeeking*). This can be attributed to women working more collaboratively, such as in Ford et al.'s (2017) study and in Song et al. (2015). In terms of *ASI* and *AMI*, the lower the sexism rating the more likely that the help seeker is seen to be a woman. Overall, the model's exact causality is somewhat ambiguous, as the variables do not create a clear picture, potentially due to being removed from context and not having answers featured in a thread.

### ***Gender in Technical Help Offering***

In Model 3, predicting gender in technical knowledge offering, the candidate predictors that were dropped during the feature selection process were *Platform*, *Education*, *Age*, *ASI* and *AMI*. In the same manner as Models 1 and 2, platform was later included as a nested random effect in subject. This model is unique of the three in this Section, as it is the only instance where *ASI* and *AMI* were insignificant. This was unexpected, as it had been hypothesised that the sexism measures would be significant in each instance, as the models are examining perceptions of gender in programming. I theorise that there is Bayesian rationality here, similar to that observed by Cao et al. (2018), discussed in Chapter I, Section II. In a Bayesian approach, prediction is based on prior knowledge. As a respondent sees the *GenderBalance* of a platform as being increasingly male, this in turn increases the likelihood that they will predict the user offering technical knowledge to be male, when holding respondent gender constant. Moreover, there is evidence of in-group

biases. As in Model 2, men are 86% more likely to see a user offering help to be a man. The association between technical knowledge and masculinity holds across men and women in my study. The descriptive nature of stereotypes is evident, as they dictate how people typically act. As *ASI* and *AMI* were not significant indicators, this is an extension of Bayesian rationality; the male dominated nature (*GenderBalance*) of platforms leads to a user offering technical knowledge (*Technical Help Offering*) being seen as a man, which contributes to stereotypical beliefs. The strongest finding of Model 3 is that given a unit increase in *Hostility* there is a sizeable (162%) increase in the likelihood that a user offering technical help (*GenderHelpOffering*) is perceived to be male, holding all other variables equal.

### **Conclusion: To be seen, and not heard**

The overarching finding of this chapter is that gender intervenes in coding cultures through stereotypes and perceptions of hostility. Stereotypes serve to influence and type others in the absence of traditional embodied identity markers. The models show that stereotyping, assumptions of *GenderBalance*, and *Hostility* should not be discounted in the analysis of gender in anonymous spaces. Though the *Gender* of the respondent remained significant in two of the Models, it would be a mistake to see it as the fundamental casual factor. Model 1 shows that a user's gender is not a significant predictor of *Hostility* across anonymous platforms. In Models 2 and 3, *Gender* is significant. This suggests that the specific gender of a user in anonymous online communication should not be treated as determining their perceptions of hostility in learning to code. In conjunction with the literature, this analysis forms the basis of the methodologies for Studies II and III. The laying of such a foundation is crucial, as it shows a degree of generalisability across platforms and indicates that the experimental design should focus on sexism and performativity, rather than on conceptions of a "possessed" or "real" gender.

I conclude that the more hostile an environment is perceived to be the more likely it is that technical knowledge will be seen as the purview of men. This conclusion is reflected in the social psychology literature discussed in Chapter I, Section II (Kuchynka et al., 2018; Master et al., 2016). Cheryan et al.'s (2009) study into ambient belonging points to how associating a space with masculinity results in perceived hostility for women. While my findings align with Cheryan et al.'s (2009), I additionally find that the association between masculine dominance and hostility holds for men. Moreover, my study shows that such a hostile environment leads to assumptions that competence is masculine. Model 3 supports my contention that it is the way an anonymous space is perceived that dictates who is seen to participate, not the platform itself. Anonymity is a crucial factor, as it is the assumptions of what is visible that shape perceptions of who is competent in entering creative coding.

Given the relatively unclear picture of Model 2, there appears to be a tension between how collaborative learning and incomprehension are associated with women, while a willingness to express one's ignorance and learn from it in a technical field is seen as masculine. Therefore, Study II will pay particular attention to the way in which questions are asked, and whether there is a performative difference in the manner in which questions are asked, onto which gender and hostility can then be mapped. Moreover, this initial work has illustrated that a valuable focus and contribution in Study II will be a discourse in context approach to gender in CMC, that accounts for peer-parity and situational understanding (Ford et al., 2017; Lamerichs & te Molder, 2003). Building on the results of Study II, Study III will further explore who is asking for help in hackathons, and how requests for assistance are performed. Model 2, whilst ambiguous when viewed in isolation, has thus highlighted an avenue of focus in the complementary studies.

My novel finding here is that stereotypes are crucial in anonymous spaces, despite claims to liberation through disembodiment as women learn online (Kramarae, 2001). Gender-based stereotypes are determinants of hostility across platforms, rather than a respondent's own gender, holding the gender balance of a platform equal. Furthermore, a belief in hostile male stereotypes

is a relatively stronger predictor of platform hostility than female stereotypes. The gender of a user does contribute to perceptions of seeking and offering technical assistance, with Python programming as an in-group bias for men. Stereotypes and visibility are important in sense-making in anonymous online technical spaces. Dominant masculinity is also shown to be seen as hostile for men, and this leads me to avoid seeing homogeneity of masculinity as welcoming to all men. As a preliminary finding, this can help to explain the extremes of performative masculinity evident in creative coding spaces. If someone's claim to a masculine identity as a "nerd" is threatened by more overt displays of masculinity, they may try to prove themselves and reclaim mastery. This recovering of legitimate identity in mixing the nerd with a hegemonic "frat house flavour" is what contributes to brogramming, discussed in Chapter I (Hicks, 2019). The geek masculine narrative views hegemonic masculinity as hostile, while assimilating a measure of the behaviour to be accepted into the in-group.

The findings of this chapter lead me to conclude that gendered visibility should be discussed in terms of discourse, and not just population. The effect of a platform should not be overstated, as researchers should consider the affordances of a space, rather than implying that each platform has its own specific, bounded, community. Contrary to the established literature, my results showed that possessed gender was insignificant in modelling perceptions of hostility of a platform. Instead, I found that a majority male audience is what led to an online space being socially read as hostile. I argue that the assumed gender population of an online space can signal belonging, with a majority male population signalling hostility across genders. The gender of a user does have a role in assumptions of technical knowledge, but it is minor in comparison to perceptions of hostility and assumed gender balance of a platform. Like Cheryan et al. (2009), I find that men are the in-group, legitimately participating in hostile technical spaces. These findings lead me to surmise that women need to be discursively visible in order to challenge hostile perceptions.

Building on the exploratory approach of this Study, Study II will emphasise visibility being careful not to overstate user gender as a determining variable. It will also seek to add clarity to gender performativity in seeking and offering technical assistance, placing emphasis on features shown to be significant through the variable selection procedure. Here, I wish to emphasise that the problem of sexism and technological knowledge can not be solved with technical solutions alone. There is a mutually constitutive relationship between online and offline manifestations of sexism as it is a fundamental aspect of technology culture. Platforms such as Reddit and 4chan are generally seen as more hostile to women (Massanari, 2015b; Milner, 2013). Anonymous spaces are not exceptional, but sites with this affordance permit sexism to permeate in more perceptible forms. The implication here is that anonymous platforms are required to take responsibility, visibly condemning hostile behaviour and reinforcing what is not acceptable behaviour. Platforms need to encourage moderation and create more welcome environments in order to ensure wider participation. Anonymity should not be a cover for gender prejudice. In looking to the larger picture painted by this study, I conclude that visibility is crucial to challenging gendered hostile stereotypes in creative coding: women need to be seen *and* heard.

# CHAPTER III

## STUDY II: RECEPTION TO GENDER ON STACK OVERFLOW

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*“[Stack Overflow] is not everyday society. It is a Q&A site with very specific goals in mind. Those goals are not the same as the goals one has while having a polite discussion in everyday society.*

*While it is reasonable for a new user to begin his interaction here using the rules of everyday society, my comment is meant to inform such users that they have left the everyday behind.”*

- A Top 0.07% SO User. Text from Comment on a C# post.

Stack Overflow is, in fact, everyday society. Despite the protestation above, as the most widely used programming forum, Stack Overflow (SO) is an ordinary, prosaic, part of programming. Its extensive adoption by technical experts and hobbyists alike renders the platform a nexus of creative coding culture. This study uses computational methods to ascertain how gender intervenes in programming discussions on SO, differentiating the experiences by identity salience.<sup>86</sup> As Study I explored perceptions of legitimate knowledge in anonymity, this next Study adds depth to the preliminary conclusions. Using an approach which prioritises situatedness, I embrace the importance of context in both the research subject (SO) and the research object (computation). In doing so I build on Lea and Spears’ (1991) SIDE model, considering discourse-in-context, as argued for by Needle and Pierrehumbert (2018), Buckoltz (1999) and Lamerichs &

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<sup>86</sup> As defined in Chapter I, Section II, salience is how visible a person’s identity categories (the focus here being gender) are in online communication.

te Molder (2003). Informed by Adam (2003), Tanczer (2016), and Sollfrank (1999, 2002), this study examines how gender intervenes in legitimate participation and knowledge sharing in a vast technological community. The “everyday” is not suspended on SO, rather, gender norms are powerfully reinforced as a user positions themselves within the creative coding culture. The questions this study seeks to answer are:

**RQ4:** How salient is users’ gender on Stack Overflow?

- a) How salient is gender in usernames?
- b) Is there a gendered difference in reputation?
- c) Is there is gendered difference in user tenure?
- d) Is there a difference in frequency of posting/commenting?

**RQ5:** Is there a gendered difference in Answer effort and reward?

- a) Is there a gendered difference in the code, resources, or formatting of an Answer?
- b) Is there a gendered difference in Answer score?

**RQ6:** Is there a gendered difference in users’ interactions on Stack Overflow?

- a) How does gender effect the SO network?
- b) Is there evidence of interactions based on gender?

**RQ7:** Is condescension gendered?

- a) How can condescension be operationalised?
- b) Can experiencing condescension be used to predict gender?

These questions reflect an *insight driven* approach to computational analysis as they aim to describe experiences of woman (and non-men) on SO (Nguyen et al., 2019). In Section I of this Chapter, I add depth to the discussion of programming forums in Chapter I by reviewing scholarship on gender on SO. Throughout this study I use the language of “non-men” and “non-masculine” to reflect the multiple gendered identities that do not fit into the majority, dominant category.<sup>87</sup> Following the review of scholarship, I introduce Meta SO and the Developers’ Survey. Here I examine how SO’s management and wider user base justify masculine dominance,

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<sup>87</sup> As discussed in Chapter I, language itself represents the normative gender binary. Whilst it is not a perfect term, it aims to acknowledge and encompass the range of experiences of those who do not fall into the politically dominant categorisation.

rationalising anonymity as proof of women's participation. Then, I discuss the SO Dataset, my method of gender identification, and operationalisation of variables for analysis. By presenting operationalisation prior to the specifics of my analytical approach I foreground the methodological work of this study. In Section II I present my results, examining gendered differences in user description, interaction, and reception. I conclude my findings with an examining of condescension as a method of gendered norm enforcement. In the final section (Section III) I discuss the implications of the results of the study, contextualising sexism on SO as an instance of the wider gender prejudice rife in technology. I conclude that as an ordinary, everyday tool of programming, the sexism of SO actively deters participation in creative coding cultures.

This project builds on the results of Study I, which found that gender intervenes in coding culture through stereotyping and perceptions of hostility. Stereotypes play a key role in forming assumptions and perceptions of online spaces. The exploratory analysis of Study I refutes the claim to liberation through anonymity by showing that content and population are gendered, irrespective of the gender of the perceiver. A belief in these roles and the perceived gender balance of an online space is what predicts hostility, not a user's own gender. I showed that dominant masculinity is hostile for men, and I incorporated this into my discussions here. Moreover, Study I also served to highlight the importance of gender discourse, and not just population demographics. Thus, I take an approach here that is fundamentally contextual in its approach to technical interaction, embracing tangibility of visibility in gender salience.

# Section I: Introduction to Stack Overflow and Methodology

Often called the “programmer’s paradise”, SO is a Question and Answer (Q&A) based programming forum and the largest online community of coding knowledge (Ford et al., 2016). The site boasts over 10 million registered users and more than 50 million monthly visitors, of whom 21 million are professional developers and university-level students (Stack Overflow, 2020c). In fact, 84% of developers say they visit the site at least once a week and 80% said they code as a hobby (Stack Overflow, 2020c). The site is part of the Stack Exchange network, a collection of Q&A websites on a myriad of topics in diverse fields.<sup>88</sup> Each site in the network uses a reputation system, where users are awarded points for Questions and Answers. Users with higher numbers of positive results are rewarded with higher visibility on the platform – such as an Answer to a Question being featured at the top of a list of submitted Answers. The aim of the reputation system is to allow the site to be self-moderating (Stack Overflow, 2019b). As a user collects reputation points, they receive privileges such as the ability to vote on Questions and Answers and to edit other users’ posts and Answers. In this way, power and privilege are a direct result of legitimate participation.

Stack Exchange profiles are often prominent in web search results and can be a significant contributor to finding employment in the technical industries as creative coders become professionalised. In 2011 SO released its Jobs Board, where users can actively seek employment in the technical sector. As of 2016, they can use their site login to create their *Developer Story* (essentially a live curriculum vitae) where their participation level and reputation can contribute dramatically to competitive marketability. Even though the Job Board and user’s Developer Story

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<sup>88</sup> Stack Overflow was the first platform in the Stack Exchange Network, created in 2008.

will not form part of the analysis, it is worth noting that an estimated 40% of registered users of SO utilise the platform to search for potential employment (Stack Overflow, 2019a). My research focuses on participation on the site more generally, which has gendered implications for visibility on this employment-focused use of SO. For instance, according to a survey conducted by SO, women cite “environment and culture” as the primary features of an attractive employment opportunity (Stack Overflow, 2018a). As the women surveyed prioritise environment in seeking work, it follows that the culture of SO is likely to be impacted if women use the platform to find a work as a developer.

## **Developer Survey and Meta Stack Overflow**

The research design of this study was informed by SO’s associated Meta Stack Overflow and the annual SO Developer Survey. Meta SO is a self-referential forum dedicated to Questions about SO as a platform. It constitutes part of the site where users can interact and settle disputes, usually focusing around experiences of interaction on SO. The self-moderation system of the general Stack Exchange network can lead to significant arguments, so each topic-based site has an accompanying Meta SO. This inclusion was informed by Ahmed and Srivastava (2017), whose analysis into best practices on SO used the discussion on Meta SO to examine platform specific norms. Discussions on Meta SO will be summarised later in this section.

### ***Developer Survey***

Recent iterations (2018-2020) of the Stack Overflow Developer Survey provided insights into the demographic makeup and features of the user base of the site. The 2020 survey, which gathered the opinions of over 65,000 developers on SO, quantifies the masculine dominance. Of those who responded to the survey, 91.5% identified as male, 8% as female, and 1% as non-binary (Stack Overflow, 2020).<sup>89</sup> Nonetheless, Ford et al. (2016) contend that around 20% of the *visitors* to

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<sup>89</sup> These figures are consistent with past Developer Surveys.

Stack Overflow are women. Most studies into gender biases focus on platforms where gender is available on a user's profile, where gender inference has a form of ground truth to work with. In this study, I will use the Developer Survey as a lower threshold. However, informed by Ford et al. (2016) I did expect to have between 8-20% women in my sample. I identified that 16% of my sample were women, which fell within these parameters.<sup>90</sup>

Looking to the user base of SO, I first examined features that allow a comparison to be drawn between Study I and III. Overall, non-binary identifying people begin programming earliest, and men start to code earlier than women, but most people have written their first line of code by the time they are 16 years old. Moving to education levels, 75% of SO users have the equivalent of a bachelor's degree or higher (Stack Overflow, 2019). 63% of respondents' degrees were in Computer Science, Computer Engineering, or Software Engineering. Among the respondents, both in the United States and internationally, women are about twice as likely as men to have had three years of coding experience or less. This finding is also evidence of the effect of an informal gender filter, in which women have less coding experience than men, which ultimately disadvantages them in a professional marketplace.

The Developer Survey also provides evidence for the multi-sited research design of this thesis. In my respondent data, I find that Reddit and Twitter were in the top five most popular social media channels used by respondents. In addition, the 2019 Developer Survey found that 26% of respondents had participated in a hackathon (Stack Overflow, 2019), which amounted to 25% of men, 26% of women, 27% non-binary, and 17% unknown gender. This validates my approach to research design that focused on creative coding culture, rather than specific sites of communication.

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<sup>90</sup> The "women" I refer to here are users who were identified as "feminine" or "mostly feminine".

In Chapter I Section II, I highlighted how gender stereotype becomes a self-fulfilling prophecy by internalising low expectations and negatively impacting ability. We can return to this assertion here as the 2019 Developer Survey explored self-appraisal of ability. In the survey users were asked “For the specific work you do, and the years of experience you have, how do you rate your own level of competence?” In Answering this Question 68% of men rated themselves above average, as did 63% of non-binary and unknown, and 53% of women (Stack Overflow, 2019). This shows that SO respondents generally see themselves as competent in the work they do, with men having the most confidence (rating above average) in their ability.<sup>91</sup> As the Question is specifically phrased for an evaluation based on years of experience, there is a gendered difference, with men growing in confidence a lot more quickly than other gender identities (Stack Overflow, 2019c). Another question participants were asked was: “Compared to last year, how welcome do you feel on Stack Overflow?”. The vast majority of respondents (74% of men, 73% women, 62% non-binary) noted little change, positive or negative (Stack Overflow, 2019; 2020).

The final feature of the Developer Survey that is of interest here is users’ opinions on the platform itself. In 2019 and 2020, SO asked users what aspects of the site they would most like to change, and this showed some interesting disagreements between genders. The words most likely to differentiate users who identified as men included “official, complex, algorithm”, whilst the words that differentiated users who identified as women painted quite a different picture: “condescending, rude, assholes” (Stack Overflow, 2019). In 2020, this data was collected for a second time. Words used by men included “guys, big, valuable”, whereas women professed a “toxic, rude, culture” (Stack Overflow, 2020c).<sup>92</sup> Sexism on Stack Overflow is not just a matter of “assholes” (or individuals) but of a “toxic culture”. This gendered difference in participation

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<sup>91</sup> This information does not appear to have been collected in 2020.

<sup>92</sup> In Chapter I, I discuss how the use of “guys” as a collective creates a default masculine presence in online spaces.

and in perception of the SO community is the basis of this study, and the Developer Survey thus serves to inform and provide wider context to the findings of the project.

### ***Meta Stack Overflow***

The dataset does not contain users' self-identified gender. Unlike many social media platforms, programming forums such as GitHub and SO do not actively ask their users for their gender on signing up for the platform, nor is there any clear designated text box where this information could be entered. As discussed earlier, research by Ford et al. (2016) shows that an estimated 20% of the site's visitors are women, but SO's users seem to Question even this low figure. On Meta SO posts often ask why women don't seem to participate and are not visible on the parent site. When the Question is asked, Answers often follow a theme similar to the one outlined below.

*“Given that many names are pseudonyms and that there is no place to put gender on my profiles, it seems that you are assuming [there are less women on Stack Overflow]. Unless you knew who is behind the keyboard, this is just a generalisation.”*

(SO Meta User Comment)

In a somewhat contradictory fashion, users cite the functional use of anonymity (as identified in Hogan, 2013) to argue that women *do* participate on SO. The idea here is that women would pretend to be men in order to avoid the misogyny of programming forums, so seeing only men taking part proves that they do. Women are not visible on stack; QED they must be there. Not only is this circular logic apparent, but in the entire Meta SO dataset (40,926 Posts), there are only 75 posts which explicitly talk about gender, and only three of these in a manner which is directly seeking to talk about the gender balance of the platform.<sup>93</sup> The organisation of the site's moderation system means that *Questions* on women's lack of representation can be marked as

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<sup>93</sup> Posts that discussed gender were found by searching the *Question*, and associated *Answers* and *Comments* for terms likely to appear in a discussion on gender. The terms searched for included; gender, sex, feminism, feminist, woman, women, girl, female, men, man, male. Posts were then read manually to determine their relevance.

“duplicate”: once a post is marked in this way by three users, it is closed, and eventually deleted.

A representative selection of the 72 Meta post titles that talk about gender are included below.

*“Did anyone else notice, that users apply ‘pretty girl’ avatars trying to enhance their chance to get answered?”*

*“A fact based refutation of an assertion from that ‘stack overflow isn’t very welcoming’ blog post”*

*“Changing new users; expectations of this site ‘before’ they ask their Question by requiring them to pass a test ... women and minorities are not being singled out / treated differently by this page.”*

*“Can you make a women's version [of the moderator chat] that says, ‘My eyes are up here’?”*

(SO Meta User Post Titles)

These titles show that exclusion on Meta SO is apparent in “refutations” of posts that acknowledge hostility and assertions of so-called feminine advantage. The “duplicate” nature of these debates suggests that SO is closed off to participation from non-men, actively challenging attempts towards acknowledging a gender problem. These comments also point to how exclusion is also felt by “other minorities”, which is assumed to be a hostile statement towards non-white racial or ethnic groups. This comment highlights the intersectional experience of exclusion on SO. It is my hope that the methodological approach and findings of this study can inform future research in this area. The following section details academic work into gender on SO, framing the study in the wider scholarly discourse.

## **Gender on Stack Overflow**

In addressing gender inequality in technology fields, efforts to increase women’s entry have focused on issues related to self-confidence and gender stereotypes. Given the wide coverage of sexism in formal institutions of technology, women can turn to online forums in an effort to avoid discrimination based on their identity. The presupposition is that if you can obscure your identity through the function use of pseudonyms, you cannot be discriminated against (Hogan, 2013).

However, as outlined by Schwartz and Neff (2019) in Chapter I, gender can dictate how an individual perceives their capacity for action and the choices available to them, even on online platforms. Research has shown that women are generally less likely to contribute to sites of user-generated content, regardless of topic (for a discussion of this on Wikipedia see: Shaw & Hargittai, 2018). Despite many sites of knowledge production framing their decentralised structure as meritocracy, they are dominated by masculinity and this results in a skewed representation of knowledge (Shaw & Hargittai, 2018). On SO, women have been found to be less aware of the platform's features, deterred from participating by the site's intimidating community size (Ford et al., 2016). Research also shows that the main barrier that women cite as a deterrent is feeling that they lack the adequate qualifications in order to participate (Ford et al., 2016b). In their study into *peer parity*, Ford et al. (2017) also find that women are more likely to participate in a conversation on SO if they see other women already taking part, or even if women are just a visible presence. These findings ratify the framing of gender as social structure. Rather than a result of "natural" dispositions, Risman (2004) shows that social norms are developed when actors occupy similar positions in the social structure. In this way, individuals evaluate their own options (or affordances) vis-à-vis the alternatives of similarly situated others (Scarborough & Risman, 2017). Gender defines who is conceived of as "similarly situated others" (Risman, 2004, p. 432), thereby defining what action is possible. If a platform is seen as all male and dominated by masculinity, it will appear improbable that a woman could legitimately participate. Moreover, Nguyen et al. (2016) argues that computational researchers can provide the most insight by focussing on the dominant role of social structures such as gender. This is not to ignore agency, but to account for how it is restrained and restricted by gender (Nguyen et al., 2016; Schwartz & Neff, 2019). In drawing together the work of Risman (2004), Ford et al. (2016, 2017) and Schwartz and Neff (2019), I propose that the visibility of women is crucial for the possibility of legitimate participation in creative coding.

### ***Reputation, Identity, and Difference***

Claims regarding the democracy and meritocracy of SO rest on the “fairness” of the reputation system in rewarding participation on the site. However, the gamification of such reputation systems has been shown to impact men and women’s behaviour differently (Niederle & Vesterlund, 2007). In speaking of “difference” the challenge here is not to conflate social construction with determination, as discussed in Chapter I, Section II. Reputation systems are not a genderless quantification of participation on a platform, nor an apolitical score, but rather a product of a system that excludes and devalues femininity and affective labour (Brooke, 2019b). As discussed in the Literature Review (Chapter I, Section II), research into “success” on programming forums often does not account for the fact that reputation systems act as a measure of established norms. Similarly, reputation metrics based on tallies of interaction fail to take into account context, and how gendered hostility can be masked in social norms. In the affordances of SO, this includes marking Questions as duplicates or off-topic. SO does acknowledge problems with “not being very welcoming”, but it couches hostility towards women and marginalised groups as hostility towards “new coders” (Stack Overflow, 2018b). As such, SO does little to recognise that its problems are based in prejudice, not experience.

Recent work has gone some way towards accounting for gendered differences in reputation on SO. Focusing on women’s underrepresentation in the computing labour market, May et al. (2019) examined reasons behind the low participation and success rates of women on SO. They find that there are significant “gender gaps” in activity; women are more likely to ask Questions, while men provide more Answers and cast more votes - as an evaluation metric of the work of others (May et al., 2019). They use a measure commonly used in econometrics, the Oaxaca-Blinder decomposition, to decompose the outcome differences between men and women in terms of

difference in their activity.<sup>94</sup> Overall, May et al. (2019) found that activity differences, predominantly the differences between the amount of answers given by men and women;

*“drive success inequality ... men who are generally more competitive [than women] thrive in this environment ... [and] women are discouraged from answers.”*

(May et al., 2019, p. 2010)

The study proposes that the primary causes for a gender gap in reputation on SO is the number of Answers posted and age of the account. Nevertheless, May et al.’s (2019) research invokes assumptions of sex-difference, such as the “more competitive” nature of men, which is a conflation of gender determinism as discussed earlier. A key finding, that I replicate later in this chapter, is that women have on average 55% of the reputation of the men. The median woman has 73% of the reputation of the median man, suggesting that many of the top reputation earners are men. In contrast to other studies (Such as Vasilescu, Capiluppi, & Serebrenik, 2012), they find that men are more active across all measures – Answers, Questions, edits, upvotes, and downvotes (May et al., 2019). In my focus on gendered interaction on SO, I account for reputation and scoring differences across non-binary gender identifications. In this manner, I was able to ascertain if the salience of femininity impacted users’ reception and participation in creative coding culture on SO.

## **Dataset and Users**

The Stack Overflow data (XML) was retrieved from the Stack Exchange Data Dump hosted on the Internet Archive.<sup>95</sup> The Data Dump is Creative Commons Attribution-Share Alike 3.0 licencing, intended to be shared and remixed, so there are no copyright concerns. The Posts in

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<sup>94</sup> The Blinder-Oaxaca decomposition is a statistical method that explains the difference in the means of a dependent variable between two groups by attributing the gap, in part, to (1) differences in the mean values of the independent variable between the groups and (2) group differences in the effects of the independent variable.

<sup>95</sup> <https://archive.org/details/stackexchange>

the dataset span from the founding of the site in 2008 to the most recent quarterly “dump” (upload) at the time of writing (September, 2019). The Data Dump also contains substantial metadata, meaning data that provides a description of information in the dataset, such as suggested edits and location. Although deleted posts are included in the dataset, they are marked as *PostsWithDeleted*, and only limited metadata is available. I used the complete dataset, not focusing on a particular technical specialism or other form of community. Ethical approval was granted in May 2019.<sup>96</sup>

### ***Sampling and Cleaning***

Following the retrieval of the Data Dump, the “Users” file was cleaned, and an appropriate sample was selected based on three criteria.<sup>97</sup> First, users were selected on the basis of location – narrowing down the sample to the USA, UK, and Canada using simple dictionary-based matching to account for western cultural understandings of gender and comparison with Studies I and III. Unfortunately for researchers, location on SO is optional and supplied in a free text format. I accounted for the quirks of such data with first-hand examination at each stage. This proved to be a valuable method as it unveiled such patterns as the tendency of Americans to provide their state (i.e. New Jersey, or NJ) or providing the name of large cities (e.g. London) in the UK. Secondly, users were selected on the basis of being active for at least a week to filter out throw away accounts that had not participated on the site or were not used at all, even to lurk.<sup>98</sup> Finally, deleted accounts were filtered out using a regular expression, as they were still identifiable through their user number. This procedure resulted in a sample of 560,106 users.<sup>99</sup>

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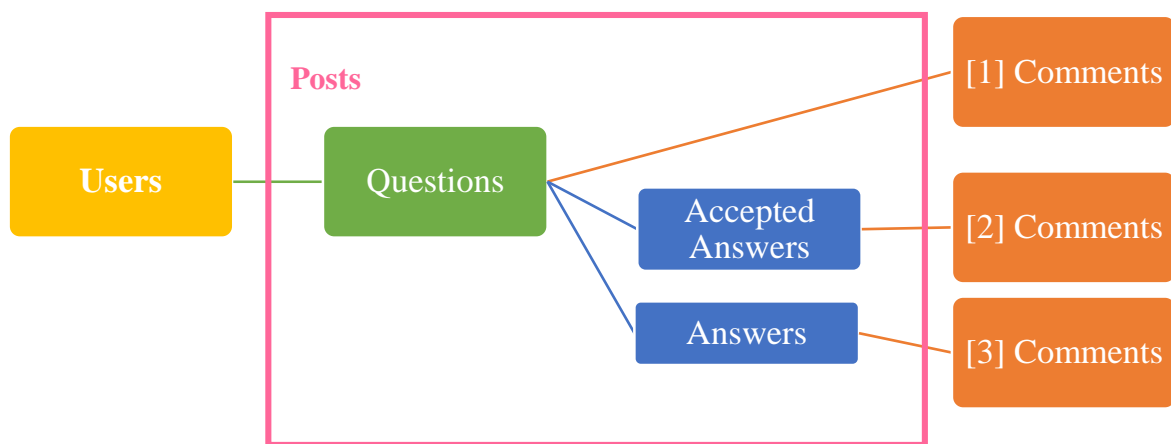
<sup>96</sup> Internal Research Ethics Checklist approval number: SSH\_OII\_IREC\_19\_024.

<sup>97</sup> The SO Data Dump was separated into Users, Posts, Comments, Tags, Votes, Post Links and Post History. There is a readme.txt file and the nuances of the structure are clearer to those who use the platform, but it provided its own challenges in cleaning and structuring the data. Firstly, *Posts* refers to both *Questions* and *Answers* posted by users on the platform and they are the most visible for users and lurkers.

<sup>98</sup> Time active was the time between the first interaction on the site and the last access date (the last time a page was accessed when a use was logged in).

<sup>99</sup> A regular expression (or regex) is a sequence of characters that define a search pattern.

In the Data Dump there are standard Answers which are voted on by users who have 15 reputation or above – Answers are upvoted that are in theory helpful, well researched, while those that are not are downvoted. *Accepted Answers* are those that the asker sees as the apparent best solution to their problem. For many casual users (and lurkers) their use of SO does not extend beyond the Question and accepted Answer. In addition to Answers on SO, users may leave comments in order to request clarification, leave constructive criticism, or add minor additional information. To visualise this structure, Appendix II contains a screenshot of a Question on SO that was used in the writing of this chapter, and Figure 6 contains a tree diagram of the data structure I employed in analysis.



*Figure 6 Tree Diagram of Stack Overflow Database*

Following the initial processing of the data, I split the posts file into: (1) Questions; (2) Accepted Answers; (3) Answers. These datasets only included posts from users ( $n = 560,106$ ) selected during the initial processing stage. I also then filtered the comments into those that were posted in reply to Questions/Answers, and those left by users in my original sample. The figures are contained in Table 12.

**Table 12 Overall Dataset Sizes (Matched)**

<b>Dataset</b>	<b><i>n</i></b>
Users	560,106
Questions	2,115,887
Accepted Answers	1,091,629
Answers (Total)	6,485,035
Comments	5,018,703

In my analysis, I have chosen to use two forms of pairs. Using pairs of text is argued in sociolinguistics to be advantageous as it allows the researcher to take account of context in their writing and analysis (Wang & Potts, 2019). First, I will use *Question* → *Answer* pairs, which is chosen due to its high visibility and standard form of use on the site. Second, I will use *Question* → [1] *Comment* and *Answers* → [2, 3] *Comment*, which are the comments for clarification of edits that appear on a user’s *Question* and *Answers* respectively. This is also supported in the sociological conception of the *dyad*, or the smallest possible social group (This was discussed in Chapter I, Section II.) I hypothesise that the experience and awareness of the dyadic interactions are seen to prevent women and other non-dominant groups from participating on the site. I expect comments to be the locus of unpleasant interactions that do not necessarily break the community guidelines, but do deter participation.

**Table 13 Dataset Sizes: Contextual Pairs**

<b>Pair</b>	<b><i>n</i></b>
Question → Accepted Answer	700,683
Question → Answer	733,434
Question → Comment	427,895
Answer / Accepted Answer → Comment	227,293

Where indicated, *Question* → *Answer* and *Question* → *Accepted Answer* are combined into a single metric for simplified analysis. In using these pairs, I am examining communication in context, and with a lens that is informed by user experiences, as outlined in previous research.

### ***Gender Identification Procedure***

In computational research design processes gender is often produced from a masculine perspective, where women are characterised by an absence of male traits (Chapter I, Section II).

This has led to much discussion on what is considered “fair” in machine learning approaches to the study of inequality (Hutchinson & Mitchell, 2019; Selbst et al., 2019). These debates, however, rarely engage with how social identity is embedded in social experience and context (Corbett-Davies & Goel, 2018; Vidgen et al., 2019). For instance, the label “Black” is a political category that has social consequences in differentiation, systemic inequality, and segregation (Benthall & Haynes, 2019). Modelling procedures inevitably compress social reality to make it machine readable, potentially losing explanatory power in the process. If a researcher’s method only allows them to collect data from a binary model of gender, they will ultimately produce research that presumes gender is a binary (Benthall & Haynes, 2019; Keyes, 2018). In using inclusive methods, researchers can rely on self-disclosed information, whilst noting the restriction that some platforms put in place (Keyes, 2018).<sup>100</sup> In this project I focused on usernames, a user-centred alternative to gathering information on a particular gender.

This study aims to avoid a binary understanding by using multiple categorisations in naming gender. Gender is named only if an SO user’s display name is a “real name” (given name, such as Siân Brooke), where that name is considered to be “male” or “female”.<sup>101</sup> There are several existing Python libraries and paid APIs that provide this service, such as the NLTK names corpus, which contains 2,943 male and 5,001 female names.<sup>102</sup> Research into gender and SO most commonly uses *genderComputer*, a tool developed by Vasilescu, Capiluppi, and Serebrenik (2012).<sup>103</sup> *GenderComputer* is written in Python, built on a database of first names, as well as *gender.c*, an open source C program for name-based gender inference. This library is used by a wide range of studies into gender and Stack Overflow (Ford et al., 2016; Lin & Serebrenik, 2016;

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<sup>100</sup> In my case, Stack Overflow does not collect users’ gender.

<sup>101</sup> In line with the ethical procedure of this research, “real names” are included if a user chose to submit it as a username or display name on their Stack Overflow profile.

<sup>102</sup> Natural Language Toolkit. A suite of Python libraries for natural language processing.

<sup>103</sup> Code available at <https://github.com/tue-mdse/genderComputer>

May et al., 2019; Vasilescu et al., 2015). Inferring a user’s gender from their name and location, *genderComputer* is specifically built from Drupal, WordPress, and Stack Overflow.<sup>104 105</sup>

Whilst the names database for the out-of-the-box algorithm is reasonable, I chose to expand the lists of names associated with the USA, given my sampling frame. I added additional names from USA birth records from 1939 to 2019.<sup>106</sup> Names needed to appear on birth records five times in a specific year to be included in the dataset. I expanded my corpus from ~5,000 (per gender) to 639,824 male and 959,835 female names, including typically gender ambiguous names, such as “Jamie”. For coherence, I followed the procedure of Vasilescu et al. (2012) and required a name to be used twice as frequently by men than women to infer “masculine”, and the same procedure reversed for “feminine”. By default, *genderComputer* also parses for gender-specific words, such as “Mr”, “Sir”, “Girl”. I expanded this list to include more gender-specific terms, such as “bro”. I focused on expanding the feminine associated words as this list was a third the size of the masculine words included by default. There was some room to manoeuvre here, with the algorithm’s categorisations also including “mostly male”, “mostly female”, and “anonymous”. Even with the difficulties presented by SO data (such as Siân being written as S14n), *genderComputer* is shown to automatically infer a person’s gender with high precision (~95%). Though recall suffers due to ambiguity (~60%) the inclusion of *unknown* (Anonymous) identification category improved this metric (~90%). I manually inspected a random sample of 10% of names, and found the results to be satisfactory. I used a 5-level classification, built off lists of names from 73 countries which went some way to account for non-Christian first names. These 5-levels were built from the relative confidence of the algorithm classifying masculine or

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<sup>104</sup>Drupal and WordPress are free and open-source content management system, generally used as the back-end of many websites. Commonly used for personal blogging.

<sup>105</sup> 4,144 Stack Overflow users were used in the training data.

<sup>106</sup> I chose 1939 as the cut-off to account for the so-called “baby boom”.

feminine.<sup>107</sup> Testing the classification on manually labelled data, the classifier’s accuracy was above 80% for each category, which was adequate.<sup>108</sup> The total name-based gender identification is shown in Table 14. In the analysis and discussion, these labels will be used to refer to gender in text. Whilst “Anonymous” is positioned in the centre of the table, this does not mean that I consider it to be “unisex” or a midpoint on the masculine-feminine scale. Rather, Anonymous is positioned centrally to reflect how it encompasses multiple gender identities.

*Table 14 Breakdown of Users’ Visible Gender*

	n	
Masculine	310,785	55.49%
Mostly Masculine	142,302	25.41%
Anonymous	13,800	2.46%
Mostly Feminine	12,035	2.15%
Feminine	80,184	14.32%
<b>Total</b>	<b>560,106</b>	

It may initially seem simplistic to focus on names, but this mirrors the experience of the average user with the platform, where display names are the fundamental identity marker. Given the masculine nature of technology culture (Wajcman, 2009), inferring that male names correspond to male identities is also contextually relevant. This is not to say there is not remit for identity swapping in anonymous spaces. Indeed, women may mask their gender behind neutral or masculine names in order to minimise harassment or to be treated as equals, which is particularly relevant when we consider the SO Developer Job Board discussed earlier. The subject of this project is salience, and how a space performs gender as a collective. If the space is populated by women who are required to present masculinity in order to legitimately participate, it cannot be

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<sup>107</sup> These confidence intervals were ascertained from the predictive probability of classification for each data point (user). Masculine and feminine were on separate scales, where >0.9 was the maximum classification (masculine, feminine) and 0.5 to 0.9 were “mostly” (mostly masculine, mostly feminine) and <0.5 on either scale was anonymous.

<sup>108</sup> In work that comes from this thesis steps will be taken to ensure intercoder reliability in the manual labelling of the dataset.

seen as equal. I ultimately conclude that it is masculinity that dictates the terms of legitimate engagement in technology culture.

## **Operationalisation**

It is worth highlighting that I have taken a parsimonious approach to modelling, focusing on gender salience as an intervention in creative coding culture. This means that I aim for a simple approach that provides a big picture understanding of gendered visibility in online programming forums. The more macro picture outlined here is supported with a thick description in the ethnography of hackathons in Study III. I provide nuance to the findings of Study I concerning the relationship between hostility and help seeking and offering in anonymous spaces. I use a range of statistical measures, including networks and machine learning, to examine gendered interaction on SO. The following section outlines the work that this study does in operationalising gender and gendered hostility beyond a binary.

### ***User Description***

In line with existing research in the field, my first step of analysis is to look for gendered differences in the description of users. Here I am referring to three basic features of user profiles: (1) tenure of activity; (2) reputation; (3) average frequency of interaction. Here, I look at reputation to see how far the dataset replicates existing research in the field. Existing research on SO does not analyse gender beyond a binary, so the first contribution of this chapter is to provide descriptive statistics on users' activity and reputation beyond the binary. I build on this by seeing what the effect of user tenure is on reputation, when controlling for gender.

### ***Answer Effort***

Asking questions on SO is highly structured, and a user is walked through the stages of asking a good Question, and even shown "Similar Questions" which have already been answered as they type out their title. In addition, users are provided with a detailed step-by-step guide including a prominent instruction to "avoiding asking opinion-based questions" which encourages the user

to: (1) summarize the problem; (2) describe what they've tried; (3) show some code, thereby encouraging them to provide a minimum reproducible example. When Answering a Question less guidance is provided. In submitting an Answer, a user is asked to avoid "asking for help or clarification" or "making statement on opinion" and is encouraged to "back them up with references and personal experience". In their Help Centre, SO provides a brief summary on what makes a good answer to well-asked questions on their site, but there is little structured guidance. A user is awarded the "Good Answer" badge if their post receives a score of over 25. Filling in this gap, SO users have contributed to a number of notable discussions on Meta SO which provide information on what makes a good question.

Power users such as *Jon Skeet* have published blog posts on what is a good Answer to a technical Question on SO.<sup>109</sup> Jon Skeet is Senior Software Engineer at Google, who has been nicknamed "the Chuck Norris of Programming". He is a cult figure on SO due to his contribution of nearly 35,000 Answers to the platform and his status as the user with the highest reputation. In his blog, Skeet (2009) provided guidelines on how to "answer technical questions helpfully". The advice can essentially be boiled down to: (1) read the question; (2) code is king; (3) highlight side issues; (4) provide links to related resources with context; (5) style matters (including formatting). "Helpful" Answers show awareness that the Question asker is looking to learn, not to be chastised. This section operationalises Answer effort to ascertain gendered differences, and to examine the contention that women's lower participation rates may be due to relatively lower ability, compared to men. Effort is used here as a stand in for quality, as good Answers are argued to be those that follow Skeet's (2009) advice in "answering technical question helpfully". Given the argument for the problematization of the scores Answers receive, metrics of effort are likely indicators of quality. I conclude this analysis with a discussion on the comparative score that

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<sup>109</sup> <https://codeblog.jonskeet.uk/2009/02/17/Answering-technical-Questions-helpfully/>

Answers receive by gender groupings. My aim here is to show that the salience of femininity dictates perception of a user's contribution, with salient femininity leading to a lower score, challenging existence of a meritocracy.

### ***Networks and Parity***

Peer parity, or the feeling of *someone like me*, is a theme that has received reasonable attention in the study of SO and gender (Ford et al., 2017; May et al., 2019). I will use network analysis to investigate social structures. Networks are structures of individuals and the interactions between them. More specifically, social networks are characterised in terms of nodes (users) and edges (ties, or interactions) that connect them (Hogan, 2016). As well as network averages in term of degree distribution and *k*-degeneracy, the metrics that will be used in this analysis are measures of connection. These measures are: (1) *Homophily* and (2) *Assortativity* which shows if there is preferential attachment within a gender grouping; (3) *Reciprocity*, the extent to which two actors reciprocate each other's interaction. In focusing on these three measures I look at gendered interactions; if users interact more with similarly situated others and if these connections are more likely to be mutual. For the sample selected, the combination of homophily, assortativity, and reciprocity provided an examination of peer parity on Stack Overflow.

### ***Ambivalent Sexism and Hostility***

As outlined in the Literature Review (Chapter I), research has shown that Ambivalent Sexism can be differentiated into hostile and benevolent forms (Glick & Fiske, 1996). To summarise, benevolent sexism represents evaluations of gender that may appear to an individual who retains the existing power dynamic of gender inequality as positive or encouraging gestures, often by ensuring the woman is in a place of helplessness or subservience. Hostile sexism, on the other hand, is more overt, consisting of more visible and negative attitudes towards women. This chapter aims to contribute to research on operationalising sexism, arguing that sexism is mediated by context and degree of gender salience. Again, previous work into sexism uses a binary model to illustrate gendered differences. In the case of my project, I will focus on gender in multiplicity

(non-binary) and consider the salience of gender to be a predictor of the level of sexism experienced. In doing so, I follow the work of Buchltz (1999) and Wang and Potts (2019) in examining discourse in context.

I build on the findings of Study I that masculine-dominated spaces are perceived to be associated with hostility. Immersion in Stack Overflow and its culture has pointed to *condescension* being the main social feature that deters women from participating (Brooke, 2019b). As outlined in the earlier discussion of the Developers Survey, users refer to a “toxic, rude, culture” in framing the community of SO (Stack Overflow, 2020c). Informed by these results, I predict the gender of a user based on how they are spoken to. I show that by understanding discourse in context, gendered hostility and “rudeness” can be functionally operationalised in analysing creative coding cultures.

### ***Condescension***

Complimenting my work in networks, I will also use machine learning to predict a user’s gender identification based on how they are spoken to by other users. The use of condescending language can derail conversations and, over time, disrupt healthy communities (Spertus, 1997). It is corrosive, playing a key part in a range of social roles and power relations. Condescension is closely tied in with “flaming” and other abusive communication practises that are associated with online forums.<sup>110</sup> Though it is possible to be condescending without realising it, a lack of intent does little to mitigate the damage it can cause (Wang & Potts, 2019). Since Natural Language Processing (NLP) was first developed as a field, condescension has been a topic of interest, partly due to the difficulties in its operationalisation (Spertus, 1997; Wang & Potts, 2019). There is substantial evidence that women experience more condescension than men do (Spertus, 1997; Wang & Potts, 2019). This is distilled in the pejorative term *mansplaining*, which is defined as

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<sup>110</sup> Flaming typically involves engaging individuals in an online argument in order to incite anger and emotional distress. The “flamer” does not typically have a stake in the debate/situation and is merely arguing for the enjoyment of infuriating others.

commenting or explaining to a woman in an overconfident, oversimplified, and often inaccurate, manner (Reagle, 2016).<sup>111</sup> What is fundamental to this practice of explaining is communicating to women and non-binary people differently from how you would speak to a man. The hegemony of masculinity is what makes this condescension so explicitly gendered.

Spertus (1997) has been one of the few researchers to create a quantifiable schema of condescending communication in online spaces. She highlights how publically posted “flames” (abusive or insulting messages) are generally clever and indirect, making them harder to detect reliably (Spertus, 1997; Wang & Potts, 2019). Direct personal insults or obscene language are generally less of a challenge to computational techniques and are relatively easier to detect (Vidgen et al., 2019). In looking for condescension, I follow Spertus’s (1997) approach by one-hot encoding the presence of each rule as a binary, returning 1 if the rule applies, and 0 otherwise. Due to the size of the data, this was achieved in a simple process of dictionaries and regular expression matching, which was case insensitive (Nguyen et al., 2019). The general problem here is that the majority of work is done on insults or abusive messages which are more obviously hostile (Vidgen et al., 2019). More recently, Wang and Potts (2019) have revived Spertus’s focus on condescension, but have focused on how condescension works in context. They find that context is decisive for condescension detection (Wang & Potts, 2019). With this in mind, I will look at reply pairs (Comments) as this is the most visible form of communication. Moreover, this will allow me to examine a gendered dimension in the subject and actor of condescension. The setup of the classification task is detailed in the following section.

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<sup>111</sup> Mansplaining re-emerges in Study III as a subject of analytical attention.

## Method

Here I incorporate the operationalisation into the methodological approach of this study. I first delineate the methods used to clean the text of posts and comments and how this was informed the analysis. I then show how literature discussed in Chapter I informed the selection of Social Network Analysis as an appropriate method to examine peer parity on SO. Finally, I outline my proposition for modelling procedure that predicts user gender based on how they are interacted with. This Section outlines the research design, foreground the results and analysis in Section II.

### *Text Pre-processing and NLP*

In NLP it is crucial to ensure the text is adequately pre-processed to avoid excesses noise in the dataset. The first step is to remove stop words from Posts and Comments, but I chose to keep pronouns in the corpus as my focus is gendered visibility. Next, I tokenised the text on whitespace, meaning words were split into individual units (*tokens*) based on whitespace. Following this, I used lemmatisation to group together inflected forms of a words so they could be analysed as a single item, identified as the words *lemma*, or base form of a verb. For example, in my dataset from “working” or “worked” the lemma is “work”. I also used Part of Speech (POS) Tags to extract relations between words, I used this as a flexible approach to detecting name-calling.<sup>112</sup> I used the Penn Treebank POS Tag Set (Marcus et al., 1993; Petrov et al., 2012), paying particular attention to words that were labelled as out-of-vocabulary items to develop a list of context-specific language, if the word appeared in more than 10 pairs. While this number is arbitrary, I looking for a consistency in language use to ascertain what can be cultural slang. I then manually looked through these words, discounting technical terms that the POS Tag did not recognise, such as “JavaScript”. Given the technical and Q&A nature of the dataset, I encountered a large number

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<sup>112</sup> Assigning a part of speech to a particular word in a corpus. Parts of speech are categories of words that have similar grammatical properties, such as noun, verb, pronoun etc.

of out-of-vocabulary items, so I limited this approach to refining my list of context-specific pejoratives.

### ***Social Network Analysis***

Hogan (2016) outlines “simple” networks, where nodes are considered as discrete entities and edges as a form of association between these nodes. A “whole network” is a set of nodes and the connections between them, in which a meaningful reason is articulated as to why these nodes, and not others, should be included (Ugander et al., 2011). A whole network implies a meaningful boundary (Hogan, 2016). I created a “meaningful boundary” in looking to SO users specifically from an Anglo-American locale, and following the process of gender identification, my network consisted of half a million users. As such I was focused on a partial network. Social networks can be classified along a number of dimensions based on directionality and reciprocation.<sup>113 114</sup> I represented the SO network as a multigraph, accounting for the repeated reciprocation and direction, which allows for multiple questions by a user (user A) to be answered by the same user (B). As SO is a platform of novice and veteran users, it follows that new users can ask multiple questions and that experienced programmers will be able to answer multiple questions (edges), particularly given the incentivisation of the reputation system.

### ***Classification Task***

The classification problem addressed is to distinguish between the gender of masculine, mostly masculine, mostly feminine, feminine, and anonymous users. Gender was inferred using *genderComputer* (Vasilescu et al., 2012), with the expansion detailed in the Gender Identification Procedure section. Informed by Wang and Potts (2019), I processed the dataset into contextual

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<sup>113</sup> Edges (connections) can have a direction associated with them, e.g. the difference between  $A - B$  and  $A \leftarrow B$ . Here, the network graph is directional as the edges represent communication in which an Answer is directed at a Question, or a comment is directed at a Question/Answer.

<sup>114</sup> In graph theory a parallel edge (or multi-edge) refers to two or more edges (connections) between the same two vertices (users).

(reply) pairs, focusing on *Answer* → *Comment*, and *Question* → *Comment*. As with the SO network, I removed text pairs where users added comments to their own posts. These pairs were removed because the focus of my investigation is condescension in dyadic communication, and users generally comment on their own posts to add clarification based on users' prompts/comments. Following this, I am left with a total of 427,895 *Question* based pairs and 227, 293 *Answer* based pairs. Feature selection refers to the choice of input variables used to train the classifier. In many cases, features are selected using a “brute force computation [...] with little consideration for *why* they are included” (Vidgen & Yasseri, 2020, p. 3). Such models can perform well in initial testing, but are highly susceptible to overfitting making them unsuitable for empirical research (Vidgen & Yasseri, 2020). Table 15 outlines the input features along with their descriptions.

**Table 15 Input Feature Descriptions**

<b><i>Input Feature</i></b>	<b><i>Feature Description</i></b>
Text-only	<i>One-hot encoded for the presence of specific terms. References to <u>Google</u> or <u>Homework</u>, where the implication is a lack of effort on the behalf of the poster. References to <u>documentation</u> without context, or linking to a <u>unpopular URL</u> without further explanation.</i>
Textual Content	<i><u>Structural</u> markers, such as rhetorical questions. <u>Subjectivity</u>. <u>Quoting</u> the post. Reference to <u>Time</u> or <u>Repetition</u>. Containing, <u>laughter</u>, <u>ellipsis</u>, multiple <u>exclamation points</u> or <u>question marks</u></i>
Site-Specific	<i>Terminology associated with technology culture. Informed by Spertus (1997) this is site specific <u>Insults</u>, <u>Villains</u>, and <u>Sins</u>. An <u>Insult</u> is code focused, such referring to it as “clunky” or “brittle”. A <u>Villain</u> is name-calling, such as “noob”. <u>Sins</u> generally refer broadly to a lack of knowledge, “RTFM” (read the fucking manual).</i>
Gender-Specific	<i><u>Girling</u>, literally using “girl” terminology. <u>Male default presence</u>, assuming asking is male when their inferred gender is anonymous, mostly <u>feminine</u>, or <u>feminine</u>.</i>
Poster-Gender	<i>The <u>gender of the using posting</u> (Questions, Answers)</i>

Table 15 contains a summary of each of feature arrays used in constructing the final model. I argue that phrases directed at the original poster (OP) as “you” modified with a noun phrase have a tendency to be insulting, such as “you people”. I also allowed for this to have a gendered element, to account for phrases such as “you guys”. Another heuristic based on the syntax of a sentence is imperative statements or commands, such as “you should check the documentation”. My immersion into Meta Stack Overflow, and technology culture in general, led to the conclusion that the pronoun “you” was more commonly used in condescending *Answers* than were references to “original poster”, “OP”, or even “@-ing” a user. I also borrowed structural rules for condescension in tag phrases from Spertus’s (1997) project. For instance, Spertus (1997) emphasises the use of site-specific villains in the detection of rude or condescending messages. These categorisations were informed in tandem with my ethnographic work, as well specific literature on the *obligation to know* in geek masculinity (Reagle, 2016). Reagle (2016) highlights how this obligation is obscured in jargon-laden exhortations such as RTFM (read the fucking manual), and is also evident in gender-practices of mansplaining. Therefore, building on the sociolinguistic call for context in exploring language, I also included condescension in context-specific phrases.

Table 16 shows the results of the inclusion of each array of input features, with Model 5 being the best performing model and the one used in the analysis. I created a training dataset of 6,000 comment pairs by sampling from *Answer* → *Comment* (2,000), and *Question* → *Comment* (4,000). The training data contained equal numbers of each inferred gender category. I first created a term only model, using one-hot encoding for simple text features associated with condescension on SO. Second, I included more general textual feature that are shown to be linked to gendered condescension (Spertus, 1997). I then build on this model with Gender and Site specific features, as contextually relevant understanding (Spertus, 1997; Wang & Potts, 2019). Finally, building on the findings from the network analysis I included the gender of the user replying to (commenting on) the post. For testing, I implemented a 5-fold cross validation on a

linear SVM. In cross validation, the data is split into  $k$ -folds, or a number of sections where each fold is used as a testing set, the average F1 score for each model is shown in Table 16.<sup>115</sup>

*Table 16 Accuracy of models with different input features*

<i>Input Feature Model</i>	<i>F1 Score</i>
Model 1: Text-only	0.13
Model 2: Text-only + Textual-Content	0.15
Model 3: Text-only + Textual-Content + Site-Specific	0.18
Model 4: Text-only + Textual-Content + Gender-Specific	0.19
Model 5: Text-only + Textual-Content + Site-Specific + Gender-Specific + Comment-Gender	0.22

Table 16 shows that Model 5 out performs the others. However, the low predictive accuracy of models also shows that the classification is not a linear task. As such, I use a RBF kernel using Model 5 as a baseline for performance, as detailed in the following section.

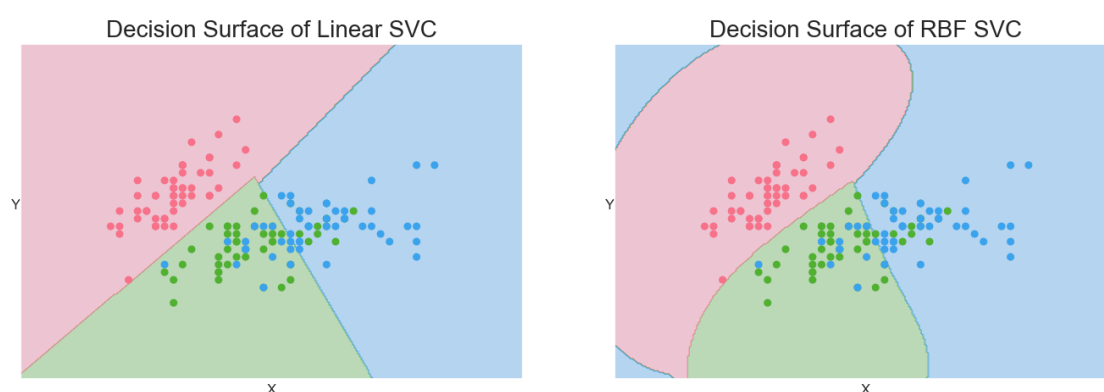
### *Support Vector Machines*

The input array for the classification task are textual features associated with context-specific condescension on SO (Table 15). Using these features, I aim to infer a user's gender, based on how others speak to them in comments on their post (*Question/Answer*). For this task I chose an ensemble method, meaning that I combine multiple component classifiers. These components were one of the most widely employed supervised machine learning algorithms, Support Vector Machines (SVMs). I will detail the formulation of these component models, before discussing the ensemble method. The concept behind SVMs that they separate data points using a hyperplane (boundary) within the largest possible margin between classes (what is trying to be predicted)

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<sup>115</sup> The F1 score will be defined in the Support Vector Machines section. Broadly, a higher F1 score is reflective of the algorithm making better guesses, minimising false positives and false negatives across what we are trying to classify (inferred gender).

(Chang & Lin, 2011; Liu et al., 2015).<sup>116</sup> SVMs are discriminative, meaning that they richly model the boundary between classifications, rather than representing independence relations in the dataset (Platt, 1999; Vanderplas, 2016).<sup>117</sup> Their object is to segregate classes (two or more) in the best possible way, defined by the widest possible margin (Albon, 2018; Platt, 1999). Two options for this kernel are linear or Gaussian radial basis function (RBF), represented in Figure 7.<sup>118</sup>



**Figure 7** Visualisations of the Decision Surface of a Linear and RBF SVM

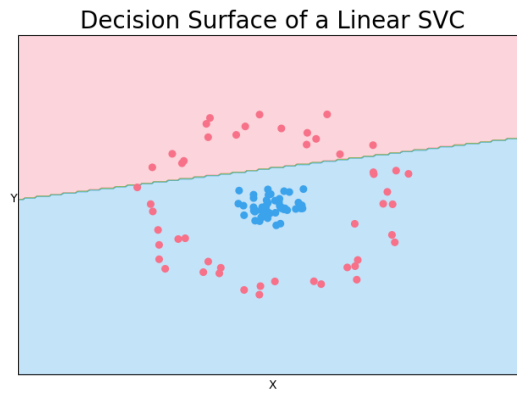
As shown, RBF SVMs draw a boundary that isn't a straight line, resulting in a much more complex relationship between data points being calculated (Liu et al., 2015). In addition to the shape of the boundary, SVMs also use a technique called the *kernel-trick* to separate data points that can not be easily divided, such as the example in Figure 8.

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<sup>116</sup> The data points closest to the hyperplane (boundary) that influences the position and orientation of the hyperplane are the *support vectors*.

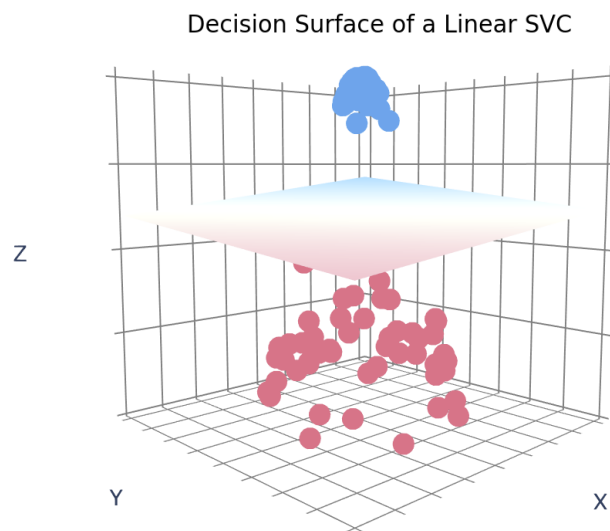
<sup>117</sup> There are generally two types of models. Generative models are based on  $P(x, y)$  and discriminative are based on  $P(x|y)$ . The fundamental difference is that Discriminative boundaries learn the (hard or soft) boundary between classes, while the Generative model learns the distribution of individual cases.

<sup>118</sup> Kernel is used as a measure of similarity. In particular, the kernel function  $k(x, \dots)$  defines the distribution of similarities of points around a given point  $x$ .  $k(x, y)$  denotes the similarity of point  $x$  with another given point  $y$ .



*Figure 8 A Classification Problem Represented in Two-Dimensional Space*

Here, the kernel takes a low-dimension input space and transforms it into a higher dimensional space to be able to classify data points (Albon, 2018). Figure 9 is the same data as Figure 8, but it shows how we are able to easily separate the data points when we add a dimension.



*Figure 9 The Same Classification Problem Represented in Three-Dimensional Space*

In other words, SVMs converts a non-separable (data points) problem to a separable problem by adding more dimensions to it. Both linear and RBF kernels employ this technique. I am using a

Gaussian RBF as the data points were not linearly separated, which can be written as: <sup>119</sup>

$$k(x, y) = \exp\left(\frac{\|x - y\|^2}{2\sigma^2}\right)$$

(Liu et al., 2015)

*Equation 7 Gaussian Radial Basis Function*

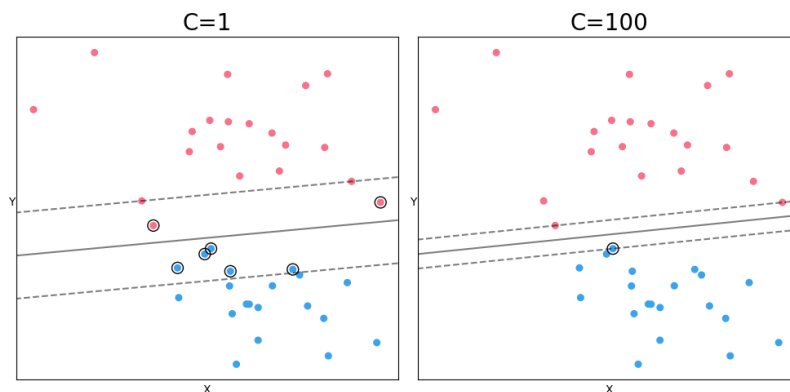
The RBF kernel acts as a processor to generate new features by measuring the distance between all other data points to a specific data point (Kim et al., 2003). An SVM classifier that uses an RBF kernel (RBFSVM) has two parameters,  $\gamma$  and  $C$ .  $\gamma$  is the spread or size of the kernel and therefore the decision region: when  $\gamma$  is low, the “curve” of the decision boundary is very low and thus the decision region is very broad (Platt, 1999). When  $\gamma$  is high, the spread of the kernel is less pronounced and the decision boundary starts to be highly affected by individual data points (variance) (Albon, 2018). If the value is too high, the model will overfit to the training data.  $\gamma$  parameter defines the influence of a single training example, or the similarity measure between two points.  $C$  (squared L2 regularisation penalty) is a parameter of the SVM learner (Liu et al., 2015).<sup>120</sup> Social data is often not clean data, and some amount of overlap between classification categories occurs. The margin around the decision boundary can be “softened” in the SVM implementation (Albon, 2018). That is, it allows for some of the points to creep into the margin if this makes for a better fit, where by tuning  $C$  I am adjusting the hardness of the margins. A large value is a hard margin, and data points cannot lie in it, whereas for a smaller value the

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<sup>119</sup> I determined that my classifications were not linearly separated by comparing the F1 score (accuracy) of a linear SVM model with a RBFSVM. The RBFSVM achieved a higher overall score.

<sup>120</sup> Regularisation is a process of introducing additional information in order to prevent overfitting. L2 regularisation adds “squared magnitude” of coefficients as a penalty term to the loss function. The loss function is the squared error, where the error is the difference between  $y$  (the true value) and  $\hat{y}$  (the predicted value).

margin is softer and can grow to encompass some points, as shown in Figure 10.



*Figure 10 The Effect of Turning Parameters  $C$  on the Support Vectors*

As with  $\gamma$ , if the value of  $C$  is set too high the model will overfit.  $C$  represents the bias-variance trade-off, as it is the cost of misclassification (Albon, 2018; Platt, 1999). To summarise,  $C$  represents a soft margin, tolerating misclassified dots, and  $\gamma$  finds a non-linear decision boundary, known as the kernel trick.

The SVM parameters were estimated using grid search with cross-validation as implemented in the Python scikit-learn (sklearn) library (Vanderplas, 2016). In this approach, I provide a range of parameters for  $\gamma$  and  $C$  for the SVM estimator, which are used to compare the models across a given performance metric (Forman & Scholz, 2009). I used 5-fold cross validation to evaluate my model by training several (5) RBF SVMs on subsets of the available input data, and evaluate each model on a complementary subset of data.<sup>121</sup> The performance of the selected hyper-parameters and trained model is then measured on a dedicated evaluation set that was not used during the model selection step. In practice, the candidate parameter values are ascertained through a logarithmic grid from  $10^{-5}$  to  $10^5$ . In my case, the parameters selected were  $C = 100$ ,  $\gamma = 0.01$ .

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<sup>121</sup> Each subset is known as a fold.

The optimisation procedure selected a smaller-margin hyperplane, prioritising correct classification of training points.

In building the model, I took into account an imbalance in the output variable gender: the majority masculine population. The standard accuracy score metric can be misleading when datasets are unbalanced. In a dataset with highly unbalanced classes, if the classifier always “predicts” the most common class without performing any analysis of the features, it will still have a high accuracy rate, which is illusory. For instance, if I guess that every SO user is a man I will have around a 90% accuracy score, while entirely ignoring any non-men. The first thing to consider in dealing with imbalanced data is the choice of evaluation metric. I used the *F1 score*, the weighted average of *precision* and *recall* (Forman & Scholz, 2009).<sup>122</sup> The metric ranges from 0 to approximately 1 for a perfect score. The F1 score achieved by my model was 0.63, successfully outperforming my base model (0.22) in classifying users (Jeni et al., 2013).<sup>123 124</sup> As this metric finds a balance between precision and recall, it is extremely useful in scenarios where we are dealing with imbalanced data. In comparing evaluation procedures, Forman and Scholz (2009) show that that computation of the F1 score using *k*-fold cross validation yields a suitable estimate of generalised performance.

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<sup>122</sup> It is the *harmonic mean*, the reciprocal average of the reciprocal. The reciprocal of  $i$  is  $\frac{1}{i}$ . First, the value is calculated for each reciprocal. Then, we find the average (arithmetic mean) of the reciprocals. Finally, you do the reciprocal of that average to find the harmonic mean. The number of true positives is divided by all positive predictions. Precision is also called *Positive Predictive Value*. It is a measure of a classifier’s exactness. Low precision indicates a high number of false positives. The number of true positives is divided by the number of positive values in the test data. Recall is also called *Sensitivity* or the *True Positive Rate*. It is a measure of a classifier’s completeness. Low recall indicates a high number of false negatives.

<sup>123</sup> Specifically, I used the micro F1 score, which calculates metrics globally by counting the total true positives, false negatives and false positives. This is preferable in my case as I have a multi-class problem where I am aiming to maximise *hits* (correct predictions) and minimise *misses* (incorrect) metric for a class imbalance.

<sup>124</sup> The baseline is the F1 score achieved by Model 5, as illustrated in Table 16.

## ***Ensemble Method***

The principle behind ensemble methods is to train multiple models. Boosting is such an ensemble technique, which attempts to create a strong classifier from a number of weak classifiers (Albon, 2018; Kim et al., 2003). Each model tries to correct the errors from the model before. Models are added until the training set is predicted perfectly, or the maximum number of models is added (Govindaraj, 2016). A method of this type that I selected to use is AdaBoost, which adjusts the weight of classes (gender) to optimise for a low misclassification rate (Freund & Schapire, 1996).<sup>125</sup> AdaBoost is sensitive to outliers, so the feature vector (input variables) was transformed by subtracting the median and then dividing the interquartile range (75% value – 25% value).<sup>126</sup> Though Adaboost is usually used with decision trees, it can be used with SVMs if the component classifiers are weak.<sup>127</sup> Li et al. (2008) show that AdaBoostSVM demonstrates better generalisation performance on imbalanced classification problems than SVM.<sup>128</sup> The idea is that for each sequence of trained RBFSVM, starting with large  $\sigma$  values (the “spread” of the data), the  $\sigma$  values are reduced as the boosting interaction proceeds (Li et al., 2008).<sup>129</sup> This process results in a set of RBFSVM component classifiers whose model parameters are adaptively different, resulting in better generalisation in the final product. AdaBoost with SVMs have been shown to outperform other methods in noisy data, such as image recognition tasks (Govindaraj, 2016). In a similar manner to Study I, the steps of the AdaBoostSVM are outlined below (adapted from Li et al., 2008).

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<sup>125</sup> “AdaBoost” stands for Adaptive Boosting and is unfortunately not a reference to Ada Lovelace.

<sup>126</sup> This was done using the RobustScaler from the Sklearn Python library.

<sup>127</sup> My model was weakened by training it on a subsample of the data. Weaker classifiers are defined by a predictive accuracy below the PPOS threshold.

<sup>128</sup> AdaBoost incorporating a RBFSVM (SVM with RBF kernel) component classifiers.

<sup>129</sup> Also defined as the amount of variability in a given set of data - whether the data points are all clustered together, or very spread out.

*Figure 11 AdaBoostSVM Algorithm*

- Step I:  
The input is a set of training samples with labels  $\{(x_1, y_1) \dots (x_n, y_n)\}$ , the initial  $\sigma_{initial}$ , and the minimal  $\sigma_{min}$ , and the step of  $\sigma_{step}$ .
- Step II:  
The weights of the training sample are initialised;  $w_i^1 = 1/N$ , for all  $i = 1, \dots, n$ .
- Step III:  
Whilst  $\sigma > \sigma_{min}$ , train a RBFSVM component classifier ( $h_t$ ) on the weighted training set.
- Step IV:  
Calculate the training error or of  $h_t$ :  $\epsilon_t$ . If  $\epsilon_t > 0.5$ , decrease  $\sigma$  by  $\sigma_{step}$ , and got to Step I. If  $\epsilon_t < 0.5$  set the weight of the component classifier  $h_t$ .
- Step V:  
Update the weights of the training samples, where  $C_t$  is the normalisation constant.

The principle behind Step V is to increase the penalty for misclassifying the minority class (i.e. feminine) to prevent them from being “overwhelmed” by the majority class. In building the final model, moderately accurate RBFSVMs are preferred to allow for larger diversity than component classifiers with higher accuracy (Li et al., 2008). The larger the diversities, the better AdaBoost performs. As shown in Figure 11, this process continues until the  $\sigma$  is decreased to the minimum value. An AdaBoostSVM classifier was selected as the most appropriate model for my data analysis, maximising generalisability through diversity. Therefore, I use condescending replies (*Comments*) to predict the gender of a user offering (*Answer*) or seeking (*Question*) technical knowledge.

## Section II: Leaving the Everyday Behind

The results section of this study will be formed of four parts. The first section is a descriptive analysis of users' profiles, examining if there is a gendered difference between reputation and user tenure.<sup>130</sup> Next, I will describe the average user's interaction on the site by gender, looking at the average counts of posts and comments. I will build on this with social network analysis, to effectively characterise interaction between users. Third, I will look at the content of these interactions, looking at descriptive measures of "effort" that is put into Answers. Finally, I will look at context-specific measures of condescension. These findings serve to highlight how masculine dominance and gender prejudice operate in programme forums as an instance of creative coding culture.

### Reputation and Activity

Previous research into gendered barriers to participation on SO, which has already been outlined here, focuses particularly on reputation. As argued, the affordances of online anonymous spaces favour masculinity to the point where reputation becomes proof of a self-perpetuating gendered system. However, a non-binary exploration of gender and reputation that includes anonymous/unknown users can be a valuable contribution to the field. I included users with a minimum of 15 and 100 reputation points respectively, to allow a comparison with May et al. (2019), and these users can be considered active on the website. Any user who gains 15 reputation points gains the ability to upvote Questions and Answers. The users here are the complete sample ( $n = 560,106$ ) showing the percentage of users of each gender categorisation in Tables 15 and 16.

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<sup>130</sup> User tenure is the time difference between the first interaction of a user on Stack Overflow and the last time they accessed the site.

**Table 17 Reputation of Users (>15)**

<b>Gender</b>	<b>% of Group</b>	<b>Median</b>	<b>Mean</b>	<b>Std.</b>	<b>Max.</b>	<b>n</b>
Masculine	38	135	1,531	10,489	888,089	118,524
Mostly Masculine	37	137	1,739	11,262	1,128,126	53,760
Unknown/Anonymous	32	120	1,209	9,630	532,305	4,546
Mostly Feminine	33	115	1,179	4,852	118,999	4,042
Feminine	27	101	1,018	6,518	376,439	21,975

**Table 18 Reputation of Users (>100)**

<b>Gender</b>	<b>% of Group</b>	<b>Median</b>	<b>Mean</b>	<b>Std.</b>	<b>Max.</b>	<b>n</b>
Masculine	22	506	2,604	13,660	888,098	68,870
Mostly Masculine	22	532	2,941	14,602	1,128,126	31,465
Unknown/Anonymous	18	465	2,176	12,944	532,305	2,486
Mostly Feminine	18	484	2,104	6,389	118,999	2,228
Feminine	13	420	1,987	9,096	376,439	11,034

In looking to differences between my gender groupings I applied the general linear model framework to test the difference between multiple groups, using ANOVA (Analysis of Variance). I used Welch’s ANOVA as the data violates the assumption of homogeneity of variance.<sup>131</sup> Here, my categorical variable of gender is used to predict a continuous outcome (reputation points). This is a predicative, rather than a causal inference; how much of the variance of the outcome variable is explained by gender? The sum of squares error is the amount of variance my model doesn’t explain. The F-statistic explains how much variation my model accounts for. The larger the F-Statistic the more variance the model explains. As the ANOVA test does not tell us where the statistically significant difference is, post-hoc testing was necessary. I conducted *t*-test between levels of gender, focusing on which groups differed from the masculine group as a theoretically driven line of enquiry. I controlled for familywise error rate using the Bonferroni correction, meaning that  $\alpha = 0.01$ . Though each model was skewed, as expected, they did not violate assumptions of multicollinearity.<sup>132</sup> In first looking to users with >15 reputation, my

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<sup>131</sup> Welch’s ANOVA is considered a robust test against the normality assumption.

<sup>132</sup> Bonferroni correction is a multiple comparison correction used when several statistical tests are being performed simultaneously. While a given value for  $\alpha$  may be appropriate for each individual comparison, it is not appropriate for the set of all comparisons.

analysis (OLS) found  $f = 21.49$ ,  $p = >0.001$ . This tells us that there is a significant difference in group (gender) means across reputation. In the ANOVA results in Table 19, the Gender row is the between groups effect, which is the overall experimental effect. The sum of squares for the OLS model ( $SS_M$ ) is how much variance is explained by gender. The model explains a significant amount of variance  $F(4,116078) = 21.49$ ,  $p < 0.05$ . The residual row is the unsystematic variation in the data.

**Table 19 ANOVA Table, Reputation > 15, (Log<sub>10</sub>) ~ Gender**

	<i>SS<sub>M</sub></i>	<i>df</i>	<i>F</i>	<i>PR(&gt;F)</i>
Gender	9.03E+9	4	221.61	<0.001
Residual	2.13E+13	16,188	-	-

Moreover, the model found that while there is a statistically significant difference between the mean reputation of feminine users and masculine ( $\beta = 512^{***}$ , std = 69) and mostly masculine ( $\beta = 720^{***}$ , std = 82) users, there is not a significant difference between feminine users and mostly feminine ( $\beta = 512$ , std = 75) and unknown users ( $\beta = 191$ , std = 167). In moving to users with >100 reputation (Table 20), my analysis found  $f = 12.12$ ,  $p = >0.001$ . This shows that there is still a significant difference across non-binary gender for reputation.

**Table 20 ANOVA Table, Reputation > 100, (Log<sub>10</sub>) ~ Gender**

	<i>SS<sub>M</sub></i>	<i>df</i>	<i>F</i>	<i>PR(&gt;F)</i>
Gender	8.76E+9	4	68.52	>0.001
Residual	2.10E+13	8810	-	-

Again, feminine users are significantly different from masculine ( $\beta = 617^{***}$ , std = 137) and mostly masculine ( $\beta = 953^{***}$ , std = 148) users, but are not significantly different from mostly feminine ( $\beta = 117$ , std = 312) and unknown ( $\beta = 189$ , std = 298) users. I can summarise that there is a statistically significant difference in reputation points across gender levels. Tenure of activity (Table 21) is also an important metric of participation and legitimacy in online forums.

**Table 21 User Tenure by Gender, >15 Reputation**

<i>Gender</i>	<i>Median</i>	<i>Mean</i>	<i>Std.</i>	<i>Max.</i>	<i>n</i>
Masculine	1907	1882	1060	4047	118,524
Mostly Masculine	1927	1908	1107	4047	53,760
Unknown/Anonymous	1818	1792	1044	4041	4,546
Mostly Feminine	1860	1829	1012	4046	4,042
Feminine	1625	1660	1050	4044	21,975

In modelling (Welch’s ANOVA) I found that there is a significant difference in group (gender) means across the duration of activity for user accounts. I also considered the possibility of an interaction effect between gender and user tenure on reputation. User tenure is the duration of activity on an account, which I filtered to a minimum being 7 days. I examined users that had above 15 reputation points, as this leads to basic privileges. With this design I am testing  $H_1$ : *There is an interaction between user tenure and gender.* The tenure and reputation were  $\log_{10}$  transformed to account for skewness. The overall ANOVA model was found to be significant ( $f = 6832, p = 0.0001$ ).

**Table 22 MANOVA Table, Reputation ~ Tenure \* c(Gender)**

	<i>SS<sub>M</sub></i>	<i>df</i>	<i>F</i>	<i>PR(&gt;F)</i>
Gender	147	4	77.84	>0.001
User Tenure	28,357	1	60,194.80	>0.001
User Tenure: Gender	117	4	62.06	>0.001
Residual	95,554	202841	-	-

Table 22 shows that the levels of gender and user tenure are associated with reputation. Moreover, the interaction between gender and user tenure as also significant, indicating that the relationship between tenure and reputation diverges, based on gender. Post-hoc testing (Welch’s *t*-test with Bonferroni correction) revealed that user tenure positively affects reputation for each level of gender.

## **Questions, Answers, and Comments**

In this section I will go over the average Questions asked by a user, as well as the number of Answers and comments. Before examining the frequency of posts and comments, I can also look

at the average time between a Question and Answer in the dataset. The average response time for a Question was 37 minutes and there was not a significant gendered difference between categorisations. Table 23 shows the average Question count by gender. Users who did not post or comment are not included in these tables.

**Table 23 Average Question Count by Gender**

	<i>Mean</i>	<i>Median</i>	<i>Max</i>	<i>Std.</i>	<i>Count</i>
Masculine	5.89	2	900	14.94	607,323
Mostly Masculine	6.05	2	822	15.83	283,940
Anonymous	5.55	2	395	14.05	23,039
Mostly Feminine	5.63	2	255	13.66	20,893
Feminine	5.17	2	1069	16.19	110,863
All Users	5.84	2	1069	15.18	1,046,058

The most prolific user was recognised as feminine and asked 1069 Questions over an 11-year period. They are in the top 0.08% users of the site and have answered 92 Questions, mainly focusing on JavaScript and C#. However, when I look to the median and mean by gender, we can see this user is clearly an outlier. In general, the pattern visible in Table 23 is that there are few differences in the number of Questions asked by users by gender.

**Table 24 Average Answer Count by Gender**

	<i>Mean</i>	<i>Median</i>	<i>Max</i>	<i>Std.</i>	<i>Count</i>
Masculine	8.77	2	4106	42.84	808,231
Mostly Masculine	9.53	2	5914	46.42	398,155
Anonymous	7.16	2	746	25.09	24,832
Mostly Feminine	8.22	2	813	26.55	25,014
Feminine	6.80	2	950	25.08	109,156
All Users	8.73	2	5914	41.82	1,365,388

Table 24 shows the average number of Answers by users in the dataset, and here I see that there is little change in the average (median) number of Answers offered by users. Table 25 shows the average number of comments on a Question and Table 24 shows the average comments left on an Answer by gender.

**Table 25 Average Comment (Question) Count Posted by Gender**

	<i>Mean</i>	<i>Median</i>	<i>Max</i>	<i>Std.</i>	<i>Count</i>
Masculine	11.19	4	3696	46.59	397,748
Mostly Masculine	12.12	4	3557	45.81	195,704
Anonymous	10.19	3	788	32.43	13,408
Mostly Feminine	10.19	3	736	28.17	12,592
Feminine	9.47	3	1076	29.33	61,399
All Users	11.22	4	3696	44.31	680,851

**Table 26 Average Comment (Answers) Count Posted by Gender**

	<i>Mean</i>	<i>Median</i>	<i>Max</i>	<i>Std.</i>	<i>Count</i>
Masculine	9.36	3	2958	38.33	510,820
Mostly Masculine	10.16	3	5521	44.97	256,844
Anonymous	8.01	3	534	23.35	15,871
Mostly Feminine	8.65	3	594	22.43	15,692
Feminine	7.89	3	993	24.76	75,171
All Users	9.39	3	5521	38.63	874,398

In the final metric of describing the content that users provided, Table 27 shows the average Question score of users. The average (mean) score falls with increased femininity. The highest score is mostly masculine, which is likely due to outliers (as shown in the max column).

**Table 27 Average Question Score by Gender**

	<i>Mean</i>	<i>Median</i>	<i>Max</i>	<i>Std.</i>	<i>Count</i>
Masculine	2.92	1	6391	23.03	1,189,227
Mostly Masculine	3.00	1	7243	22.98	545,289
Anonymous	2.42	1	827	12.73	46,843
Mostly Feminine	2.65	1	3892	23.544	41,380
Feminine	2.46	1	3277	20.03	224,395
All Users	2.88	1	7243	22.53	2,047,134

## **Code is King: Answer Effort**

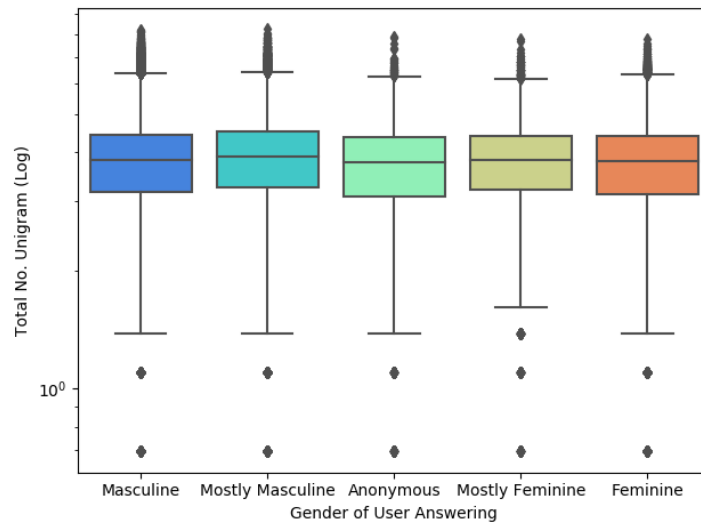
The catchphrase “code is king”, which underpins online programming cultures. The idiom means that the manifestation of any open source community lies in the products and technology it produces. On SO, it is used to mean that one cannot ask a question, or in fact answer a question, without providing ample code. This section aims to look at gendered differences in *Answer* effort. The criteria here come from discussions on Meta and the points listed in Skeets blog (See *Operationalisation* in Section I). I will be using multiple features to evaluate a *Question*, focusing

on structural quality. I first look to code snippet to text-paragraph ratio. Next, I will examine the features outlined in Table 28. The purpose is to show that it is gender and sexism, and not Answer effort, that disadvantages women on SO.

In Figure 12, I break down the text to code ratio of users by gender. Due to the multiple programming languages and forms of technical questions in the dataset, it is not sensible to count *n*-grams of characters. Rather, I will be using an approach informed by Skeet's (2009) guidance and SO's (2020b) definition of a Minimal, Reproducible Example (reprex) emphasising the use of formatted code snippets.<sup>133</sup> My ratio will be a simple ratio of code snippets to formatted paragraphs, where there is more than a single paragraph. I chose to use more than one paragraph as an entire Answer consisting of a singular block of text would count as one paragraph, but is bad practice according to the established referenced guidelines. The highly skewed nature of my network demonstrates that power users (such as Jon Skeet) can adversely affect the arithmetic mean. The dataset is the Answers of the *Question* → *Answer* pairs (including *Accepted Answers*), where both users are in the dataset. I examined the average length of plain text of Answers by gender, as shown in Figure 12. There was also shown to be no statistically significant difference in the length of plain-text in the answering practices of each gender grouping.

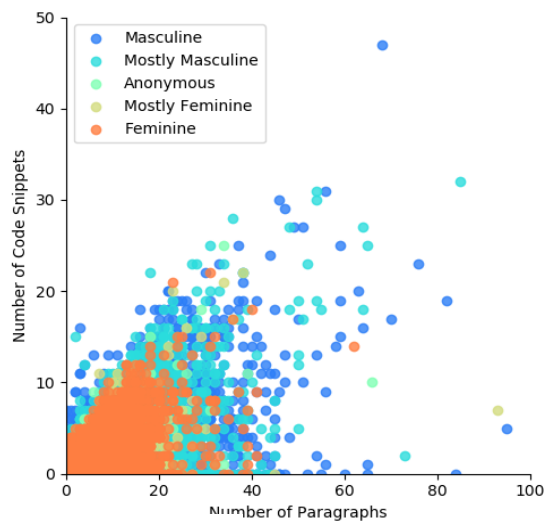
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<sup>133</sup> A code snippet is a programming term which refers to a small piece of reusable code.



**Figure 12 Average Answer Length Boxplot (Plain text Unigram)**

Figure 13 shows the distribution of the ratio of text-paragraphs to code snippets for all *Question* → *Answer* pairs of users in the dataset. What is evident here is that there is not a clear difference between genders in the proportion of text to code, which was confirmed with ANOVA testing. Though they are basic measures, this does show that the overarching structure of Answers is arguably not a contributor to gendered differences on SO. The average across all users were Answers that consist of three text-paragraphs to one snippet on code.



**Figure 13 Paragraph to Code Ratio By Gender**

In moving to more involved metrics of Answer effort, Table 28 applies the SO framework for productive (or in Skeet’s terms “helpful”) Answers to a technical Question. The sample includes 733,434 Answers for *Question* → *Answer* pairs (including *Accepted Answers*) in the dataset. The text was extracted using the html tags in the body of the Answer, for instance “<pre><code>” indicated formatted code in an Answer. The formatted code was then extracted and parsed for comment structure. I defined an External URL as having context if the URL was not orphaned from a body of text, and was accompanied by plain text, other than *n*-grams of the URL. Examples of URL context included: “The full demo in SQL is found here”, or “Common solutions for IntelliJ IDEA performances are here”.

*Table 28 Answering Technical Questions: Operationalisation of "Effort"*

	<i>Rule</i>	<i>Example</i>	<i>n</i>
<b>Code</b>	Code	<i>Fragment of Computer Code.</i>	366,183
	Formatted Code	<i>Snippet of code with line breaks and spacing.</i>	452,520
	Code with Comments	<i>Programmer-readable explanation or annotation in the code snippet.</i>	7,167
<b>Resources</b>	Internal URL	<i>URL to somewhere else on Stack Overflow, with context.</i>	27,737
	External URL, popular	<i>URL to a site external to Stack Overflow (i.e. GitHub, Wikipedia, MSDN). URL domain must be used more than 50 times.</i>	22,541
	External URL, With context.	<i>URL to a site external to Stack Overflow (i.e. GitHub, Wikipedia, MSDN) with context.</i>	19,646
<b>Format</b>	Emphasis	<i>Bold or strong, italic or emphasis. Headings used.</i>	137,160
	Structured Text	<i>Use of lists (ordered, unordered) and/or bullet points.</i>	57,112
	Image	<i>Answers that contain an image</i>	20,298
	Sectioning	<i>Update or Edit section added to text.</i>	13,523

The rules that were used as metrics for Answer effort were then aggregated (count) into three categorisations: (1) Code; (2) Resources; (3) Formatting. The score of each category was simply a total of the amount of times the rule was met. There was an overall significant difference (using Welch’s ANOVA) between the gender category of the user providing the Answer and the Answer

effort. Post hoc testing, using Welch’s t-test with the Bonferroni correction,  $\alpha = 0.01$ , showed that the differences were between masculine and feminine users ( $t = 12.08, p = >0.001$ ), masculine and mostly feminine users ( $t = 5.16, p = 0.005$ ), and masculine and anonymous users ( $t = 7.25, p = >0.001$ ). As the t-statistic is positive, I can reject the null hypothesis and conclude that there are more markers of Answer effort in non-masculine (anonymous, mostly feminine, and feminine) than masculine users.

It is key here that I add that my operationalisation of Answer effort is rudimentary, but the result is nonetheless informative. There is room for a more nuanced approach to extend this analysis, but the conclusion here is that technical knowledge sharing is gendered. Clarifying the results of Study I, these results show that it is the reception and evaluation of technical knowledge offering that is gendered, as opposed to a negative difference in content. The takeaway here is that masculine users are not shown by my metric to produce higher effort Answers.

### ***Meritocracy Myth***

The above section shows that there is potentially higher Answer effort from non-men, as simply operationalised from SO and related guidelines. A meritocratic framework, then, leads us to the conclusion that equal effort leads to equal outcome, measured here in terms of the Answer *score* (upvotes - downvotes). Score contributed to reputation, where an upvote on a post is +10 reputation, an accepted Answer is +15 reputation, a downvoted post is -2 reputation. Thus, if the reputation of Answers and posts is directly tied to reputation, and there is no statistically significant difference in the operationalisation of Answer effort, then it should follow that there should be no gendered difference in the distribution of Answer scores by gender. However, I find that there is statistically significant difference between gender groupings, as shown in Table 29.

***Table 29 Welch’s ANOVA Table, Answer Score ~ Gender***

	<i>SS<sub>M</sub></i>	<i>df</i>	<i>F</i>	<i>PR(&gt;F)</i>
Gender	3.48E+03	4	5.935	0.00
Residual	1.26E+08	733429	-	-

In Post-hoc testing, I again tested how far each gender grouping's Answer score differed from the masculine users' score using Welch's t-test with the Bonferroni correction, meaning  $\alpha = 0.01$ . There was a significant difference in the scores for feminine ( $\bar{x} = 1.91$ ,  $SD = 9.83$ ) and masculine ( $\bar{x} = 2.06$ ,  $SD = 12.29$ ) users;  $t = 3.24$ ,  $p = 0.001$ , as well as feminine and mostly masculine ( $\bar{x} = 2.16$ ,  $SD = 15.52$ ) users,  $t = 4.66$ ,  $p = 0.001$ . Therefore, I reject  $H_0$ , and conclude  $H_a$ : there is a gendered difference in the score an Answer receives, and the feminine users receive lower scores for their Answers on average.

## **He Said, She Said: Social Networks**

Of the 560,106 users in the data set, 230,335 had an edge between them, meaning that the user who wrote the initial post (Questions/Answer) and the user who wrote the reply (Answer/Comment) were included in my network.<sup>134</sup> In setting up the graph, I first removed 128,835 self-loops (edges with the same node at either end) from 57,282 nodes. These self-loops represented a user responding to their own Question (in a Comment or Answer) to add clarification to their initial post. The proportion of edges that were self-loops (by gender) were: 29% masculine, 28% mostly masculine, 36% anonymous, 35% mostly feminine, and 44% feminine. Here, women are more likely to respond to their own Questions than masculine users. Based on eyeballing instances of self-loops it appears that responding to your own Question is most commonly done if no other user provides an Answer. These self-loops are the original poster finding the Answer themselves and recording it for prosperity's sake. The final make-up of the graph was 99,933 (58%) masculine, 45,169 (26%) mostly masculine, 3,864 (2%) anonymous, 3,412 (2%) mostly feminine, and 19,275 (11%) feminine. The overall network descriptors are shown in Table 30.

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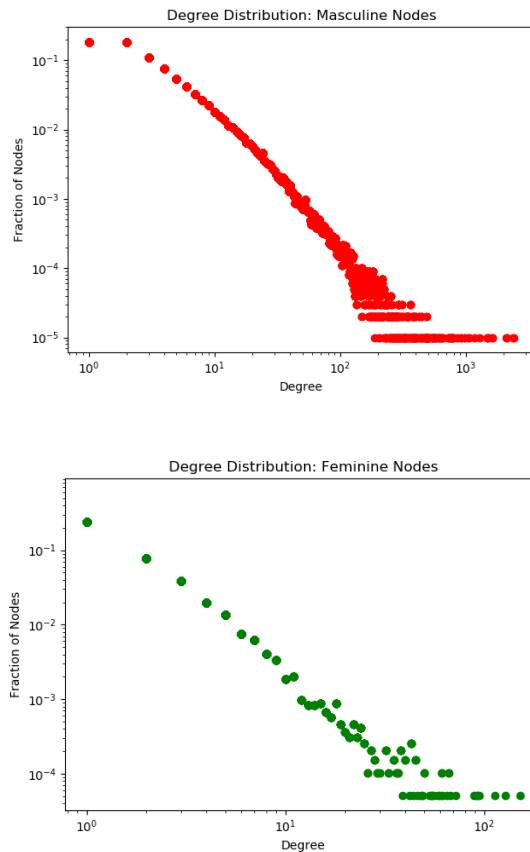
<sup>134</sup> "Answer" here refers to all Answer posts, including Accepted Answer.

**Table 30 Basic Network Descriptors**

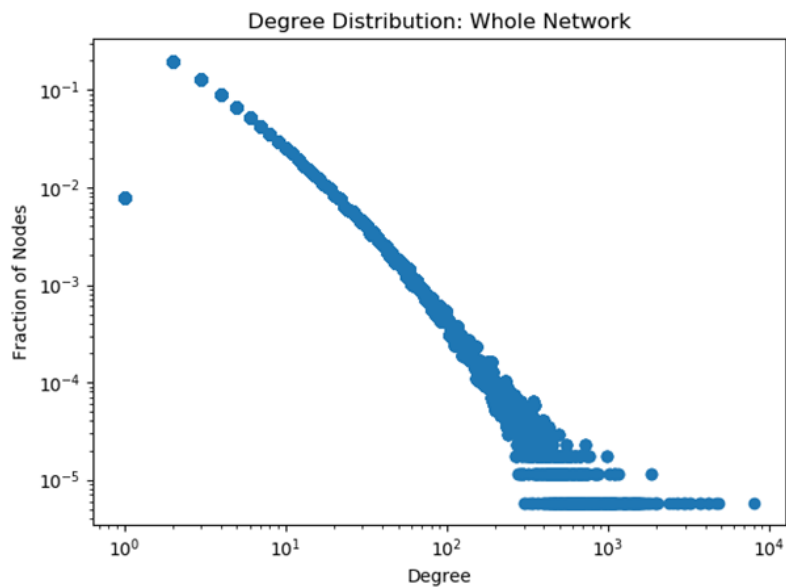
Nodes	173,053
Edges	1,616,800
Average Degree	9.34

**Degree Distribution**

Degree is a measure of the total number of edges adjacent with any given node, also referred to as a vertex. In a Facebook social graph, this could be characterised as the number of friends a user would have. In my network, degree represents an interaction pair (e.g. *Question*  $\rightarrow$  *Answer*). The degree  $k$  is the number of connections that an individual has, and  $p_k$  is that fraction of individuals in the network that have exactly  $k$  connections. A fundamental feature in the empirical study of networks is the *degree distribution*,  $p_k$ . Figure 14 is the degree distribution for masculine and feminine users (nodes) and Figure 15 is across the whole network for all users.



**Figure 14 Degree Distribution log-log scale: By Gender (Sample)**



*Figure 15 Degree Distribution on log-log scale (Sample)*

The graphs in Figures 14 and 15 reflect randomly selected subsamples of users by gender to illustrate that the degree distribution is consistent across gender groupings.<sup>135</sup> The degree distribution follows a so-called power-law, represented as  $p_k \propto k^{-a}$ , where  $a > 0$ .<sup>136</sup> As argued by Broido and Clauset (2019), one should be careful in asserting the universality of scale-free networks, yet in my specific instance my network does approximate this highly skewed distribution. Because the distribution for each gender categorisation is quite similar to that of the entire sample, I will focus my attention on the overall degree distribution. Plotting on a logarithmic scale reveals the long tail of the degree distribution, although most have a small degree. This presence of hubs that are orders of magnitude larger in degree than most nodes are a characteristic of power law networks. What I see here is the idiom the “rich get richer”; that is, users who are highly connected will become more connected more quickly than less connected users. This is also referred to as a preferential attachment process (or cumulative advantage).

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<sup>135</sup> A 10% subsample was used to plot the graph, as plotting the entire partial-network was computationally intensive and no information was lost.

<sup>136</sup> Power-laws are a straight line on a log-log and the observed distribution fits this characterisation.

Indeed, most individuals have few connections to others within my network, whilst a much smaller population are a lot more active. The average degree count by gender grouping is shown in Table 31.

*Table 31 Average Degree Count by Gender*

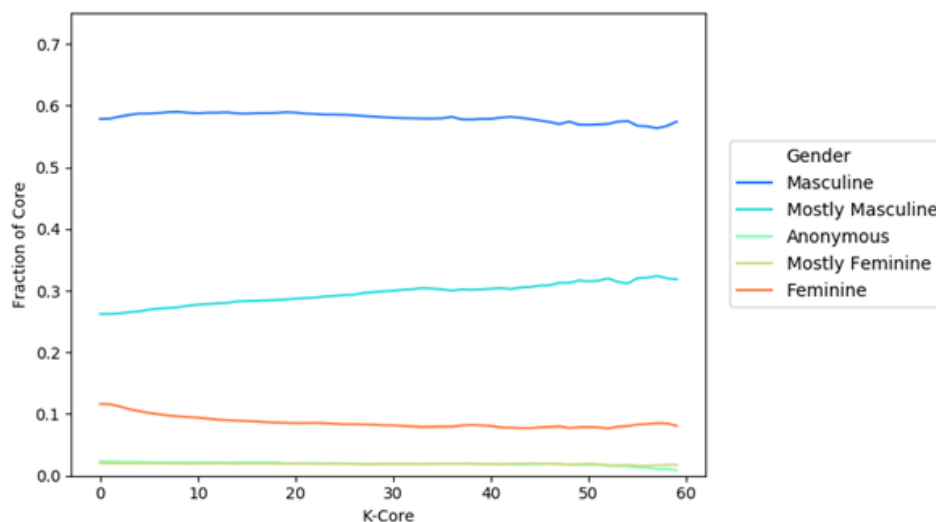
	<i>Mean</i>	<i>Median</i>	<i>Max</i>	<i>Std.</i>	<i>n.</i>
Masculine	16.33	5	5001	60.45	99,933
Mostly Masculine	16.30	5	8066	65.55	45,169
Anonymous	12.94	4	1188	40.77	3,864
Mostly Feminine	14.08	4	1527	44.05	3,412
Feminine	11.67	3	1644	41.15	19,275
All Users	16.14	5	8066	59.31	171,653

Unsurprisingly, Table 31 shows that the masculine users have the highest average degree, which decreases as the salience of masculinity decreases. I can also see that feminine users are the least connected, with the least average number of degrees by all measurements. This could be because masculine users who use their real names on platforms (which were more easily picked up by my gender classifier) are more likely to be invested in participating in the culture. Looking to the mean and median scores, some heavily connected nodes skew the average degree. Nonetheless, both the mean and median degree scores show that the more masculine a user is, the more communication they have on the platform. The connectivity of average users is clearly gendered. Below, Table 32 shows the average in degree and out degree of users by gender grouping. What is evident in this table is that masculine or mostly masculine user names means that users are more likely to receive a comment or Answer on their post. In comparison, feminine users receive the least responses.

*Table 32 Average In/Out Degree by Gender*

	<i>Average In Degree</i>	<i>Average Out Degree</i>
Masculine	7.36	7.27
Mostly Masculine	8.10	7.65
Anonymous	5.84	6.65
Mostly Feminine	6.61	6.94
Feminine	4.99	6.24

Another way I can examine the Stack Overflow network is to analyse the gendered make-up of the most connected users. This is achieved through examining the  $k$ -core degeneracy. The  $k$ -core of a graph  $G$  is that maximal subgraph  $H \subseteq G$ , such that  $\delta(H) \geq k$ .<sup>137</sup> So every vertex in  $H$  has at least  $k$  other vertices, and for a given value of  $k$ , the  $k$ -core of a graph is unique. For instance, the 0-core of any graph is the graph itself, because no vertex has degree less than 0. Starting from 0-core, I iteratively removed vertices with degree less than  $k$ . At each value of  $k$ , I assessed the gender of vertex that made up my network. The main core of the graph is its smallest subgraph which is also a homomorphic image, meaning that all vertexes have the same degree of connectivity. The largest degree in the network was 59. The fraction of core by gender for a given value of  $k$  is shown in Figure 16.



**Figure 16**  $k$ -core degeneracy by Gender

Figure 16 shows that the proportion of users of each gender identification generally holds across levels of connectivity. What is relevant here is the scale-free degree distribution, the degree of typical users, and the variance in degrees by gender. The general sparsity of the network does not imply that users are far from each other in the SO network, however it is worth remembering that

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<sup>137</sup>  $G$  is the notion used to refer to the network graph and  $\delta$  is the maximum degree of the vertex.

my sampling method was not on the basis of connectivity, but rather on nationality. Even with this sampling frame I have found a clear pattern based on user gender. I find that the low proportion of women users holds across the least and most connected users.

### ***Homophily***

The External-Internal (EI) index is the relative density of internal connections within a social group (gender identification) compared to the number of connections that group has to the other groups (different gender identification). This can also be interpreted of a measure of parity over polarisation, taking into account the interactions between feminine and masculine users, as well as just between feminine users. The EI index was -0.24, meaning there are fewer (24%) edges external to a user's gender, than internal. This is evidence for peer parity as it shows that users are more likely to respond to a user who more closely resembles them. This also shows that even when gender in multiplicity is accounted for, I find peer parity is also apparent in differing levels of gender salience.

One way to characterise the relationship between gender identification and peer parity with more depth is by using a *mixing matrices*, a manner of articulating the number of links within and between a series of categories. As illustrated in Table 33, I can represent these relationships as directed, wherein the rows are the categories of the origin vertex (i.e. the user writing the comment) and the columns are the categories of the destination vertex (i.e. the user whose post is being commented on). The diagonals of a mixing matrix are typically the most, indicating the presence of users of a gender category writing to users of the same gender categorisation.

Table 33 Mixing Matrix, All Edges

		<i>To</i>					<i>sum(rows)</i>
		<b>Masculine</b>	<b>Mostly Masculine</b>	<b>Anonymous</b>	<b>Mostly Feminine</b>	<b>Feminine</b>	
<i>From</i>	<b>Masculine</b>	<b>42.11%</b>	11.58%	0.73%	0.72%	3.21%	58.35%
	<b>Mostly Masculine</b>	11.04%	<b>14.86%</b>	0.34%	0.34%	1.51%	28.09%
	<b>Anonymous</b>	0.84%	0.40%	<b>0.64%</b>	0.02%	0.11%	2.02%
	<b>Mostly Feminine</b>	0.76%	0.38%	0.02%	<b>0.62%</b>	0.11%	1.89%
	<b>Feminine</b>	3.95%	1.95%	0.13%	0.12%	<b>3.50%</b>	9.65%
	<i>sum(cols)</i>	58.69%	29.17%	1.86%	1.82%	8.44%	100.00%

First, Table 33 shows that 42% of the communication of masculine users is to other masculine users, and if I include mostly masculine this rises to 54%. Additionally, masculine users respond to feminine users more than they respond to anonymous or mostly feminine users. Masculine users respond to feminine users to the same extent as feminine users to do. This could be considered evidence of white knighting behaviour (See Chapter I, Section II), in which masculine users respond to salient feminine users, more than to less salient feminine users or even anonymous users. There is evidence of homophily in the diagonal of the matrix, yet all gender categorisations respond to masculine users' questions more than any other group, apart from other feminine users. This is likely to be due to a higher volume of masculine users in the dataset overall.

### ***Assortativity***

Assortativity is the preference of users to be attached to (interact with) other users of the same gender identification. Defined by Newman (2002), assortativity provides a metric that accounts for differences in gendered homophily, but is most useful as a descriptive guide in ascertaining if a network is assorted by gender – a quantification of the association between nodes. The overall assortativity coefficient based on gender for my network is calculated to be 0.33, which suggests homophily between users based on their gender. That is to say, users tend to respond to users of the same or similar gender categorisation, even when gender is operationalised beyond a binary. My social network consists of posts and comments across a variety of tags so was unlikely to lend itself to cliques – which is not to say that this isn't an interesting avenue for future research. SO

cliques are less likely to be visible on SO than other social networking platforms, given that its structure is built on a Question-Answer format and on particular technical specialisms/languages, rather than on following users or the generation of a personal network.

In order to understand these results, I compare the probability of following a randomly selected edge and arriving at a particular gender. These probabilities are represented by  $p(g)$ . The probability is higher for feminine users because the number of edges connected to other feminine users is higher than that for masculine users. Though the network consists of considerably more masculine than feminine users, the average masculine in-degree is 16.33, larger than the average feminine in-degree of 11.67, resulting in  $p(M) > p(F)$ . We can also examine the gendered make-up of a user's neighbourhood, that is, whether they are more likely to be connected to a user of the same gender grouping. Here I am computing the conditional probability  $p(g'|g)$  that a random neighbour of individuals with gender  $g$  has gender  $g'$ , denoting (abbreviating) my gender categorisation to  $M, MM, A, MF, F$ . For neighbours of masculine users, I find that  $p(F|M) = 0.08$  and  $p(M|M) = 0.60$ . For feminine users I find that  $p(M|F) = 0.55$  and  $p(F|F) = 0.14$ . In all cases I find the random neighbour is more likely to be masculine. However, a random neighbour for a feminine user is almost twice as likely to be another feminine user than for masculine users. This shows evidence of peer parity in gender categorisations, even with a majority male population. This illustrates that there is a preference for interacting within gendered boundaries, and the effect is reasonably strong.

### ***Reciprocity***

Reciprocity is a foundational concept in social network analysis. As with approaches to homophily, there are several metrics that are useful in analysis. (1) I can examine the reciprocity scores for each group, that is the overall percentage of ties that are reciprocated by gender. (2) I can also examine if the reciprocity scores for each gender categorisation are statistically significantly different. Overall, the percentage of ties that were reciprocated was 24%. In Table

34 I can break this down by gender, where again the rows are the categories of vertex from and the columns are the categories of vertex to.

**Table 34 Reciprocity by Gender**

		<i>To</i>				
		<b>Masculine</b>	<b>Mostly Masculine</b>	<b>Anonymous</b>	<b>Mostly Feminine</b>	<b>Feminine</b>
<i>From</i>	<b>Masculine</b>	<b>34.35%</b>	26.21%	24.88%	25.03%	27.33%
	<b>Mostly Masculine</b>	27.44%	<b>42.65%</b>	26.91%	27.45%	29.62%
	<b>Anonymous</b>	21.42%	22.36%	<b>85.21%</b>	22.87%	23.19%
	<b>Mostly Feminine</b>	23.71%	24.53%	23.93%	<b>86.10%</b>	25.19%
	<b>Feminine</b>	21.65%	22.38%	20.44%	21.47%	<b>61.75%</b>

In Table 34, the diagonal axis shows clear evidence of homophily in reciprocity. For each gender categorisation, the highest level of reciprocity is from the same gender. The margins for this majority are large, up to three times the reciprocity for any other group. The highest levels of reciprocity are for users identified as mostly feminine and anonymous, whilst the comparatively lower reciprocity of feminine is users is likely due to lower levels of participation in general. I speculate that the high levels of reciprocity for anonymous and mostly feminine users may reflect a functional use of pseudonyms, where varying degrees of anonymity are used as a resource for legitimate participation. Overall, I find that peer parity is a significant feature of interaction on SO, and this is clearly evident even when gender is operationalised beyond a binary variable.

### **Hostility as Condescension**

This section deals with condescension on SO using RBFSVMs. My understanding of condescension is formulated to be context-specific, focusing on *Question* → *Comment* and *Answer/Accepted Answer* → *Comment* pairs (Wang & Potts, 2019). I also include context-specific language, such as “RTFM” and “n00b” (Reagle, 2016; Spertus, 1997). The specific language included in analysis came from multiple sources: (1) scholarly publications on geek cultures’ language; (2) publications and user-generated content (such as blogs) which discuss hostile

content on SO; (3) out-of-vocabulary items identified by the POS tagger. The combination of these sources means that I can include multiple forms of condescension. For instance, I can include formal definitions, such as the structural condescension of Spertus (1997) (See Table 35), as well as culturally specific slang for new users, “noob” / “n00b” / “newbie”, or the code they produce, “hacky” / “wet” / “spaghetti”. In her work, Spertus (1997) advocates the inclusion of these measures, referring to them as site-specific “villains” and “sins”. It is important to note that I am taking an approach that first breaks down and operationalises the phenomenon of study (*condescension*) and then applies a gendered lens. I am intentionally not including typical NLP features associated with gender differences in language, such as uncertainty verbs, hedging, or minimisers. These linguistic tools are resources that can be used in interaction to reflect a larger gender power balance. Rather, my focus is on context-specific condescension, and how this creates a barrier to women’s visible participation in informal, creative coding culture.

Table 35 outlines the feature-based rules that were used in the SVM model to predict users’ labelled gender. The rules were formulated using a combination of simple NLP methods, including regular expressions and POS tagging. For instance, directly quoting from the Question was taken to be a condescending act (Spertus, 1997). To look for direct quotations, I first looked for phrases (> bigram) in the comment that was in quotation marks (‘ ’, “ ”, or ' ') or italics. I then checked the Question for this exact phrase and one-hot encoded the data (presence 1, absence 0). For out-of-context male pronouns, I first looked for users who were identified as feminine or mostly feminine asking a Question. I then looked for male pronouns in the comment, discounting comments which directly cited a masculine username, such as “@JonSkeet”. On SO it is standard form to “@” a user, if you are replying to their comment, and not the user posting the Question. As well as the specific rules, Table 35 also shows an example of each instance from the SO dataset. The total number of comments which conform to each rule are also shown.

Table 35 Operationalising Hostile Condescension

<i>Input</i>	<i>Rule</i>	<i>Example</i>	<i>n</i> <i>(Q → C)</i>	<i>n</i> <i>(A → C)</i>
<b>Gender-Specific</b>	Girling	“girl” / “girls”	795	461
	Male default presence	Using male pronouns when an asker’s gender is not visible, or ignoring gendered signals (assumed)	612	262
<b>Site-Specific</b>	Villains	“noob” / “newbie” “lurk” / “lurker”	307	202
	Sins	“RTFM” (read the fucking manual) “Check the FAQ” “educate yourself” Help vampire - “little / no effort”	45,522	20,495
	Insults	“brittle” “clunky” “bitrot” “garbage in, garbage out”	9,588	4,493
	General Code	“the error is <u>self-explanatory</u> ” “Post <u>the real code</u> ”	3,371	1,823
	Google It	“Google it before asking your Question” “Solution is obvious, google it.”	3,325	1,743
<b>Text-Only</b>	Homework	“We’re not doing your homework for you”	501	260
	Time / Repetition	Reference to time as well as a pronoun (we, our, etc.) “ <u>I already</u> told you” “waste of <u>my time</u> ” “... Then <u>get back to us</u> ”	22,809	12,992
	Contains a URL: Documentation	References to documentation without context or additional text. “Have you read the documentation?” “Ok, and what do the docs say about APIs?”	1,075	617
	Contains a URL: Unpopular	An external URL, such as one for a blog the user wrote, provided without context or explanation.	44,141	10,230
	Contains laughter	“HaHa” “Lol” / “lmao”	962	610
	Contains an exclamation point	Literal “!”, counter > 1.	2,906	13,741
<b>Textual Content</b>	Contains Question mark	Literal “?”, counter > 1.	33,706	68,244
	Contains a Ellipsis	Literal “...”, counter > 1.	3,414	13,837
	Structural condescension	Tag phrases: two-word phrases consisting of a contraction followed by another word and a Question mark. “It’s really hard to make progress when you don’t listen, <u>isn’t it?</u> ”	21,172	10,085
	Quoting	Direct quotation of the Question: “You say ‘It extracts all nouns and noun phrases easily’ but I don’t see the options.”	52,386	28,824

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Subjectivity <sup>138</sup>	<i>Superlative and comparative adjectives</i> “personally” / “personal standpoint” “IMHO” / “In my opinion”	56,724	28,947
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The counts in Table 35 show the frequency of different forms of condescension. It is important to note here how commonplace these specific forms of hostility were and how they can bolster hostile barriers to participation. From the plain frequency count the most common forms that condescension takes are forms that are less overt and out of the purview of a typical Code of Conduct. For instance, if we compare the frequency of site-specific villains compared to site-specific sins we can see that villains are a lot less common. I propose that this is because even when it isn't a profanity, name-calling is a relatively easy to spot to the culturally initiated. “Rude or offensive comments”, according to SO, involve name-calling, bigotry, inappropriate or sexually suggestive language, harassment and bullying. SO does not make direct reference to sexism or racism in the flag. If a comment is flagged as “rude or offensive”, name calling is a clear indicator that it should be removed by a moderator, meaning that these sorts of comments would have been removed from the dataset and from the view of users.

Site-specific sins, such as being a “help vampire” and putting in little or no effort into your Answer are less tangible than villains. Even breaking this down, there were over three thousand instances of users simply being told to “Google it”. While this might seem innocuous, the lack of effort that is implied behind “Google it” was considered condescending and hostile by every discussion on the matter, including being listed as “unacceptable behaviour” and “unfriendly” in the *Be Nice* Code of Conduct (Stack Overflow, 2020a). In addition, condescension is more visible in the comments on Questions than on Answers. As new users are typically novices, they are more likely to ask a Question than to provide an Answer, meaning that they are more likely to experience

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<sup>138</sup> In manually refining this rule, I had to discount the phrases that included the word “request”. This is because “request” has a specific technical meaning, such as “request access”, or in web development, or the use of APIs.

condescension and hostility. This finding locates hostility on SO, showing how the in-group is maintained through hostility to those seeking technical knowledge. This simple frequency metric shows that users who ask Questions are more likely to experience hostility than those who are providing Answers.

This final element of the Study used boosted RBFSVMs to predict gender from how a user is spoken to in the comments. I was able to successfully predict a user's identified gender based on their reception on SO with an F1 score of 0.63. As well as the SO condescension features outlined in Table 35, I included the gender and reputation of the user who replied to the post (Table 16, Model 5). By including these features, I acknowledged gender structure in interaction, and how hostility is mediated by gender, as found in Study I. What is pertinent here is that not only can it be operationalised beyond a binary, gender can also be predicted using features based on a contextual understanding. In building simple models this way, computational research can avoid accusations of determinism in critical social research. Not only does this work have methodological implications, but it also indicates that gender intervenes in creative coding through condescension and gendered hostility. Future research should explore combining such content and context with social network analysis, as my study shows how gender operates in each context. Gender dictates not only who you speak to, but also how you are spoken to in technological cultures. I conclude that a person's gender salience dictates how they are perceived and therefore received by the SO community.

## Section III: Trouble in Paradise

In their discussion of Stack Overflow, Ford et al. (2016) highlight how the platform is referred to as “programmer paradise”. I problematize this conception of “paradise”, showing that even with a more comprehensive (non-binary) understanding of gender, we can see that femininity is chastised in programming cultures. Due to its ubiquitous presence, SO is a platform where researchers can study not only specific programming communities, but also wider practices of creative coding cultures. May et al. (2019) propose an alternative reward system to migrate gender differences in outcome and “success”. Their proposition is focused on the decision that SO made to grant users half the reputation for having a question upvoted (+5) compared to having an Answer upvoted (+10), largely in an effort to stop users gaining the reputation by asking a large volume of questions. May et al. (2019) challenge the value judgement that regards questions as holding less merit than answers, arguing that the appeal of SO is the ability to gain user-generated answers beyond textbook solutions. May et al. (2019) also propose that rewards to “good questions” might help to make the site more inclusive by offering a less competitive and speed-orientated way to build one’s reputation. These contributions are incredibly valuable in showing how the systems of platforms can propagate hostility and sexism. However, I argue for caution in technical solutions. As Morozov (2013) argues (Chapter I, Section I), complex social problems are not solved by technology. This chapter provides an overview of mechanisms of gendered intervention on SO, showing how narratives of hostility to “new users” serve to hide the rampant sexism that characterises the culture.

### **Outsiders and Insiders**

The starting point of this study was the masculine insider and non-masculine outsider. Reputation of users has been used in previous studies as an indicator of belonging and investment in the culture of the platform (Ford et al., 2016; May et al., 2019). I support the finding of existing work

that identifiably feminine users have significantly less reputation than any other gender identification. This finding held even when I operationalised gender categorisation beyond a binary, and when I considered different thresholds of reputation, to account for basic privileges (15 or 100 points). Adding nuance to this result, I also found that the relationship between user tenure and reputation is mediated by gender, supporting the contention that gender intervenes in creative coding cultures, even in online forums. My simple descriptive of user profiles thus illustrates that reputation and associated privilege are not just a result of time spent on the platform.

In the next section I compare levels of engagement across identified gender categorisations. I examine the average frequency of interaction for users, accounting for both types of post (Questions, Answers) and comments. Contrary to May et al. (2019), I found no significant difference in the frequency of asking and answering questions by gender. Looking to comments, this pattern is repeated, where the frequency of comments appeared to decline with increased salience of femininity of users. However, this difference was also not statistically significant. Taken with the significant effect of gender on the relationship between tenure and reputation, this finding suggests that it is not simply the level of engagement that accounts for gendered differences in reputation.

From the initial descriptive analysis of users, I conclude that it is not simply the frequency of interaction that contributes to women's lower reputation. Whilst May et al. (2019) attribute differing "success" to divergences in levels of activity, I challenge their normative qualification of success. In focusing on reputation, researchers can blind themselves to the content of the interaction. In this case, women's lack of visibility on the platform is not simply a matter of relatively lower levels of engagement, but of a smaller population due to systemic biases. As argued in Chapter I, Section II, merely ascertaining what site-specific metrics show a gendered difference is not sufficient in examining the functioning of gender prejudice. I support the conclusions of Ford et al. (2017) that it is the content of communication, informed by one's own

understanding of ability, that contributes to feelings of belonging and parity. In the next section I complicate the picture of gender, examining features other than platform-specific measures of success.

### ***A Just World: Effort***

In Chapter I, Section I, I outlined how we use storytelling and the construction of narrative to understand how the current state of events exists. In Section II of the same Chapter, I then showed how these narratives feed into causal attributions, using the example of how gender can provide the simplest explanation for “natural” ability. This ideology is underpinned by an assumption that technology is a meritocracy, or *just world*, where aptitude and perseverance are the fundamental predictors of success. My findings refute this assertion, showing that a user’s salient gender impacts how their knowledge (Answers) are received. Informed by cultural artefacts, I operationalised markers of Answer effort on SO.<sup>139</sup> I focused on Answers, rather than Questions as this is the site of knowledge-making, or help-offering in the terms of Study I. I show that whilst feminine users receive the lowest scores for their Answers, there are significantly more markers of Answer effort in non-masculine than in masculine users. This finding fundamentally challenges the narrative of a just world, of meritocratic reward on SO. Through a simple operationalisation of Answer effort and post score I argue that saliently feminine users are negatively received because of their gender, not because of the effort level of their participation. Technical help offering is a gendered practice where normative roles powerfully redistribute legitimacy as masculine.

### ***He Said, He Said***

In the third section, I found that the connectivity of users is gendered. There was strong evidence of homophily and reciprocity, supporting the scholarship of Ford (2017, 2016) and Mishkin

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<sup>139</sup>Primarily Meta Stack Overflow discussion and highly regarded user-generated content, such as Google developer Jon Skeet’s blog.

(2019) on the importance of peer parity in women's engagement with coding cultures. I show that gender salience is crucial in defining a user's network, as users are more affiliated to those with a comparable gendered experience. This parity will be examined further in Study III, as my participant observation of hackathons will examine how gender functions in embodied communication. Furthermore, the  $k$ -core degeneracy (Figure 16) showed that the fraction of users by gender was generally maintained across levels of connectivity. Feminine users were as present in the maximal connected subgraph ( $k = 59$ ) as in the main graph. Identifying the problems of the platform's culture, SO falls back on a narrative of being "unwelcoming to new users". I show that SO is specifically unwelcome to feminine users, as the minuscule proportion of users that are feminine is maintained across user connectivity. I find that women do not stop participating, but rather very few seek to participate in the first place. Nonetheless, it is imperative here to avoid replicating a survivorship bias. This is the logical error that occurs when we conclude that because a number of feminine users "survived" or became power users, the entire system is meritocratic. Rather, the lack of women visible in the network is indicative of a male-dominated culture, which Study I found to be directly linked to perceptions of hostility. I conclude the networks section of this study by noting the need for increased visibility of women on SO in order to encourage further participation of non-men visitors.

### ***Condescension and Mansplaining***

In the final part of the analysis I illustrate how asking questions is more likely to receive hostile comments than answering, based on a basic frequency count. I then develop a simple model to show how interactional features can be used to predict salient identity categories. Building on the exploratory analysis of Study I, I show that gendered hostility is based on *who* asks the questions and *who* is doing the evaluating. The reasonable success of the model in predicting the gender of users seeking technical help based on the presence of metrics of condescension shows that gender is a key component of hostility on SO. Not only does this show the prominence of elitism on SO, it also shows how predictive features can be based on a situated understanding of a social context,

and not just on what men and women *do*. I conclude that gender intervenes in programming forums through evaluation of knowledge, reception to participation, and visible condescension.

## **Perception is Reality**

I found that perceptions of gender fundamentally change how a user is received on Stack Overflow. Mediated by salience, feminine users ultimately encounter prejudice in the critical resource that is “programmer’s paradise” (Ford et al., 2016). The painting of programming as a meritocratic utopia is profoundly flawed and wholly inaccurate. I showed that the salience of masculinity significantly and positively affects a user’s reputation and reception on the platform. Femininity negatively impacts the reception of effort, even when these values are higher than masculine users. To conclude this Chapter, I outline the wider implications of my findings in terms of the lived experience of gender prejudice.

### ***Shaming, Seeing Others, and Resignation***

In Chapter I, Section I, I briefly noted Goffman’s (1963) work on stigma; how a person feels shame when they fail to meet the standards of another. Goffman’s account emphasises the centrality of shame in the maintenance of social norms and normative structures such as gender. As a potential cause of shame, condescension is an imposition of superiority, deserved or not. Responses to such assertions of normative power structures define the recipient as in the outgroup, as condescension punishes those who dare to seek knowledge that is prohibited on the basis of gender. On SO, a user is shamed for not knowing that an apparently “easy” Answer already exists, or that they did not even know enough to try to “Google” a solution to their problem. Discouraging comments deter the recipients from continuing their involvement in coding culture, and these comments are gendered in their intention and receipt. Because of the nature of SO, a user does not need to actively participate in order to see the condescension. As shown in Appendix II, comments are visible on all posts. In simply searching for an Answer, and not posting, condescending comments on a Question are visible to someone browsing. This shaming leads non-masculine potential or new users to feel unwelcome and rejected, meaning that adequate

representation and participation are difficult to achieve.<sup>140</sup> This is despite the fact that I found no evidence of masculine users providing higher effort answers.

The constant visibility of condescension and dominance of masculine users on SO means that potential users quickly know they will not be welcome. Even without direct personal experience, awareness of gendered hostility creates an active filter to non-masculine participation. The perception of hostility and a masculine-dominated space which lacks empathy then becomes a self-fulfilling prophecy which puts off new users who do not conform to the dominant stereotype. In creative coding culture, condescension thus chastises those who seek knowledge outside of the purview of their gender.

### ***Elitism and Gatekeeping***

In introducing this Study, I looked at how respondents to the SO Developer Survey rated their own competences. To recap from the SO data, 68% of men rated themselves above average, as did 63% of non-binary and unknown, and 53% of women.<sup>141</sup> This shows that SO respondents generally see themselves as exceedingly competent in the work they do, with men having the most confidence (rating above average) in their ability. Condescension is a fundamental communication tool to signal superiority to others. As a resource, condescension works to establish the majority as mediocre and those who condescend as competent. This world view is validated by upvotes, supporting the geek revenge fantasy and meritocracy myth outlined in Chapter I. The *power users*, as shown in the degree distribution of the network in Figures 14 15, can be motivated to keep others out who they believe are not elite. The maintenance of meritocracy myth, and the openness of platforms, serves to justify their status, and discussions on Meta act to self-reinforce the toxicity of gendered power structures. Work by Salganik et al. (2006) shows that initial small differences in online spaces are amplified overtime. Cumulative

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<sup>140</sup> As the most common recipients of condescension.

<sup>141</sup> These gender classifications reflect those recorded in the SO Developer Survey.

advantage means that already popular users will get more popular, receiving more upvotes for their contributions than less popular users, further cementing their status (Salganik et al., 2006). All interactions are not equal. The perpetuation of this cycle occurs when condescending comments are posted by users with high reputation points, where their certified insider status magnifies the impact of their hostility. The elites thus play a key role in gatekeeping.

Condescending comments in the dataset are often not specific, and while they are generally gendered this does not mean that their effects are confined to women. Comments often reference the OP's lack of ability in broad terms. In this way the impact can be extensive. In the worst case scenario, people may withdraw from programming, deciding it's not for them, or that they don't have the skillset necessary to pursue continued involvement in the informal and formal avenues of creative coding. In another scenario, they may not interact on SO or avoid using it entirely. Yet, the platform is a valuable resource providing personalised and specific responses to real world programming problems, often within minutes. The consequences of the hostility of SO are not limited to a momentary experience of shame, but it is a culture that accepts that people can be actively bullied out of tech, limiting access to employment opportunities, and ultimately leading to generalisations on the hostility of the tech industry. What SO is failing to realise is that if you have more diverse perspectives, you'll get better questions and better answers. The masculinity of tech is reinforced by clumsy discussions on hostility towards "new users" that mask gender prejudice.

## **Conclusion: Solving for Sexism**

I find that online technical communities are organised by gender. This result holds when gender is operationalised beyond a binary, even with the inclusion of the anonymous categorisation. In terms of participation, I find that feminine users interact less than masculine users, supporting previous work in the field (Ford et al., 2017; May et al., 2019). However, I challenge that level of participation has a linear effect of reputation and reception on SO. I find that non-masculine users' post contains significantly more markers of answer effort than masculine users. Despite higher

effort, feminine users receive lower scores for their answers. This shows that technology culture is not a meritocracy of open participation, but legitimate knowledge is heavily mediated by gender. This finding challenges work that seeks to find technical solutions to the problem of sexism in online technology cultures. Technical spaces are social; they are not exceptional.

In building on the finds on this work, future research should examine if gendered differences in reception of knowledge are mediated by technical subject and intersectionality. To add nuance to the findings of this study is to further clarify how power operates in technology culture. First, we should ask if my conclusions break down if we control for technical focus. As there are more women involved in some technological fields than others, how does gender balance affect homophily and condescension? Secondly, we should investigate how names signify racial and ethnic identity. There is a clear bias towards the Anglosphere in this study due to the location based sampling frame. Going forward, scholars have a duty to explore intersectionality in reception to contributions on programming forums; How are racial and ethnic biases reflected in evaluations on SO? Are contributions by users with “English” names received more favourably? These questions are increasingly important as programming and technical literacy becomes an ever more desirable skill. In emphasising technical ability in employment and education applications, what identity categories are implicitly prioritised? This study opens the way for a nuanced understanding of power in technology culture.

Online forums are manifestations of technology culture, characterised by the same gender structures that permeate each and every instance. For SO, what is discussed as hostility to new users is hostility to difference, ultimately hostility to gender. Scholarship on participatory culture often fails to acknowledge how identity dictates group membership. Observation without participation (“lurking”) can reveal to a user that they do not belong. As shown by Ford et al. (2016), women do not participate on SO because they fear condescension and antagonism from the majority masculine population. In addition, Study I found that a majority masculine population has direct consequences for perceptions for hostility. In examining participation, scholars need to

ask what barriers are erected by visible hostility and a homogenous identity. For activists, the path forward lies in publicising the current disparity and simply advocating for openness. In hiding behind the languages of “new comers” and “sampling bias”, SO fails to acknowledge how technology culture permits sexism to flourish. To use technical solutions to address sexism in creative coding culture is to miss how fundamental gender is to technology culture. The leaky pipeline is simply not solvable. We need not “plug” the leaks, but rather we should consider what flawed processes allowed the leaks to emerge in the first place.

# CHAPTER IV

## STUDY III: GENDER AND EXPECTATIONS AT HACKATHONS

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*It was 9AM when I arrived at the train station for the hackathon. As I left the station, I felt my phone vibrate and it flickered off. It was out of battery and I was without directions. My own worried stare was reflected back at me by the black screen.*

*I looked around me, peering through the curtain of rain, hoping to glimpse a sign for the venue as I knew my destination wasn't far. I noticed several small groups of young men all hurriedly marching in the same direction. They were hunched over, with their heads bowed to provide some relief from the hammering downpour. With few other options available to me, I made a decision, and fell in step behind the closest group.*

*They were talking excitedly to each other, with large bags straining from hurriedly packed duvets and pillows. They were dressed in a uniform of loose-fitting grey hoodies and crumpled jeans, complete with scuffed trainers and rectangular dark rimmed glasses. I hoped that the combination of their attire and bedding was an indicator that they were also attending the hackathon. There was a round of laughter as one of their members, a tall slender young man, raised his hand to prevent his fedora being lost to the wind. As we turned a corner, I sighed with relief as the huge glass facade of the venue appeared around a cluster of industrial buildings. There was a noticeable quickening of pace, and the buzz of conversation increased.*

The activities of hackathons have attracted attention as sites of intensive creativity and innovation (Coleman, 2010; Irani, 2015; Pe-Than & Nolte, 2019). They are 12-36 hours in which teams of programmers can celebrate and innovate in a singular technical project. Reiterating the discussion in Chapter I, Section I, they espouse the Facebook founder Mark Zuckerberg's now famous motto "move fast and break things" (Levy, 2010) - as places for risk taking with a low cost of failure. As hackathons have become more commonplace, leagues and organisational structures have emerged.

around them. In this study, I focus on hackathons affiliated with The League,<sup>142</sup> a student (College/University) hackathon association. The League hosts over 200 weekend-long competitions a year, catering to more than 75,000 students across North America and Europe. The League advertises that it achieves 25% representation of women at its events, which is 9% higher than USA Computer Science / Computer Engineering undergraduate enrolment in the UK and USA. These huge events are a nexus of young adults who are interested in technology.<sup>143</sup> They are affiliated to universities and the League, but are run by student volunteers and student-led Societies. Hackathons are informal manifestations of local programming culture.

The epigraph at the start of this chapter reveals a stark pattern: where are the women? As the throngs of young men crowd into the hackathon venue, it becomes apparent that I *do not fit in*. Around me the hackers embody an extended male adolescence, united in their social awkwardness and love of technology. I am noticeably shorter, barely reaching the shoulders of those in the queue around me, jostled in the excitement. My beige coat, white shirt, blue jeans, and blonde hair are a shock of colour relative to the collection of dark attire favoured by the other hackathon attendees.<sup>144</sup> As I reached the desk to register for the event, I was instructed to collect a branded t-shirt to act as my ticket around the venue. Only available in men's sizes, it was clear that as a woman I was not accounted for.

In Chapter I, Section I, I highlight how hackathons were intended to be open meritocracies since their inception. They are spaces in which individuals can come together to work, compete, and

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<sup>142</sup> The official hackathon organisation will be referred to throughout the study as “The League”. More details on the anonymization procedures are found in the ethics section.

<sup>143</sup> You are not required to be enrolled at a university in order to participate.

<sup>144</sup> I had intended to project a relaxed but professional image in my clothing at hackathons. However, after the first event it was apparent that even a shirt and jeans was considered formal in this context, which meant I was often presumed to be an event sponsor or company representative. From this point, I opted for an Oxford Internet Institute hooded jumper and loose-fitting jeans in order to seem more at home in the environment. Chang (2019) points to how women in technical spaces will favour clothing that hides their figure, for the sake of unwanted advances and to be taken more seriously as a programmer by conforming to a masculine stereotype.

demonstrate their technical expertise (Coleman, 2010). Yet, they retain an enduring male dominance in each iteration. In Chapter I, Section I, hackathons were discussed as temporary organisations that bring together groups of people from a cross section of skills and places to partake in a competition of creation. For Coleman (2010), accomplishing complex tasks and producing a final project in the face of extreme time constraints reinforce the importance of coordination and social mechanisms. Hackathons are creative coding culture in the flesh.

Following the assertions of a prominent gendered division and absence of women in hacking in Chapter I, this chapter will focus on visibility in the physical spaces of hackathons. Driven by the work of Dunbar-Hester (2019), Toupin (2014), and Coleman (2010), I shall explore the reclaiming of gender in the lived experience of creative coding. Moreover, this study will also involve examining the emergence of hypermasculine practices of programming at coding events, as a radicalisation of Kendall's geek masculinity (2000, 2002). Participant observation in the study of hackathons is not uncommon (Briscoe & Mulligan, 2014; Cruz & Thornham, 2016; Jones et al., 2015; Richterich, 2017), but little work has been done on how gender mediates participation in the embodied, cooperative, and competitive elements of hacking. The notable exceptions to this trend are Dunbar-Hester (2019), Irani (2015) and Toupin (2014). Yet, to my knowledge, no ethnographic work on hackathons and gender has been done where the researcher is able to fully *participate* and compete as a programmer.<sup>145</sup> In presenting my analysis, observation notes in the chapter will be accompanied by images of the hackathons. The League provides hackathon organisers with photographers to document the event. The images are made publically available on the League's website and the hackathon's social media channels. The image in Figure 17 shows me attending a hackathon. Women featured prominently in many of the League's photographs, which is suggestive of their desire to present themselves as diverse. I have blurred

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<sup>145</sup> As a woman who codes, I become a subject in my own enquiry. The ramifications of this are discussed in "Being a *girl* at a hackathon", in the methodological section of this chapter (Section I).

out the faces of hackathon attendees in the featured images, which will be discussed more in the ethics section.



*Figure 17 The researcher attending a hackathon in the East Midlands*

In my analysis I will introduce the concept of *ambivalent irony* to refer to a diverse range of cultural practices present at hackathons and throughout the coding culture (Milner, 2013). Despite this use of irony, I argue, if someone makes an ironic sexist comment, they are still sexist. “Ambivalence” here refers to statements that invite opposite evaluations. The research questions that drive the enquiry are:

**RQ8:** How is gender visible at hackathons?

- a) How does gender mediate perceived ability?
- b) How is masculinity presented and received?
- c) How is femininity presented and received?

**RQ9:** What does communication at hackathons look like?

- a) How is the anti-social geek enacted in social spaces?
- b) What objects are important? Why?
- c) How are online communication methods used?

These questions build towards the wider thesis aim of understanding how gender mediates creative coding culture. Below I explain how through the use of participant observation I can understand aspects of gender in coding culture that have thus far been absent from the literature.

Following this, I shall introduce the structure of hackathons, then I will lay out the analytical themes and observations. Finally, I will align my findings with existing scholarship and reflect on the contributions of this study to the larger Feminist Project.

## **Section I: Methodology and Ethics**

In Studies I and II I examined coding culture as an online phenomenon in which one's gender identity can be purposefully obscured. Study I showed the role perceptions in forming gender based assumptions of technical knowledge. Study II examined how these perceptions dictate how a user is received in a popular programming forum, looking at how gendered visibility can result in prejudicial evaluations based on femininity. In adopting participant observation as an ethnographic method, I am entering the social frame of creative coding culture, learning the meaning of interaction through direct engagement with those involved in it. Anthropologists often caution against the implication that data from online sources is place-less, and instead underscore the need to understand the context in which technology is embedded (Forsythe, 2001; Luhrmann & Stoller, 1991). In Study II, I emphasised the importance of contextual pairs, in representing communication as dyadic and situated. In this Study, I go beyond dyads and consider the multifaceted sociability of hackathons. I draw on the ethnographic method to unearth the complexities of interactions surrounding technology in creative coding, extending the findings of the computational work through more traditional sociological enquiry. As outlined in Chapter I, Section II, computational methods often miss much of the magnificent *messiness* of the social world. In reducing a phenomenon to "features", the complexity and interdependency of identity categories can be lost. In this final Study of the project, we exchange the language of data variance and noise for a framework of descriptive thickness and embodiment.

Hine (2000, 2015) proposes that the inherent flexibility and heterogeneity of spaces associated with online cultures demand an adaptive methodological response. Such an approach is reminiscent of the sociological imagination, in terms of the maintenance of malleability and the avoidance of rigid sets of procedures. This provides its own challenges. For instance, the lexicons of the hacker and the technologically competent community can prove taxing to researchers.<sup>146</sup> I draw on the *hermeneutic circle* in formulating knowledge, combining instances of meaning to achieve an incremental understanding of the language, and the typologies that operate within creative coding culture (Hine, 2015; Whorf, 1956). According to Hine (2015) such “thick description” methods (See Geertz 1973, p. 27) acknowledge that a culture is saturated with symbolism, and can only be understood through capturing the meaning in contextually ordinary activities. Outside of technical terms, this also refers to the characterisation of “nice guys”, which is discussed in depth in Chapter IV, Section III.

## **Observing Hackathons**

Participant observation is a method of ethnography, in which the researcher partakes in activities in the field of study. At the hackathons I took on the roles of hacker and volunteer, experiencing the event in order to come to theoretical informed interpretations.<sup>147</sup> The majority of hackathons take place over weekends in standard university term time. In total, I conducted research at seven hackathons. Two of the events acted as pilot studies, so I could get a base understanding of how the events were structured and operated in practice. The pilot studies took place in London and Reading in June-July 2019. At these events I made contacts and refined my methodology in conversations with hackathon veterans and organisers. In addition to these conversations, the observation schedule was informed by the conclusions of Study I and the (then preliminary)

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<sup>146</sup> As can be seen by Eric S. Raymond’s (1996) “The Jargon File”, published in *The New Hacker’s Dictionary*, which consists of 588 pages of definitions relevant to the culture.

<sup>147</sup> Hacker is formally understood as the term for an attendee of a hackathon.

findings of Study II. The final observation schedule is available in Appendix III. The five hackathons that form the basis of analysis in this chapter were geographically dispersed, taking place throughout the United Kingdom. These events formed part of an international timetable, where teams could enter multiple hackathons with an official affiliation to the League. Teams would gain points for their attendance, winning competitions, and other activities (such as games) at the hackathons. These points then dictate the position of each team on a leader board, which is published online.

The League sponsors over 200 weekend-long hackathons each year, aiming to cultivate skills and communities, and even to lead to employment. Each event had between 200-300 attendees, with the main period of research taking place between October 2019 and January 2020.<sup>148</sup> The focus of my enquiry at these events was the general trends of interaction, and the influence of gender. There was also room to incorporate unexpected displays of resistance to the normative (masculine) framing of geek identity by event attendees. In contributing to the larger feminist project of this thesis, the observations of this study aided a rounded view of the role of visibility and performance in hacking culture. Moreover, my experiences of hackathons added contextual understanding and embodied space to the online dimension of “programmer’s paradise” (Ford et al., 2016). As expected, Stack Overflow was used extensively by hackathon participants, often visible on screens throughout the venues.

In analysing how people communicated at hackathons, I paid attention to personal narratives and to discourses that indicated group membership and exclusionary practices, for both the participants and the judges of these events. This attention to narratives drew on the theoretical

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<sup>148</sup> The organisational committee of one event that was to take place in late March was majority women and they were interested in recommendations for their event that could make it more welcoming to women. I engaged in extensive discussions with the organisers regarding their past experiences of hackathons and this data will inform my discussion. Unfortunately, the event was cancelled in line with the restrictions put in place following the Covid-19 outbreak.

framework discussed in Chapter I, Section I, in which I presented storytelling as a practice of meaning making. Physical signalling was also noted, such as indicators of familiarity or aversion. Who interacts with whom, who initiates verbal interactions, the length of interactions and their tone/dialect, as well as the human traffic of who entered or exited the space, also formed part of the criteria for observing behaviour. Communication between hackathon attendees often began several months earlier, at the time that they purchased tickets. This was coordinated through conversations started by the organisers on the messaging platforms Slack and Discord.<sup>149</sup> I also used participant observation within these spaces (informed by Hine, 2015), gathering initial impressions on the communications of my participants.

I observed how people acted, engaging them in natural dialogue about their actions.<sup>150</sup> It was not an intervention and was as unobtrusive as possible to make it unlikely that the events observed were staged or deceptive. Though I did not conduct post hoc interviews, I did discuss events with participants as they occurred, seeking clarification on particular terms and jokes.<sup>151</sup> My use of participant observation, while brief, reflects the intense nature of the hackathon itself, and appropriately captured the temporary move to in-person gathering in an ordinarily online culture.

### ***Being a girl at a Hackathon***

As my opening epigraph demonstrated, I was marked as different from my participants by my gender. I am physically feminine-looking with blonde hair and blue eyes, and contrasted starkly with the high proportion of men at the hackathons. My own comfort, or discomfort, at these events, was an important part of my data gathering. My gender positioned me as an outsider to

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<sup>149</sup> The use of these instant messaging platforms is discussed in more depth in the *Introduction to Hackathons* section.

<sup>150</sup> This is discussed more in-depth in the ethics section of the methodology.

<sup>151</sup> Post hoc interviews were discounted as I wished to examine gender operating in interaction, in context. Interviewing *after* the hackathon would encourage reflection on gender performance which, while valuable, is not the focus of my enquiry.

the event, from the offer of t-shirts that were in male sizes only to being walked into and jostled.<sup>152</sup> As I illustrate in Chapter IV, the lack of eye contact that I received, or even awareness of my presence, left me often feeling completely invisible and ignored at hackathons. In this way I found that conversations about experiences of exclusion was something that bonded women together at these events, if only temporarily.

Since the ethnographic part of this research took place after online data gathering (including an operationalisation of condescension in Chapter III, Section I), I may have been predisposed to a critical perspective regarding the aspirational versus the actual inclusion of women. Upon entering the building, it immediately became clear that despite the aims of the League to be inclusive, my own experience would defy their optimism, a discrepancy to which I was attuned. In addition, my lived experience and my familiarity with and research into online life generated my own associations - for instance, the overtones of geek masculinity with fedora wearing and the particular brand of humour that comes hand in hand (Brooke, 2019a).

As I have indicated in the Introduction to this project, my own use of Python and R within this research is a meta comment on women's ability to code. I ensured my own familiarity with these languages prior to the data collection, as well as web frameworks, partly in order to live the experience of a female coder.<sup>153</sup> With that familiarity, I was able not only to attend these hackathons, but to participate following the ethnographic method, in such a way as to understand how gender mediates coding culture through my own experience. Simultaneously, the acquisition of these necessary skills proved that I was technically "worthy" of belonging in this culture. This in turn helped me to Question whether it was my gender, rather than technical skill, that marked me as an outsider to hacking culture. As such, it was disappointing that I featured prominently in

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<sup>152</sup> These experiences are discussed in depth later in the analysis.

<sup>153</sup> A web framework is software that is used to support the design of online applications. I focused on Django, a free open-source full-stack Python framework.

the photography of hackathons (see Figure 17), because it confirmed my suspicions that the “inclusivity” of the events was more of a branding exercise than an accurate depiction of the creative coding cultures.

### *Ethics*

Ethnography requires informed consent, which is commonly granted by gatekeepers of a community. I disclosed to the organisers of the hackathon that I would be undertaking research and sought their approval before attending. The draft of the initial contact email and the Information Sheet are provided in Appendix IV. The hackathons are affiliated with the overall hacking League, but they are discrete events put on by volunteers and student societies.<sup>154</sup> The affiliation to the League provides local organisers with support and mentorship in running a hackathon, as well as promoting the event, giving discounts for resources and vendors, and certain prizes. Informed consent was thus attained from the organisers of the events, rather than the overarching League. Before I attended a single event, I had spoken in depth with multiple organisers from across the country. In fact, at the first hackathon my name was recognised by one of the attendees in the queue behind me as “the gender researcher”, as they were on the committee of another hackathon later that month. The League did not respond to my emails regarding my research at their affiliated events. Since they (as a company) are not directly involved with the running of the events this did not affect my ability to undertake the research. The League did have “representatives” in attendance, although these were the student organisers of other affiliated hackathons, whom I had contacted previously.

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<sup>154</sup> Qualifying for League affiliation is a lengthy process. The average hackathon I attended took 10-9 months to organise and formal affiliation will often only be granted once the hackathon is in its final stages and the criteria are met. In order to qualify for affiliation there are several important thresholds to meet, the most important of which is a guaranteed number of attendees (usually a minimum of 150). As a result, the hackathons that gain affiliation are already well positioned for success. It was common for League affiliation to be granted only weeks before the event was to take place.

When I attended the hackathons I ensured a reasonable level of informed consent, by briefly explaining my research to anyone I spoke to. In addition to verbal information, I carried information slips regarding a brief summary of my research and anonymization processes, which I provided to people I directly engaged or worked with (See Appendix IV). I am also careful to obscure any identities or defining characteristics of individuals. Any individual names used have been changed. Accounts of the events themselves are anonymised but include information about the region of the United Kingdom they took place in. I also use photographs in presenting my analysis. Photographs taken by the researcher do not include people, meaning that the images are easily used. Where indicated, images of participants of the hackathons are taken by the event organisers as part of the publicity for the overall League. In the featured images I have obscured the features of participants in order to keep them anonymous.

Traditionally, ethnographies have lasted for many months or even years, yet hackathons typically last no more than 36 hours. Applying the ethnographic method of participant observation, I was able to experience the intensity and brevity of the hackathon, which gave me a visceral understanding of the events and the culture which they foster within a short space of time. In *Studying Those Who Study Us*, Forsythe (2001, pp. 130–131) explains the issue of “informant bashing”. When researching English-speaking participants, it can be ethically complex to be critical of those who give us their time, especially when analysing informants’ work in terms they would not have chosen themselves (Forsythe, 2001). The researcher can be the subject of review by their informants.<sup>155</sup> I was concerned that making myself known as a social scientist would result in me being viewed by hackathon organisers as not possessing sufficient technical knowledge. However, I can reflect on my abilities to highlight that my misgivings were

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<sup>155</sup> The main comments I received when I identified myself as a researcher were about the University of Oxford and what it was like to be enrolled there. These conversations served to create a friendly ice-breaker with participants.

misguided, as my competences in Python and several web frameworks were adequate. As such although I am self-critical, my primary consideration is towards my participants (as per ASA Ethical Guidelines).<sup>156</sup> Formal ethical approval was granted in March 2019.<sup>157</sup>

Participation can be a complex area in ethnographic methodology; to what degree should I have participated at the hackathons? What if I were to rally more women to buy a ticket? Could my presence in their photography potentially have encouraged more women to buy tickets the following year? Each of these questions are necessary parts of ethnography, the “participant” part of participant observation. In each case where I contacted organisers, I offered them a report on how they could make their events more inclusive for women. On only one occasion was the (woman) organiser interested, and initiated a series of phone calls on expanding the inclusivity of her hackathon. In the feminist mission of this study I engaged with advocacy not just in the representation of informants (hackathon attendees), but also as a political project. Scholars such as Ahmed (2010) argue that feminist scholarship should not be separated from its subjects, but should involve actionable consequences as the “feminist killjoy”. My work not only aimed to characterise gendered exclusion in its current form, but also to reveal the steps that can be taken to dismantle a masculinist hegemony and to act as a “killjoy”.

### *Analysis*

My approach entailed an iterative process of theoretical sampling, comparing and contrasting examples from the data to build theoretical categories, which were then compared and interrelated to form the basis for this study. Categories were adjusted throughout the fieldwork to confirm current paths of inquiry and focus my study. These categories were refined through a process that involved a continuous reviewing of the literature and discussions with both colleagues and

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<sup>156</sup> American Sociological Association.

<sup>157</sup> CUREC 1A Ethical Approval Number: SSH OII C1A 19 010.

informants, including an iterative coding of field notes and observation materials. Although each hackathon brought with it a new assemblage of individuals, vendors, and venues, by the third hackathon, I had confirmation of particular patterns of interaction and role-based gender structures. The anecdotes of normative understandings and structures of convention within the ritual were accounted for through these frameworks. I then conducted observation at a further two hackathons, and after no significant new categories emerged, I determined that I had reached theoretical saturation. The more events I attended the clearer it became that the league structure means that many of the events are attended by the same people, and the same teams. Generally, half of the attendees of each event were committed League teams, and the other half were local young people and students interested in technology. Attendees who had travelled to the event via train or car generally lived within an hour radius. At the end of the fieldwork, I reanalysed field notes and the memos I had produced during the study to further clarify what interactive practices seemed important to consider.

The choice of participant observation acknowledges the importance of ritualism and community in creative coding, and utilises an informed bias to build on the foundations of the earlier studies. The feminist project of this thesis comprises an argument for a methodology where computational and ethnographic methods are compatible. As women seek to hold their own in the lived experience of hacking, they are situated in a constant audience that may judge them, asking: can women write code?

## Section II: Hackathons and Being Nice

As a model of knowledge exchange, the hackathon is a fast-paced design orientated event in which programmers/coders collaborate, often competitively, on software projects. The term stems from a portmanteau of the words “hack” and “marathon”. Hack, in this sense, generally refers to exploratory programming, rather than digital trespassing, whereas marathon refers to the extended period spent solely on the defined project.<sup>158</sup> As discussed in Chapter I, Section I, the term appears to have first been used in 1999. The events have grown in popularity since the mid to late 2000s, increasingly viewed by venture capitalists as opportunities to develop new software and to locate areas of innovation with velocity (Irani, 2015). The majority of academic literature (and non-academic coverage) focuses on hackathons that occur in North America, yet half of these events take place in Europe. The images in Figures 18 and 19 show the main working space several hours into a hackathon at two of the observation sites.



*Figure 18 The main hackathon space at the event in the East Midlands*

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<sup>158</sup> Unauthorised access to a computer system or personal account.



*Figure 19 A hackathon in the West Midlands*

All of the hackathons I attended, which were advertised through the League, followed a very similar structure. They all took place on weekends inside of university term time, and were run by student volunteers with the assistance of a League representative. The League representative was a student organiser for another hackathon. The League representative for an event in the East Midlands was the organiser of a hackathon in the North East of England, and so on.

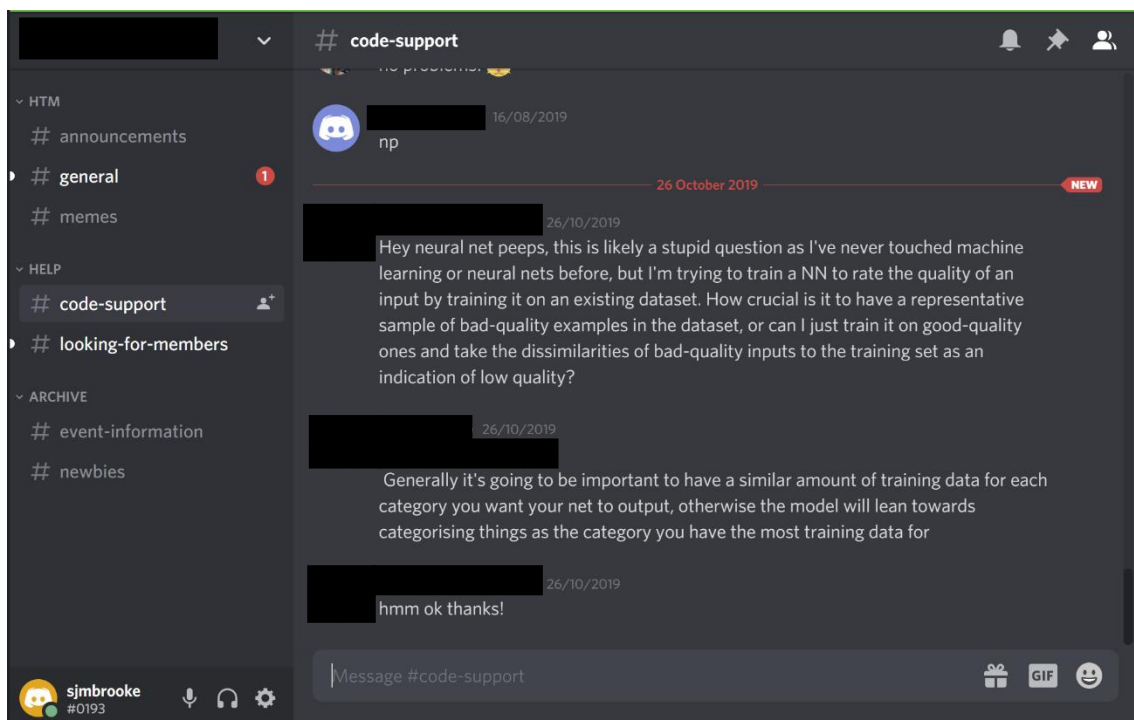
## **Introduction to Hackathons**

Hackathons last over 24 hours to allow additional time for introductory talks and prize giving at the end of the event. Hackathons are free to attend, but potential attendees are required to apply to take part, listing their motivations and skill sets.<sup>159</sup> After your application to the event had been accepted, you would be invited to join a particular communication platform to arrange teams in advance, socialise, and even share memes. In this way, although the hackathon itself was short, it

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<sup>159</sup> I contacted organisers first and only filled out an application if instructed to do so.

was preceded by this period of communication online. The two platforms that were favoured by event organisers were Slack and Discord. While Slack is a relatively widely used proprietary instant messaging platform for collaboration and discussions in the workplace, Discord (See Figure 20) is specifically designed for video gaming communities. Both platforms are instant messaging based, and have the feature of setting up “channels” which are content focused chats. Here, attendees could ask questions in the “Organisers” channel, find teammates in “Looking for Team”, and ask for technical assistance from “Sponsors” or “Mentors”.



*Figure 20 Screenshot of the Discord Server*

The platforms were used throughout events, to notify attendees when a workshop was about to take place, if there were food available, and other such communications. The platforms were largely anonymous, with very few people using their name and hardly anyone using an image of themselves. These platforms continued to be used during the hackathon. Coleman (2010, p.56) saw the same trend in Hacker cons, as participants “virtually communicate ... even while in the

presence of others”. The hacking (or working on your project) began after the opening ceremony, and ended around midday on Sunday. A sample schedule is included in Figure 21.

<b>Time</b>	<b>Day One: Saturday</b>	
10:00	Doors Open / Registration	
11:00	Opening Ceremony	
12:00	Hacking Starts	Team Building
13:00	Lunch	
16:00	Sponsors Workshop	Sponsors Workshop
17:00	Sponsors Workshop	Sponsors Workshop
18:00	Sponsors Workshop	Sponsors Workshop
19:00	Dinner	
20:00	The League Event	
21:00	Sponsors Workshop	
22:00	Game 1	
<b>Time</b>	<b>Day Two: Sunday</b>	
00:00	Midnight Snack	
01:00	Game 2	
08:00	Breakfast	
12:00	Hacking Ends	
12:30	Groups Presentations: Part 1	
14:00	Lunch	
14:30	Groups Presentations: Part 2	
16:00	Closing Ceremony / Prize Awarding	
17:00	Event Ends	

*Figure 21 Sample Hackathon Schedule*

Upon arriving at the hackathon in the morning, participants are generally left to find a specific spot to set up. For some of the attendees at hackathons I observed, it was not uncommon for attendees to arrive with whole desktop computer set ups, including several monitors, and, in one case, a flat screen TV and complete box sets of every season of the television show *Blackadder*. The scene was reminiscent of the “sleepovers” of early adolescence. Once people have arrived and spread out across the venue, there is an announcement on the loud speaker (every event had this set up) and participants are directed by event volunteers into an adjoining large room or lecture theatre for the Opening Ceremony (Figure 22). These ceremonies were far grander than I

had expected, and resembled product launches that one might see for the latest iPhone or Samsung device. The first speaker would generally be one of the organisers of the event, and it would be pointed out that the organisational committee was identifiable by branded hoodies for that particular hackathon. These hoodies appeared to be prized, with attendees who had previously planned a hackathon wearing hoodies that denoted the year and event they organised.



*Figure 22 Opening ceremony of a hackathon that took place in the West Midlands*

Once the lead organisers had outlined the hackathon structure, they would then introduce the next people to take the stage. At every event, this was the sponsors. The corporate representatives went first, with a League representative always featuring as the last speaker. The sponsors at the events fell into several categories, each represented by one or two people and each presenting their “Challenge”. The sponsor challenges are competitions that are secondary to the grand prize of the hackathon; each event sponsor sets at least one and each comes with its own prize. First are the technology giants, including GitHub, Amazon, Microsoft, and Google. These sponsors usually set the larger prizes, commonly providing the grand prize in addition to their own challenges. These are then followed by smaller, more specialised, technology companies and start-ups, such as: Twilio, Qualitrcs, or Domain.com. Like the larger tech companies, these sponsors will promote attendees to use their products, and assistance for those looking for employment or

internships. Their challenges generally focus on a use of their product with a twist, such as “Funniest domain name”.

As well as technology companies of varying sizes, financial corporations and banks are also common. Sponsors here include BlackRock, Capital One, and Sterling Bank. These sponsors will often provide data, such as credit card transactions, and will award prizes for best use of it. The ethical practices of this data gathering and its use at hackathons, including whether attendees could access the data after the event, were not addressed by the sponsors. The sponsors tend to be focused on hiring developers, and promote their company as a prospective employer, thereby further raising the stakes for participants to perform well at the event.

Finally, there are sponsors who do not fit into specific categorisations. These range from Bentley Motors, to the Chartered Accountants Institute, to the local City Council or Coffee Shop. All sponsors will have physical stands in the events, where attendees can approach them to ask questions. The final sponsor is from the League, who endorses the general ethos of the event, but also promotes the Hardware Lab they make available – well stocked with Raspberry Pis and other technological curiosities.<sup>160</sup> The League representative will also refer to a Code of Conduct (CoC), and that by attending the event you are agreeing to it, but the code is never actually explained. Like Stack Overflow, the League also sums up their CoC as “*Be Nice*”. The League CoC is not explicitly quoted or explained beyond a reference to its existence. The code of conduct reads:

*“[The League] stands for inclusivity. We believe that every single person has the right to hack in a safe and welcoming environment.*

*Harassment includes but is not limited to offensive verbal or written comments related to gender, age, sexual orientation, disability, physical appearance, body size, race, religion, social class, economic status, veteran status, sexual images, deliberate intimidation, stalking, following, harassing photography or recording, sustained*

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<sup>160</sup> Raspberry Pi is a series of single-board computers developed in the UK to support the teaching of basic Computer Science in schools and developing countries. By February 2015 they were the bestselling British computer.

*disruption of talks or other events, inappropriate physical contact, and unwelcome sexual attention.”*

(The League, Code of Conduct)

It is worth highlighting here that for identity categories other than gender, the hackathons were reasonably diverse. In regards to race, the hackathons were not as dominated by whiteness as I expected.<sup>161</sup> However, diversity was a feature of the multicultural cities the hackathons took place in, rather than an aspect of events themselves.

After the opening ceremony, attendees filtered back to the hall, in which the main hacking would take place. As everyone settles down at their stations, a large countdown clock appears on screens around the venue. For those who did not have teams, a Team Building session would happen in a space adjacent to the main area.<sup>162</sup> The sessions consisted of individuals standing in an awkward circle, and one of the student organisers would attempt to coax people together, based on their skills or the type of project they would like to work on. Even though people were ostensibly here for the explicit purpose of team building, they often seemed reluctant to be brought together.

Following the end of Team Building, lunch would arrive. All League events are entirely free to attend, and so is the food and drink provided. This would most likely be a local business, such as a Toastie van or a BBQ of Pulled Pork. There was always provision for dietary requirements: from vegetarians and vegans, to Halal and Kosher. Food was always brought back to chosen workstations, and attendees would often be surrounded by piles of half-eaten meals and snack wrappers, drink cans, and coffee cups. From early afternoon, the sponsors would run workshops which promoted their project or services. These workshops would always be announced over a loudspeaker and on the chosen communication platform, such as Discord. Examples of workshops

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<sup>161</sup> This observation will be discussed in more depth later in the Chapter.

<sup>162</sup> Meaning those who arrived at the hackathon without their team already in place, either with friends, peers, or pre-organised.

include “Exploring ML (Machine Learning) with Google Cloud Platform”, or “Majestic: “Scala’, The most beautiful programming language you’ve probably never used”.<sup>163</sup> These events were reasonably attended, mainly by those hoping for an insight into winning the relevant sponsors’ prizes. These workshops run into the evening, with dinner announced at around 7 P.M. Dinner was always hot junk food, typically burgers or Domino’s pizza. After dinner, at every event, League would run a !Light workshop. !Light was marketed as a “fun game” where participants were challenged to build a website using HTML and CSS without loading the webpage. Marketed as an opportunity to practise front-end development, these workshops were often better attended than those run by the other sponsors.<sup>164</sup> This is likely due to an investment in the League by the participants, and that the League rep is “one of them”, as opposed to the polished Bank representatives.

The events would often have designated times for games to be played by participants. It was also very common for games and gaming consoles to be set up throughout the venues, for attendees to play at any time. As well as board games and retro consoles (e.g. Nintendo64), high tech set ups would also be at participants’ disposal. For instance, a hackathon in the East Midlands had an Oculus Rift set up, a virtual reality headset and platform. A television would be nearby, where others could watch the player’s performance in the game. At the time I was watching, the game selected was Star Wars, which led to a lively debate on the film franchise. The games that had a designated timeslot (shown in Figure 21) included Werewolf, a social deduction game that requires a significant number of players in order for it to be enjoyable. This game was played at every hackathon I attended, in a ritualistic fashion.<sup>165</sup> The second, non-digital game that was

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<sup>163</sup> Majestic is a company that “surveys and maps the Internet and has created the largest commercial Link Intelligence database in the world”. This is a direct quotation from the hackathon schedule.

<sup>164</sup> Front-end development is the practice of producing a website that a user can see and interact with directly. Generally, it is the creation of the visible part of a website.

<sup>165</sup> The ritualism of hackathons is discussed in detail in Chapter I, Section I, *Hackathons and Hackerspaces*. Hackathons are not just occasions or work, but ritual in their formulaic embodiment of coding culture.

scheduled at every event was The League's Cup Stacking. In this setup attendees would work in teams of two to create the tallest tower of plastic cups stacked on top of each other. The inclusion of this game is indicative of the League's American roots.

Each event would have designated sleeping areas and spaces in which attendees could "be on their own if it all gets too much" (Hackathon Organiser). These rooms were small, in comparison to the volume of attendees, and it appeared to be assumed that attendees would sleep in blankets at their desks, if at all. This followed on from my own sighting of the men in fedoras clutching bags with blankets and pillows inside. There was no separation of sleeping area by gender or other basis, and while attending hackathons I personally would arrange accommodation outside of the event, but attendees would largely just take small naps at their workstations. In discussing sleeping arrangements and their intense technical labour, it was not uncommon for attendees to reference the need for "another weekend", to recuperate from the activities and long hours of the hackathon.

In the last few hours of the time that attendees were permitted to work on their projects, many would be milling around the main hall, picking at snacks. The attendees of the event were visibly exhausted, and even those who left the event to sleep ultimately had little rest. Deodorant and toothbrushes would be supplied to attendees, but it appeared that these were rarely used – evidenced by a multitude of unopened boxes, not to mention the odour of the venue. By midday on the second day, the hackathon venues would be unpleasant. They were often badly ventilated, so the odour of junk food and sweat was noticeable. Despite continued efforts by organisers to collect rubbish, tables and workstations would continue to be covered in packaging and half-eaten food.

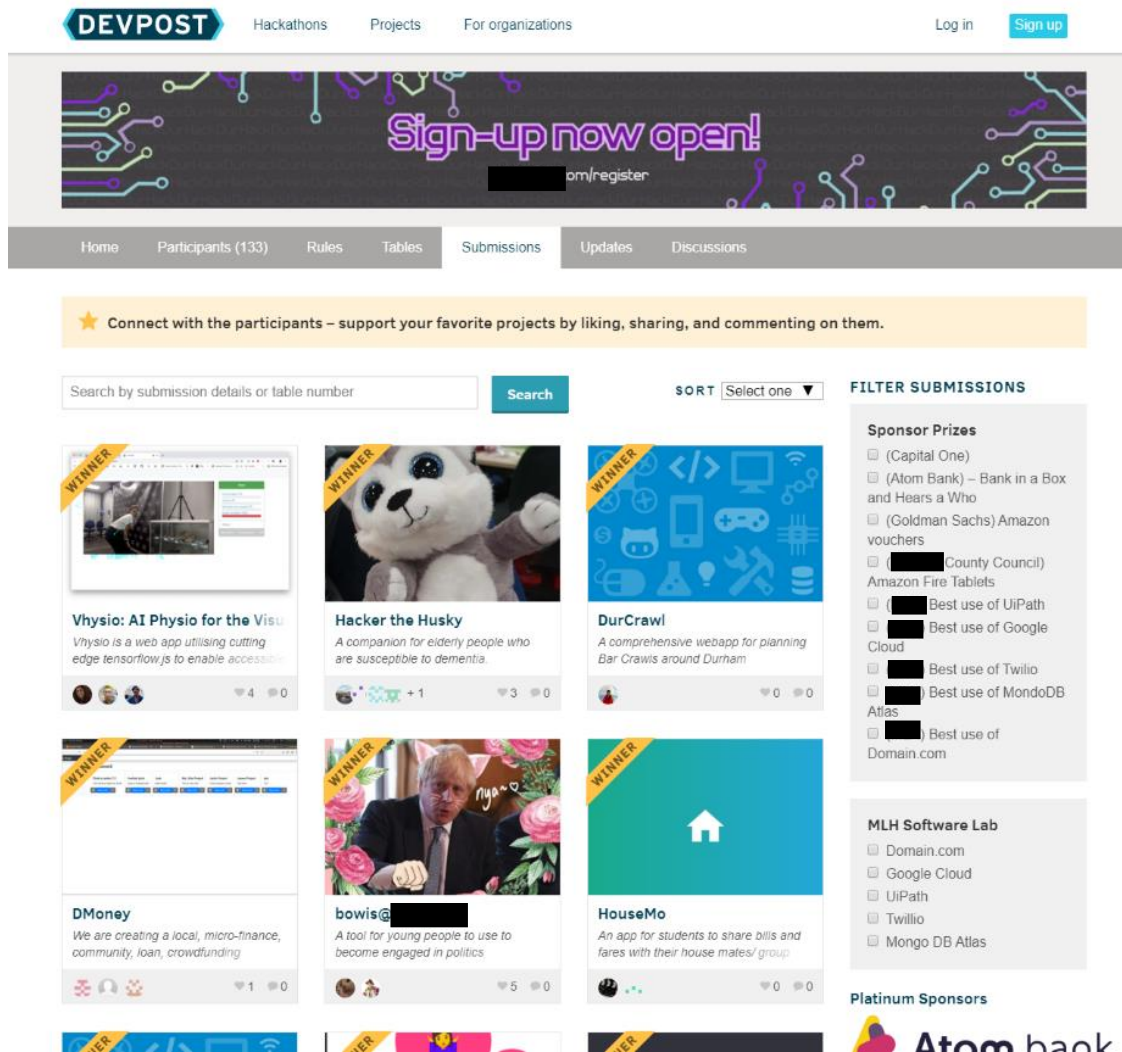


Figure 23 Screenshot of Hackathon Devpost

After a breakfast buffet was opened, usually consisting of pastries and croissants, participants would be reminded of the approaching deadline, and to upload their projects. In order to be considered for a prize, projects would need to be uploaded to Devpost, a platform specifically built for software engineers to participate in competitions. Projects produced at hackathons and uploaded to Devpost (Figure 23) would be available past the end of the Hackathon, with the winners of competitions and their prizes clearly marked. The attendee's names and Devpost

profiles are also clearly visible.<sup>166</sup> On the right-hand side of the page we can see that submission can be filtered by the prizes that were won and the software that was used.



*Figure 24 Presentation of Bomb Defusing Game*

After the hacking finishes, attendees are again directed by hackathon organisers to the large theatre in which the opening ceremony took place. Whilst attendee numbers noticeably diminish from the time of the opening ceremony, a large majority remain to see if their project will be recognised by the organisers and sponsors. After a short introduction, each group stands up and presents their projects to the audience and sponsors. Projects included *hAccess*, a platform that used a gig economy framework for charity work, and *Adam in my Pocket*, a bare bones virtual assistant of “None other than the man himself ... lvl 99 wizard, chair of the [University] Computer Science Society, contributor of project [redacted] and mother of dragons”.<sup>167</sup> Projects could also be hardware based, such as the bomb defusing game pictured in Figure 24.

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<sup>166</sup> Users of Devpost are able to choose what their publicly available username will be and the site content is easily accessible.

<sup>167</sup> This [redaction] was included in the text for comic effect by the hackers.

After each group has presented for 3-5 minutes, there is a short break as the sponsor decides the winners. Each sponsor then gets on stage and spends 1-2 minutes announcing who will be awarded the sponsor's prize. Each winning group then takes a photo with the sponsor representative and their prizes. There is an awareness that this is a competition, and that attendees desire to win, yet attendees appear to be more invested in showing their project to a group of their peers than winning. Although winners are pleased with what they have achieved and receiving the prize, there are no clear displays of disappointment from non-winners. What is evident is that groups have bonded, often presenting their projects with a series of in-jokes and comments that only their group members understand. It was clear that for the young men part of the appeal of hackathons was finding *someone like me*. It is not uncommon for a team member or even a group to erupt into laughter when a joke is made during their presentation. After the prizes are awarded, the student organisers thank the attendees and promote other League events. After a round of applause thanking the organisers and volunteers, the event draws to a close and participants filter out.

### ***Be Nice***

In the description of the hackathon schedule above there are several themes that I wish to draw attention to and problematize. Firstly, the CoC was merely referenced in passing by the League representative, its existence usually indicated with a plain PowerPoint slide featuring a URL. It was not read out and no information was provided as to what would happen if it was breached. This signalled that the League's reference to "being nice" was not equivalent to a commitment to tangible action to tackle harassment.

Secondly, sessions supposedly for Team Building were highly competitive and individualised. Each person would each have a set idea of what they wanted to achieve and what they were looking for. Their aims would fit such narrow definitions that no one at the Team Building would fit another's requirements. In every instance, these team building events were *exclusively* attended by men, sometimes wearing headphones. When I attended, every opportunity was taken to ignore

my presence. Unless I actively spoke up and sought to be in a team, the hackathon organisers did little to alleviate this. Similarly, throughout the event the majority of attendees were focused on their projects, often working in silence wearing large, antisocial headphones. As the hackathons went on, the technical setups of individuals merged with the imagery of a stereotypical teenage boy's bedroom; bedding, discarded snack packaging, and intense expressions lit by the glow of monitors.

Thirdly, League hackathons are purportedly open to anyone, and it is widely advertised that you don't need to be able to code to attend an event; just have an existing interest in technology. Yet, every workshop and event was structured on the basis that its attendees could code in at least one language, with no introductory, beginner, or entry-level workshops. No provision at all was made for those looking to gain a technical skill.

What were the ostensible values of the hackathons - inclusivity, team building, openness – contrasted with actual events. The value of the ethnographic method here is the rebuttal of the narrative of meritocracy that was shown to be a pillar in coding community creation in Chapter I, Section I. In the next section I will continue to query and problematize the devotion to diversity by characterising the gender roles enacted at hackathons.

### **Section III: “Be a man and integrate!”**

Chapter I outlined the importance of applying narrative enquiry in making sense of the social world. In this Chapter, I have outlined my experiences at hackathons and will now turn to the functioning of gender in these spaces. This story points to the multi-causality of women's exclusion in creative coding culture, and is indicative of gender as a social structure. I first outline gender roles, as the foundation to their function in coding culture. Second, I use Cheryan's (2009)

concept of ambient belonging to inform my understanding of the use and value of objects at hackathons. Next, I discuss my experiences with embodiment in hacking in terms of sensory experiences. Finally, I incorporate a dialogue on memes as meaning making, demonstrating how creative coding culture exists online and offline concurrently and without segregation. This section tells the story of hackathons, before I align the findings with the literature in Section IV.

## **Gender Roles**

In this section I outline how gender sets the rules of engagement in interactions at hackathons. In Chapter II, I discussed the specific characterisations and stereotypes of men and women in technology that result from the overarching gender structure. I first consider women who embodied the insider status of hackathon organiser, and how the expectations of this role were mediated by their gender. I then look to how masculinity mediated the central activities of hackathons, focusing on team building and competition. I will further examine how femininity was visible in its manifestation as caregiver, but invisible as a legitimate hacker identity. The gender roles at hackathons were ultimately defined in relation to the salient multiplicity of masculinity.

### ***“Hashtag Feminism”***

Women are not the passive subjects of a male-dominated culture. All of the organising committees I contacted were aware of the gender imbalance they faced at their events, and most felt that women were simply not interested in attending. The exception to this was a hackathon planned by Annabel, who was actively seeking to encourage women to participate in the event. This was the only organisation committee I encountered that was encouraging women to participate as a matter of importance, and was the only committee led by a woman.

When I reached out to Annabel we exchanged a series of emails and eventually a Skype conversation. She was interested in strategies I could recommend to encourage women to participate. She told me that particular efforts were made to ensure that women were visible in

the online presence of the hackathons as well as communication channels, including using a feminism hashtag in social media posts leading up to the event. She expressed a general exasperation at male members of the committee who did not see this as a priority, or even an issue that needed addressing. Using feminist hashtags (#WomenInTech, #FeminismInSTEM) in advertising the hackathon had been opposed by other organisers as unsavoury, “too political”, and potentially off-putting to their male attendees to make it a “social justice issue”.<sup>168</sup>

In my meetings with Annabel, I informed her that research had indicated that encouraging people to arrive in teams would likely encourage women’s participation. As Mishkin (2019) saw, young women’s likelihood of learning to code correlated strongly with having friends to learn with. We discussed how arrangements such as advertising separate sleeping areas and other such facilities might also encourage women to participate. Annabel was also considering a women-only workshop, but was unsure if she wanted its content to be technology or tech culture focused. However, she was worried that such a workshop might discourage men from taking part in the event altogether. I was only able to have a few conversations with Annabel before the hackathon was cancelled, but it became clear that in her battle for women’s inclusion she felt very alone in the male-dominated culture.<sup>169</sup> There was an expectation that as the woman on the committee all responsibility for gender representation fell to her, as if she were able to represent all women, everywhere. She was also acutely aware that she was often assumed to take on secretarial and administrative duties, which was “not what the president does”. There was a gendered expectation that because she was an organiser, and a woman, no administrative assistance was necessary.<sup>170</sup> She found that no man wanted to provide administrative assistance to a woman leader. My

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<sup>168</sup> This is a reference to Social Justice Warriors (SJWs) as outlined in Chapter I, Section I. It is a pejorative framing of feminism, where the SJW references feminist views solely to elevate their own status.

<sup>169</sup> The hackathon was cancelled due to the Covid-19 pandemic.

<sup>170</sup> Annabel also emphasised that all former presidents (who had been men) had a volunteer administrative assistant who helped them keep track of the various tasks other members of the committee would perform.

discussions with Annabel show how the burden of diversity is placed on women in technology culture. Organisers (men) were hostile to visible attempts for women's inclusion, expecting that representation and administration were women's "work".

### *"Toby is Alpha"*

Previous work in the field (Chapter I, Section II) meant that I anticipated the nuances of geek masculinity, but I was also attuned to legitimate and stigmatised deviations. The competitive structure, lucrative prizes, and presence of tech companies had led me to expect the presence of more hegemonic forms of masculinity. Although not as overt and hostile as Hick's (2013; 2017) characterisations of the "brogrammer" in Chapter I, normative masculinity was most apparent in the representatives of financial companies such BlackRock, Capital One, or Starling Bank.<sup>171</sup> These representatives were accomplished developers, but their appearance marked them out in stark contrast to the average hacker. They were also young and predominantly men, but were tall, clean shaven, and well groomed. They were athletic and wore tight clothing, stood upright and confidently. Whereas the average attendee avoided eye contact, they would actively seek to speak to others and garner interest in the projects they were developing. They did not, however, embody the frat house culture that Hicks (2013, 2019) discusses in American brogrammers. Rather, they embodied the masculinity of start-up culture; cool and calm, with an air of confidence about them. This appearance however, lost them some ground with the attendees who conformed to geek masculine tropes. Like Hicks (2017), attendees saw the attention to their looks and more manicured appearance as indicative of a lack of technical ability. It was indicated by members of my team at one event that the representatives were perhaps compensating for their technical abilities with a more business-based masculine appearance.

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<sup>171</sup> This is likely partly due to them being at the hackathon in an official capacity, as a representative for a corporation. But there is also likely a difference in the overtness of sexualised masculinity in the UK and USA. Brogrammers are defined by their incorporation of "frat house culture", which is not reflected in UK University structures and does not have as much resonance in the UK.

The sponsors seemed to be aware of this perception. When approaching groups who were coding or working on their project, they would ask questions and make jokes to show that they were among the initiated and did in fact understand the technical aspects of the discussion. Though this was generally tolerated by attendees, they did not seem comfortable in their presence. In one instance, an all-male group was approached by a representative, who when discussing the project would make a fist with one hand and punch the palm of his other hand, to add emphasis to his words. When the group noticed this, they started mimicking the sponsor, seemingly unaware that he was able to see what they were doing. As they got more excited, they shouted “Toby is alpha!” and descended into laughter at the representative’s expense. The “alpha” cited here is an ironic reference to alpha and beta masculinity, where the alpha refers to hegemonic interpretations and the beta is more geek-like traits (Milner, 2016). The tensions between the geek and hegemonic masculinity illustrate how gender mediates perceptions of ability. In joking about the “alpha” nature of masculinity in the presence of the intended subject, the geek hackers were asserting their status in creative coding culture.

### *Queerness*

Not all performances of masculinity were heteronormative. Queerness was visible across events, and the rainbow LGBTQA+ pride flag was displayed in stickers, badges, and lanyards. At one of the hackathons I was able to have lunch with one of the organisers and had the opportunity to explore this in depth. As we sat down at a table at the edge of the hackathon’s designated food hall, I noticed that *Anthony’s* hoodie was decorated with a large collection of badges, indicative of LGBTQA+ pride. I had already had a series of discussions with Anthony in the lead up to the event, and felt comfortable in enquiring about the badges.<sup>172</sup> Anthony told me that it was important

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<sup>172</sup> Our lunch was a matter of friendly convenience. I was attending this particular event as a volunteer and had built up a friendly working relationship with Anthony after we had bonded over a mutual interest in a prematurely cancelled Sci-Fi television series – *Firefly*.

to him to share his identity as a gay man through these badges, showing that hackathons were an accepting place. He also vocalised his concern that he was finding it difficult to understand why women felt unwelcome though “other minorities” did not. Together with the visibility of LGBTQA+ memorabilia at the event, my conversation with Anthony shows how the inclusion of queerness was not viewed in the same political terms as women’s exclusion. Feminist narratives were unsavoury and “too political”, whereas other inclusions were more palatable to creative coding culture.<sup>173</sup>

Outside of my conversations with Anthony, volunteers, hackers, and organisers would be proudly displaying rainbow (pride) flags on their laptops. There were a multitude of designs, and though some would be simple and clear, in others the rainbow flags would be more subtly included in a cartoon design for a sticker or a badge pinned on clothing. One organiser had dyed their hair to match the pride flag, a crown of a complete rainbow. Hair dyed in pastel and electric shades was not uncommon at these events, and these bright colours were counter to masculine norms. In Dunbar-Hester’s (2019, p. 209) research into collaborative hackerspaces (Chapter I), vivid hair colour was a resource employed by individuals with a non-binary gender identification as it “provided to interlocutors a relatively neutral aspect of [their] appearance on which to focus their reflexive comments about [their] presence”. Dunbar-Hester (2019) points to how even for those who were reflective about their own gender-identification, femininity was deeply rooted in internalised stereotypes. One of her informants, who self-described as masculine non-binary, stated: “I need to check my own assumptions. If I see someone presenting feminine, I do presume they are in marketing or HR” (Dunbar-Hester, 2019, p. 208). Thus the vivid hair colours can indicate the felt presence of a heteronormative gaze at hackathons, not gender inclusivity and a resistance to stereotyping. As a whole, the brightness of the pride flags and any other colours

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<sup>173</sup> Online forms of creative coding, such as Reddit and Stack Overflow, are hostile to assertions of feminism. This likely powerfully reinforces the implicit anti-feminist narrative across the hackathons

stood in stark contrast to the sleek greyscale surroundings of the events and the drab, dark clothing of the attendees. This queerness, however, was always relatively linear; it was a masculine embracing of feminine norms and did not operate in any other form. What brought geek and LGBTQA+ cultures together was the shared experience of marginalised masculinities.

***“Am I alone here?”***

At every hackathon, it was assumed that attendees would formulate their own teams with minimal intervention on behalf of the organisers, as discussed in the *Introduction to Hackathons* section. There was a Slack/Discord channel set up for this explicit purpose. Many events would allow attendees to reserve (for free) tickets for an entire team in one booking, and teams were allowed to comprise up to four people. It is also worth noting that teams of one were also permitted and that these were universally comprised of a single man. The majority of attendees would have teams set up in advance of the event, meaning that when it came to the in-person team building there were at most twenty individuals looking for a team, out of several hundred attendees. On one occasion, the Team Building workshop was attended by one person, who posted on the Slack channel for finding team members “Is it just me? Am I alone here?”. Despite the fact that the post was read, it did not receive a reply. This reflects that the social bonding at hackathons may be limited to those who you already know, as well as an acceptance of the stereotypical anti-social geek in teams of one.

A hackathon in the West Midlands had the largest number of hackers turn up to find teams in person.<sup>174</sup> As described in Section II, this organised session was attended by archetypal representatives of the geek masculinity that dominated these events. They stood in an awkward circle, not speaking to one another and avoiding eye contact through messy hair and pulled up hoods. Many kept their hands, or a few fingers in the pockets of their jeans, perhaps trying to

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<sup>174</sup>The largest event had an estimated 350 attendees.

suggest an air of cool disinterest. After ten minutes, an organiser arrived. He also resembled the awkward geekiness of the team-builders, but his hair was bright blue and he was louder, enjoying the status afforded by his organiser hoodie. He clapped his hands, and started encouraging people to talk to one another, but with no avail. Finally, he settled on asking the attendees what skills sets they had and what they would like in others. As attendees spoke, they would visibly step back, avoid eye contact, and proclaim their expertise. Their demeanour was awkward and shuffling, yet confrontational, and they each had a set idea of what they wanted to achieve at the event. Each attendee was unwilling to compromise their specific worldview and objectives; as described in Section II, this made the team building nearly impossible and the frustration of the organiser was palpable. As the session progressed, I noticed that dotted around this area were women, sitting at tables, facing the team-making session, with all of their bags by their feet. There were five of them in total, all sitting on their own. They were not partaking in the team building, but were observing it as outsiders. After the men standing in the circle finally began to make compromises and form teams, the women looked disappointed and began collecting their possessions as if to move on. I approached one of the women closest to me and asked her if she was looking for a team, she looked embarrassed but informed me that maybe this event was not something she was interested in after all. A short conversation with her led me to believe that women saw forming their own team as an alliance of the marginalised. In doing so they were accepting their exclusion.

When I attended the team building sessions, I was invisible. At the third hackathon, I decided to be more forward in my search for teammates. I had to fight to be acknowledged, rebutting the attempts to ignore or dismiss me. When I spoke, heads and eyes would drop, avoiding being cast in my direction. Despite my active pursuit of a team, I still only found myself allocated when all other teams had been formed. I was the last resort. Even then, I would have been disregarded if the organiser had not told the remaining young men we would be in a team together. This experience was deflating, approaching humiliating. Forming the team on this note set the tone of the event, I was a subsidiary of the team and felt alone.

These experiences of women as outsiders, and eventually leaving the event prematurely if they did not come with a pre-established team, were common across events. At a hackathon in East England I was approached by another woman who asked if I wanted to be on a team with her. She introduced herself as Megan, and she had travelled on the train from London for the hackathon. We shared our misgivings about joining a Team Building workshop, having both attended hackathons before. Instead, we decided to approach pre-existing small teams around the venue. I was pleasantly surprised by how quickly we found Josh and George, who knew each other from University. We decided our project would use machine learning to automatically generate memes to enter the hackathon's memes competition.<sup>175</sup> Megan was working with Josh on the backend development of our project, which they were writing in JavaScript. After 4 hours of working on this, Megan started getting an error code that she didn't understand. Josh refused to help her, or even glance at her screen. He said he was too busy to solve her problem, but would often leave the group to play on one of the videogames that was set up. I attempted to help her, but my skillset does not extend to JavaScript. After an hour, Megan stood up and informed me that she was just going to go home, because this was a waste of her time.<sup>176</sup> She promptly packed up her computer and the rest of her possessions, which did not cause Josh or George to even look up from their screens. After she left, I asked Josh why he hadn't helped her. He shrugged and told me it would be quicker if he just did it himself.

Just as the women sitting around the room had slowly decided to leave upon seeing the lack of cooperation in the teambuilding circle, Megan had given up on the entire event when her teammate refused to understand an error. It was noticeable at the hackathons that the events started

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<sup>175</sup> For our training data we used the Slack API to pull memes from the meme competition submission channel and the Reddit API to pull them from r/ProgrammerHumour subreddit. The main difficulty we faced in our project was recognising the text on the memes, which we dealt with through a mixture of automatic recognition and manually typing out the text.

<sup>176</sup> She informed me and not the team. She made direct eye contact with me alone, returning their efforts at ignoring her.

with a higher proportion of women than they ended with. Women seemed to leave the event throughout the day and by midnight the people left would be those who had arrived with pre-established friendship groups. Also, women were not only excluded from existing groups, but were met with hostility when they showed friendliness towards others. At a hackathon in the East Midlands I was sharing a table with several other hackers from different teams, as it had good access to power sockets to charge our laptops. A quiet young man at the table was approached by a woman of about the same age. She told him “If you still don’t have a group you can join us!”, and gestured towards a group of women nearby. They appeared to know each other from University, and as she tried to invite him into her team he voiced criticism of the project they were working on. He was resolute that his idea was better, and showed some hostility in rebutting her. As she left he went back to staring at his screen. As she explained what happened to the other women in her group, she was visibly frustrated with the reception of her efforts. This interaction shows how women were not always outsiders attempting to break into a group at an event, rather, when they attended it would be in pre-formed and pre-arranged groups with their peers. I was sometimes acknowledged by other women at the event. There were small exchanges of eye contact and sympathetic smiles, but little dialogue. But women often attended in locked-in groups, not wanting to threaten their clique by reaching out to other women. Also, they were still *others* in their participation in the culture, working with other women in order to have their skills recognised and not dismissed by the typical hacker attendees.

### ***Winning***

What perhaps does not come through in discussion of particular activities at the event is the general attitude towards winning. Hackathons are, after all, a competition. The grand and sponsor prizes were generally used to motivate the direction that a group’s project was taking, but they were not the main focus of the event. For the majority of participants across events, the joy was being in a culture made tangible. As hacking began, general conversation would turn to the venue as others who were participating. The dominance of the geek stereotype in attendees of the

hackathon was noted by attendees. They would discuss how the event was for “people like them” and how they didn’t often feel such a sense of belonging.

The competitive elements of hacker culture were manifest in every interaction. This took two main forms. First there was more direct competition, in terms of who could do what and fix what problem. The self-assessed competent participants were icons of geek masculinity taking a benevolent approach to others, helping where they saw themselves needed and taking pride in their status and usefulness. Once they had set themselves up as the source of authority and technical knowledge in the group, they would become visibly relaxed with the feeling that they were on home turf. The purpose here was to display one’s own knowledge (not to assist a member of their team) in a practice I characterised in Study II (Chapter III, Section III) as mansplaining. This was evidenced by how quickly they would either take over the task, or leave the person to figure it out for themselves.

Status accrued by competitive knowledge was accompanied by a strong tenet of benevolent sexism. In any mixed-gender team, women would be presumed as being in constant need of help or having something explained to them. Women were presumed to need constant monitoring when they did not, and not given assistance when they requested it. Like Megan’s experience, regardless of how legitimate a point was, women’s seeking help was rarely well received. This links back to Study I of this project, where I showed that stereotyping leads men to be seen to possess technical knowledge. In one instance, I watched as a heavily bearded Italian software developer invested 30 minutes in mansplaining the punchline of a technical joke to the woman who had just told it to him. She listened quietly, with pursed lips and narrowed eyes as her own knowledge was modulated. This shows that a subtext to the larger hackathon competition is a social competition for legitimate knowledge. It is being recognised as competent and skilled by one’s peers that is the true prize, one that is almost unobtainable for women. There is a structured competition, but a gendered hierarchy defines the terms.

The second form that competition took was indirect competitive knowledge. In conversations team members would take immense pride in displaying knowledge that was more obscure or niche than the knowledge offered by the previous person. For instance, this might start with an assertion such as “You know you can connect Fortran and Python?” which may be followed by a statement such as “Yes! Did *you know* in Fortran you still have to allow room for punch card spacing?” which would then be followed by a similarly structured statement, in a circular fashion.<sup>177</sup> The askers here are not truly interested in whether the other person is aware of the information they are offering, but showing that they know something more obscure and technical than the person who went before them. Each iteration of the statement is uttered in a louder tone than the last. The content of the words is not aggressive, but the body language shows finger jabbing, puffed out chests and tight postures. These displays of competitive knowledge in benevolent and more hostile forms were all uniquely masculine. The real prize in the hackathon was not winning the overall competition, but the status and an acknowledgement of your competencies by the overarching culture.

Gender was critical in navigating the competitive space of the hackathon; individual men competed against each other and were unwilling to cooperate, while women who hoped to join teams, share knowledge, ask for help, or even tell a joke, were met with presumptions of ignorance. Women would often be the subject of a specific form of mansplaining reserved for computing culture: “techsplaining”.<sup>178</sup> When faced with technological challenges, women were far more likely to leave the hackathon altogether.<sup>179</sup>

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<sup>177</sup> Fortran was specifically developed to be human readable, as discussed in Chapter I.

<sup>178</sup> A popular culture term which one of my informants described as “assuming someone is an idiot when explaining something to them”.

<sup>179</sup> In Chapter I, Section II, I discussed how women are more likely to leverage their personal networks in learning a new skill. I also outlined how peer parity is more important for women, as shown in the work of Mishkin (2019) and Ford et al. (2017).

### ***“I’m a cool mom”***

Although women’s legitimacy as hackers was contested, they were readily accepted as caregivers. When it came to working in teams, if a woman was leaving the group to go and get food or drinks she would often ask if anybody would like anything from the table of snacks or similar such set up. In comparison, when one of the men would get in up, in a mixed or single gender team, they would be far less likely to enquire if anybody required anything. These young women would often make comments about how they were the “cool mom” or the “mum of a group”. As well as representing the emotional labour they partake in, these statements also hint that there is not a sexual or romantic element to their relationship. This is an instance of *emotional labour*, a thesis coined by Hochschild (1983) to refer to the management of one’s feelings and expressions based on the emotional requirements of a job, here, the informal job of group mother. The *feeling rules* dictate the societal norms regarding the feelings of emotion, forming pastoral roles in one-directional gendered terms.

The women-as-caregiver role was even more apparent (or literal) in some teams, where attendees came with their mothers. These men would be in their late teens and early twenties, and would often come with large computer set ups, including blankets and a variety of equipment.<sup>180</sup> They would be wearing large headphones, and seemed shut off from the vibrant hackathon happening around them. Their mothers however would be incredibly talkative, often initiating conversations with people around them. One woman struck up a conversation with me when she walked past, asking about the dietary choices at the event and if I had everything I needed. Later, she saw another woman of a similar age on a nearby table, which resulted in an energetic conversation. These mothers appeared to attend hackathons regularly, as they understood the functioning of

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<sup>180</sup> Such as a TV and entire box set of *Blackadder*, mentioned in the *Introductions to Hackathons* section.

such spaces. I had come across no previous accounts of hackathons that mentioned these women's presence. They were confident, and vocal about their lack of technical ability.

On the whole, women were almost invisible to the young men at these events. In interactions women would be the initiator, with the men they were talking to avoiding eye contact or any socialisation at all. As a woman, this could be quite an unusual experience; one where I felt slightly out of phase and invisible. I would constantly be in close proximity to hundreds of other people, yet I could feel entirely unseen. Other than my gender, I did not appear dissimilar from the average attendee of the event, yet eye contact was avoided to the extent that I was often physically walked into or knocked by young men, even when seated.<sup>181</sup> Moreover, when I would approach someone to discuss the event I would often be ignored or met with a startled response. There was some interaction between young men who were not familiar with each other, but this tended to be issue/topic based, without small talk. These encounters often left me with the sensation of being an outsider, breaking contextual norms by seeking interaction.

Discussions of the lack of visibility at hackathons did serve to temporarily bond women together. At a hackathon in the Northeast, I was following a large group of attendees (all young men) through a large doorway in order to attend a workshop run by Microsoft Azure.<sup>182</sup> As I got to the doorway, I noticed there was a young woman in an organiser's hoodie struggling to get through the door with some large, empty cardboard boxes. I stepped back to let her through the doorway, unintentionally halting the procession behind me. As she passed by, she told me that she "may as well be fucking invisible" as she had been trying to get through two sets of doors for close to thirty minutes. I tried to find time to discuss her experiences as an organiser, but she seemed to constantly be running between jobs – while other organisers lounged around the venue. In my

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<sup>181</sup> Despite this being a salient experience for me, men never seemed to mention being bumped into, nor did I see this happen between men.

<sup>182</sup> Microsoft's Cloud Computing service for building, testing and deploying applications.

other conversations it became apparent that experiences of invisibility were common, felt by woman across events, particularly if they did not come in pre-established groups. The experience was exhausting, made them feel out of place, and incongruous.

### ***Conclusion: Gender Roles***

Taken together, the stories outlined in this section illustrate how gender impacts roles and sociability. I have shown that hackathons are not cooperative spaces, but rather are profoundly marked by gender. Women are overlooked, disregarded, and excluded. Gender is characterised by: (1) an aversion to vocalised or obvious feminism; (2) multiplicity of masculinities with competitive knowledge seeking in which women cannot participate; (3) queerness does not negate gender roles; (5) women are care givers, invisible in their labour. Gender permeates each interaction, setting the rules of engagement.

### **Materiality: Tampons and Hardware**

Here I describe the objects of hackathons. These artefacts encapsulate different aspects of gender and creative coding culture. I continue to show how inclusions and exclusions are gender based, marking the culture as masculine. Building on the work of Cheryan et al. (2009), I propose that ambient belonging at hackathons is dictated by objects. As hacking culture is embedded and embodied, material objects are manifestations of the community.

#### ***Tampons and Pronouns***

Despite the fact that the events were dominated by geek masculinity and men, there were signals of women's (and non-masculine) presence. Firstly, upon registering at two of the hackathons I was presented with a name badge with three blank spaces for the wearer to fill out. It was indicated that the first space was for your name, the second for your handle (usernames from a platform of your choice), and the third box was reserved for preferred pronouns. Although the hackathons were male dominated, the inclusion of this box at least signals an intention towards inclusion in the objects participants were presented with. However, this box either went largely unfilled on

the name tags of participants, or it was instead replaced with another handle. Another performance of gender-based inclusion was in the women's toilets at hackathons in the East Midlands and East England, which contained League branded bags with a small supply of women's sanitary products (tampons, sanitary towels, etc.).

The presence of these bags at multiple events is interesting, as it indicates a wider acknowledgement of women's attendance.<sup>183</sup> Moreover, it is an additional reflection on the experiences of people who menstruate, an acknowledgement of gendered bodies.<sup>184</sup> As the pronoun box on name badges reflected gender, a "biological" or embodied understanding was present in the supply of these products. Although the preferred pronoun text box and the sanitary products could be criticised as tokenism on behalf of the League as an organisation, this does not mean they do not have meaning. It is important not to stigmatise empathy with such indictments. The inclusion of gendered products is not the same as utilising their inclusion for publicity benefits. For attendees of events that are 90-95% male identifying, the inclusion of objects that indicate an identity beyond essentialist maleness is a positive step. The sanitary products in particular indicate an expectation of a non-male presence, and the practicalities of an event that spanned over 36 hours. No doubt, those who desired to use such products were relieved to see them provided. However, there is room to expand these provisions across more events, in addition to taking steps to encourage women (and non-men) to attend in the first place.

### ***Clothing***

As outlined in the introduction to hackathons, each event has its own t-shirt that acted as ticket, the organisers wore hoodies, and various other clothing items (socks, t-shirts, jackets, hoodies etc.) can be acquired for free from sponsor tables. All of these items of clothing were available

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<sup>183</sup> Their positioning in the women's toilets, however, meant they were only visible to women and those who used women's toilets.

<sup>184</sup> It is important to clarify that not all women experience menstruation and not all those who menstruate are women.

only in male sizing. Yet when applying to League hackathons online, you are asked to disclose your gender; the organisers were therefore seemingly aware of the exact demographics of their attendees. Even when I was offered the choice to order a t-shirt in advance through the website, the choice was male-sizing only.

At a hackathon in the West Midlands, I acted as a volunteer, which required me to wear a different colour t-shirt to the hackers. I was asked to be available to set up snacks and suchlike, to earn my keep, but was still able to participate in the general competition of the event. Here, two things occurred which challenged my feeling of belonging at the hackathon. First, the young man who presented my shirt to me at the event held my wrist and asked if I would like “help taking off my shirt”. This blatant comment was my first interaction at the hackathon, and I had introduced myself as the *gender researcher* who had previously been in contact.<sup>185</sup> Second, the T-shirt that I was handed was the smallest available, a men’s sized large that reached my knees. Though the appearance was rather comical, it seemed as if I was wearing the ill-fitting costume belonging to someone else.<sup>186</sup> In this way my experience of the hackathon uniform was that it was literally designed for a different kind of body to my own, and that despite the advance knowledge that I, and other women, would be attending, this basic provision was not made. This particular form of material exclusion was a constant reminder that I did not belong.

### ***Hardware and Software***

In the projects and discussions around computer technology at the hackathons, one clear role-based gendered difference was in the materiality of technology. Linked to competitive knowledge and gritty mechanical understandings of masculinity, hardware was the purview of men and

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<sup>185</sup> It was unclear if the inappropriate comment was *because* I had introduced myself as a gender researcher, or *despite* it.

<sup>186</sup> The over-sized clothing had the effect of making me seem a lot younger than I am, which was noticeable as I moved around the venue. However, following the advances of the hackathon organiser, I was relieved to be more covered up.

elegant software was feminine. The tendency for all-male teams to choose hardware-based projects was also apparent across events. Men were more likely to choose retro-inspired or mechanical projects, that could even involve soldering on the event floor. Hardware-based projects presented at events included bomb disposal games (shown earlier in Figure 24) and drone<sup>187</sup> software. As well as more retro projects, there was also a reasonable amount of entries based on Internet of Things (IoT), born out of the League's hardware lab.

Masculinity was directly associated with hardware expertise. The exclusion of women here could be as obvious as turning a back on them, or simply refusing to discuss the technology. In a conversation at a hackathon in the East Midlands, a group of young men near me were talking excitedly about their "set ups", the personalised computers they had built with substantial computational power and graphics to match. As the topic turned to a specific set up, constructed by one of the young men, another shouted "be a man and integrate!" this statement was met with a round of laughter from those involved in the interaction. "Integrate" here refers not to social participation, but to combining a hardware device (such as a graphics card) into another (such as the Central Processing Unit).<sup>188</sup> "Being a man" in this context is sarcastic, and is also characteristic of the multiple layers of interaction that occur in a bounded culture. It is firstly poking fun at the marginalised masculinity of those who fix computers, and secondly it is providing ironic advice. Integrated graphics were not for committed players of video games.<sup>189</sup> What is performed here is an expression of competence and belonging. The in-joke is that those who possess technical knowledge understand the basis of the joke, and its juxtaposition with gendered norms.

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<sup>187</sup> A drone is a flying robot that can be remotely controlled or fly autonomously through software-controlled flight plans in its embedded systems, working in conjunction with on-board sensors and GPS.

<sup>188</sup> Integrating (for GPU in this context) would not be "manly" as it involves compromising on graphics. A dedicated GPU, however, has its own source of memory, meaning that if designed appropriately, it can produce better graphics. As such, dedicated GPUs are often favoured by serious gamers.

<sup>189</sup> This description fits the average hackathon attendee.

### *Python is for girls*

The gender differential in usages of technical tools spanned across levels. For instance, it was masculine to use C but feminine to use Python. The masculinity of C follows from the same logic as hardware, as it is the language that Python is written in. In literal terms, C is *closer to the machine*. It is closer to “machine code” than Python, the code that is directly understandable by a computer’s central processing unit. Gendered cliques associated with programming languages emerged across events. As one attendee remarked, “Python is for noobs” because it is higher-level language that more resembles natural language, and is not for “real programmers”. One comment (joke) on the communication channel of the hackathon read: “Python is for girls anyway; everyone knows that PERL is the language of true men”.<sup>190</sup> When attending these events, my language of choice is Python, which made me the object of ample condescension. The hostility of the culture here equates good with *manly* and bad with *girly*, even perpetuating the stereotypes in joking. Notice here that the language uses an adult form of a masculine adjective, and a juvenile form of the feminine, a conceived power imbalance. Low-level languages are masculine as they are less abstract and closer to the machine, to the hardware, which means that they can run extremely quickly and directly on the processor. Higher-level languages (like Python) are “girly” as they have strong abstraction, meaning that the process of developing a programme is simpler and arguably more understandable.<sup>191</sup> Masculinity comes from the ability to use difficult tools well; tools that promise improved speed and power to those who can master them. Yet, even when women are striving for legitimacy by carefully selecting the tools they choose, it is unlikely that the skill and elegance of their code will receive much acknowledgement.

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<sup>190</sup> The language of “true men” as it is incredibly dense and a lot less friendly to programmers than Python.

<sup>191</sup> This tension of the masculine being closer to the machine, but the feminine being more understandable was discussed in depth in Chapter I, Section I, *How did we get here?*

Returning to my discussions with the hackathon organiser Annabel, she told me that: “eventually you receive some acknowledgement, it’s always, “wow you really wrote this? ... hey, you’re pretty good for a girl””. Women’s technical expertise was always thrown into doubt by their gender. It would also often be presumed by non-team members that women had not contributed to the technical background of the project at all. For example, in machine-learning based projects it was presumed that women would use (what I have termed for the sake of differentiating) “point and click AI”. Such platforms include Google Cloud AI, where the user works with an interface, rather than writing any code. Here, the femininity is the absence of coding, working with a simple user-friendly web-based interface. At one event, my team made it through to the final round of the competition which meant that we were to present our work in front of all of the attendees on the main stage. After we had finished presenting, I went to sit in the audience and a fellow attendee turned to me and congratulated me for doing such a good job on the presentation, adding: “it must be nice to just sit back and let the guys to the technical stuff”.<sup>192</sup> While frustrating, these comments allowed me to participate in the event as a woman does, and experience the embedded nature of being a woman at a hackathon. As I identify as a woman, I am able to experience first-hand what I observe and what is disclosed to me by participants. Overall, there is a gendered division of labour in programming and the selection of tools. In Wajcman’s (2009) terms, masculinity is found closest to the machine.

### ***“You’re not a real hacker without them”***

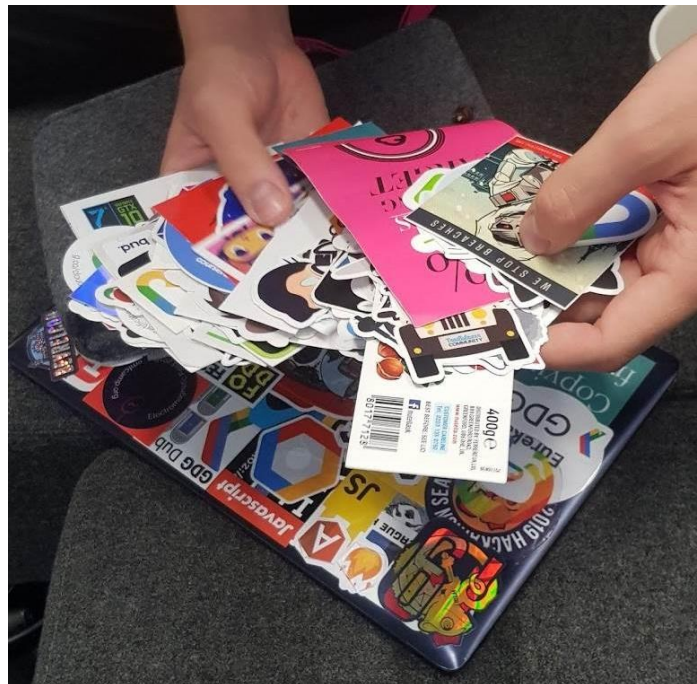
From the very first hackathon I attended stickers were everywhere. They covered the lid of every laptop, of every attendee, at every event.<sup>193</sup> The choice and placement of stickers might appear chaotic, but they were all carefully considered and arranged with precision. A hacker would often

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<sup>192</sup> Such comments were rarely refuted or acknowledged by my teammates, even when said directly in front of them.

<sup>193</sup> Unfortunately, I was using a laptop loaned to me by the department, so was unable to signal “belonging” to other attendees in this way. However, my high spec Lenovo ThinkPad did garner some appreciative comments from my teammates.

collect a sizable volume of stickers before placing a single one on the laptop lid. At one of the pilot studies I was able to sit with Andy, a previous organiser of another hackathon, who explained the stickers to me. Andy told me that the stickers appeal not only because of the graphic designs, which often featured cartoons, but they also reflected experiences and taking part in the culture. For example, In Figure 25, the shiny sticker of a chameleon with the number 19 is to show that Andy attended and showed his project at a hackathon associated with the 2019 League season. We can also see several stickers that referenced Andy’s expertise as a full stack JavaScript developer, meaning that he was able to write the software for both the user side (front-end) and the server side (back-end) of a website.<sup>194</sup> He also had a number of Google Developer Groups (GDG) stickers, relating to his participation in a Google initiative to create local communities of developers.



*Figure 25 Laptop Stickers at from a pilot study, Photo taken by researcher*

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<sup>194</sup> As it is focused on the part of a website that a user interacts with, front-end development is focused on how a website is used and what it looks like. This focus on appearance also means that it is feminised, concerned with making a website “pretty”. Due to the masculine dominance of hackathons, this gender division was less apparent than others.

Not only did Andy have the stickers on his laptop, but when I started questioning him about them he became very animated. He proceeded to reach into his rucksack and, after some searching, produced a small grey pouch. He tipped the pouch out on to the sofa next to us and a large collection of stickers of varying sizes, colours, and designs fell out (See Figure 25). He let me look through his collection, and was encouraged by my interest in them. There were several with a cat-like cartoon on them, which I recognised as Octocat, the mascot of the source-code hosting service GitHub. Andy shuffled through his collection, and picked out a particular Octocat. He proudly presented it to me and told me that “This Octocat shows that you met me!”. Andy also was a Campus Expert for GitHub, which meant that he represented his University and helped them access free software from GitHub and their partners (including IDEs software, Amazon, and Google Cloud). The vast majority of these stickers are not purchasable, they are only available at certain times and in certain places by meeting certain people. As such, a laptop covered in stickers is the ultimate signifier of belonging. The stickers show that you have participated in an event, have skillsets, and know the in-ways of the culture. I asked Andy if having the stickers would help with me fitting in at events, and he told me “Oh yes! You’re not a real hacker without them!”. Andy also pointed out how important it was for him to have a pride sticker visible, as it was “who I am”.

Stickers featuring the hackathon on the logo were available for attending events, with additional stickers being available for demoing. Sponsors would also have a range that they handed out to attendees, when approached at their stand. These were arguably less prized than the League stickers, which were seen to come with some status. The prevalence of these stickers throughout hackathons illustrates how their unique combinations could act not only as a curriculum vita, but also as signifiers of cultural belonging. To emphasise this, the women at events often had stickers that proudly proclaimed their competencies as technologists who were women. Some were the logos of organisations such as “Girls Who Code” and others were images of women in hijabs,

programming on computers. Therefore, simple laptop stickers were huge signifiers of belonging in technological communities, even in their rejection of the typed male-only programmer.

### ***“Fat guys on the Internet”***

Coleman (2010) proposes that the stereotypes of Red Bull drinking, eating junk food, and staying up all night are wrong. Nonetheless, my observations found that this cliché dominated the events.<sup>195</sup> Though women were poorly represented, the events did not reflect a default whiteness. I surmise that this representation is most likely due to the events taking place in larger multicultural cities in the UK, and being attended by students and young people within an hour radius of travel – which usually encompassed London.<sup>196</sup> The stereotype of hackathons outlined by Coleman (2010) was often referenced when attendees were discussing what their expectations were.<sup>197</sup> In one illustrative instance, a team member returned to our table with his arms full of Red Bull energy drink. He was carrying such a large number of cans he had to drop them all on the centre table and they cascaded across the surface. He laughed as put them down and exclaimed: “If we’re going to ruin ourselves, we may as well do it in style!”<sup>198</sup> This statement was met with a round of laughter, as each group member reached for a can of the energy drink. As well as an abundance of snack food and drinks provided throughout the day, pizza deliveries would arrive at midnight, and sponsors would also hand out chocolate and other small prizes. There would be some fruit juices and fruit provided, but these did not run out.

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<sup>195</sup> Coleman’s research focused on civic (political) hackathons. In my wider experience of attending hackathons, civic events tend to be more heavily associated with political solutions and generally attract participants with less programming experience. Civic events are more politically minded and less focused on what is technically possible.

<sup>196</sup> Particularly in the Midlands and the north of England.

<sup>197</sup> This could be evidence of Anthony Giddens’s double hermeneutic, but is also likely due to the prevalence of geek masculine tropes in programmes such as *The Big Bang Theory* or *The IT Crowd*.

<sup>198</sup> Alcohol was generally discouraged by hackathon organisers and wasn’t observed at any event.

***“This place is going to stink!”***

As well as comments on the stereotypical geek nature of the snacks provided, there was also verbal acknowledgement of embodiment in smell. At the same time as the teams were setting up they would acknowledge the physicality of the venue and the demands that a 24-hour work marathon (and 36-hour event) would have on their bodies. Smell was a constant source of comment and reflection across all events, encapsulated in the common phrase “this place is going to stink!”. As an experience mediated by a social world, smell has distinctly gendered associations.

In addition to objects, sensory experience indicates ambient belonging. Taste, smell and touch are all noticeably absent from many ethnographic accounts. The anthropologists Luhmann and Stoller (1991) argues for the inclusion of sensory aspects of fieldwork as a vital element of understanding. Drawing from the work of Simmel (1950), senses lead to an emotive response and contribute in practical terms to a relationship with another person. Senses, for Simmel (1950), mediate social relations. In theorising sensory ways of knowing, McSorely (2020) argues that smell provides a direct and continuous supply of information from the surrounding atmosphere, which cannot be switched off and is reinforced with every breath. For McSorely (2020, p. 157), smell “continuously mediates between the present and the absent, the proximate and the distant, the interior and the exterior”. Smells are a fundamental experience of our environment and we understand them as “good” and “bad”. The dichotomous polarisation of odours is intrinsically gendered. “Men are supposed to smell of sweat, whisky and tobacco . . . [while] women, presumably, are supposed to smell ‘good’: clean, pure, and attractive” (Synnott, 2008, p. 449).

The “stink” of hackathons described by attendees, and noted by the researcher, marks the space as masculine. They are distinctly flavoured with an aroma of body sweat and junk food, which strengthens as the event goes on. The multiplicity of masculinity embraces bodily odours as a facet of geeks and more hegemonic forms in athleticism. However, geek masculinity has strong associations with poor bodily hygiene, which is referenced in the culture’s own collection of

stereotypes. The playful concept of *neckbeards* was also discussed at the hackathons. In one of my pilot studies, I asked an attendee who used the term if they could explain what it meant. They replied “It’s for like fat guys on the Internet who like have bad hygiene, don’t look after themselves, and have their beard growing out of their neck”. Another team member (who identified as a woman) added: “neckbeards are also arrogant and immature, and like, hate women”. It was accepted among attendees that “stinking” was both a stereotype of the attendees (neckbeards, masculine geeks) and a practical result of working on a project for 24 hours, and sleeping in the same clothes. Gender served to mediate its reception.

### ***Conclusion: Ambient Belonging at Hackathons***

The materiality of hackathons marks them as masculine spaces. Though there are indicators of non- male bodies, in pronouns on name badges and sanitary products, without additional measures this is tantamount to virtue signalling. There is space for signalling inclusions and belonging in the clothing provided by the hackathon and vendors. At no event were women provided with anything other than a small man’s size. As Chang (2019) shows, women in technical cultures often obscure their femininity in loose-fitting clothing through a combination of choice and necessity to function in the masculine environment. The embodiment of hackathons is stereotypically masculine, riddled with the signifiers of geek masculinity, in Red Bull and junk food. The sensory experiences of hackathons as smelling masculine characterise the extended adolescence of geeks.

### **Fedoras, Virgins, and Irony**

Here I will outline the observations that related to memes and wider Internet culture. My aim is to demonstrate that in examining gender as structure in creative coding we should be careful not to emphasise an offline-online dichotomy. Unless technology is actively avoided, it is involved in the everyday experience of sociability. This section shows how the jokes of creative coding culture are simultaneously communicated across electronic and embodied interaction.

### *\*Tips Fedoras\**

In contrast to Coleman (2010), my observation of hackathons a decade later found an abundance of stereotypes, surpassing my expectation. In the opening epithet of this study, I recount how I was able to find the venue of the hackathon by following the young men who embodied the stereotype. Geek masculinity was an ever-present, defining feature of the hackathons, which organisers often leaned towards. At a hackathon in Eastern England people who attended four Sponsor Workshops were rewarded with a hackathon branded fedora (Figure 26). For the uninitiated, the links between technological culture and a hat associated with film noir might appear unclear, but it encapsulates intensely gendered meaning in its associations with “nice guys”.



*Figure 26 Branded Hackathon Fedora*

The fedora has become a symbol and perfect memetic representation of socially awkward, usually white, young men.<sup>199</sup> These men are seen to be gauche and pretentious, wearing the hat in a bid to appear interesting to others. The humour of the fedora memes are fundamentally cringe-based,

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<sup>199</sup> Fedoras were worn at hackathons even when they were not provided as a joke by the organisers.

a form of humour that is particularly popular on platforms such as Reddit and 4chan (Massanari, 2015a). The fedora, and the young men wearing it in iterations of the meme, are direct references to the heterosexual incompetence that Kendall (2011) points to in geek masculinity. The association of the hat and this incompetence are encapsulated in the memetic phrase *\*Tips/Doffs Fedora\**, “*M’lady*”.<sup>200</sup> Intentionally addressed to women, the phrase refers to the misogynistic practice of men assuming that women need to be helped or defended, with the expectation of romantic/sexual reward in return. At the hackathon in Eastern England (with the branded fedoras) the phrase “tips fedora – m’lady” was frequently repeated throughout the event<sup>201</sup>. Memes can function as communally agreed stereotypes, representing how a collective understands gender (Brooke, 2019a; Milner, 2013). There was verbal joking as hackers proclaimed they were “just nice guys!”. Another layer to this memetic object is that the fedora wearer is likely to become hostile and outwardly express misogynistic aggression, if their advances are not well received. Returning to the hackathons, it is likely that the fedoras are intended to be ironic, the organisers found humour in leaning towards the geek stereotype. It is also reflective of in-grouping, as the joke choice of a branded fedora was never explained. My observations led me to conclude that the ironic intention behind the hat may not necessarily be realised by all of its wearers. This possibility is supported by the fact that hackers bring their own fedoras to events. Even in its supposedly ironic use, it propagates a geek masculine, male nerd, stereotype. It is uniquely worn by men throughout the event and signals that the in-group is not only geeks, but male.

### ***“Dank memes are not offensive ones”***

As outlined in the description of these events, it is commonplace for cloud-based instant messaging platforms Slack and Discord to be set up for attendees of events to communicate and

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<sup>200</sup> Note here that the \* symbol is used to denote action. By wrapping the phrase “tips fedora” in the asterisk, the indication is that the hat is being “tipped” in a bow of the head as an indicator of chivalry and flirtation.

<sup>201</sup> This statement was not repeated to women specifically, but was a larger recognition of the gendered “nice guy” trope.

for organisers to send out announcements. At each hackathon, memes were widely shared among participants in the public channels prior to and throughout the event. At a hackathon in the West Midlands, the meme channel had the message “dank memes are not offensive ones” pinned to the top of the message board. A “dank meme” is an ironic expression to describe memes that reflect in-jokes that are intentionally bizarre or trite (Wells, 2018).<sup>202</sup> While the origin of the term is unknown, it is generally understood that “dank” was originally coined as a term for high quality marijuana, and it is used satirically as a synonym for “cool” (KnowYourMeme, 2020). At the same time, there is an intrinsic acknowledgement that memes can be “offensive” (For a detailed discussion see Brooke, 2019). The tagline “dank memes are not offensive ones” is thus a comment on producing in-joking memes, and warns against posting those that are openly hostile.

At one of the hackathons there was an explicit “best meme competition” with a dedicated Slack channel in which submissions were posted. The prize was a drone, which was considered to be quite substantial by the hackers. The winner was decided by a popular vote of attendees. Now understood as a crucial unit of online communication, memes embody shared experiences and group knowledge within a given culture (Brooke, 2019a; Maddox, 2017). Although memes are usually characterised by their virality and spread, these memes represent the defining of cultural boundaries and the creation of boundaries in who gets the joke (Milner, 2013). Here, the memes operate on the basis of an understanding of technological culture and of hackathons. The image in Figure 27 is known as the Distracted Boyfriend; it is a *labelled stock photo* in which a man looks at a woman who passes him as he is walking with another woman, presumably his partner, who looks at him appalled.<sup>203</sup>

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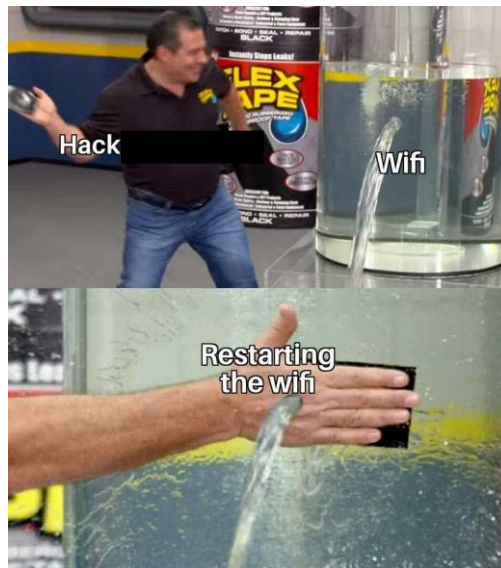
<sup>202</sup> Arguably, the bizarreness is in relation to how much it has mutated from the original, but it still serves as an in-joke and a reference to the original form.

<sup>203</sup> *Labelled Stock Photo* is the meme genre of the Distracted Boyfriend.



*Figure 27 Hackathon meme submission: Distracted boyfriend*

As in the format of the Distracted Boyfriend, gender in memes is defined by the male gaze (Brooke, 2019a; Milner, 2013). Memes are largely authored from a masculine perspective, which is normalised in the male-dominated spaces of hackathons. Figure 27 uses the format of the meme to suggest that attendees of the event might choose to make memes for the chance to win a drone, rather than work on more typical hackathon projects. Though memes were popular and shared at all the events attended, the competition element illustrated the substantial overlap between event attendees and online cultures of meme sharing, such as Reddit. The majority of memes submitted to the competition directly reflected experiences happening at the event. However, this somewhat backfired for one of the hackathons when attendees began posting memes that reflected their dissatisfaction with the running of the event and the resources available. In Figure 28, there is a selection of memes that were taken from the meme channel that are reactions to the Wi-Fi repeatedly going down and the announcements that the organisers were no longer providing travel reimbursements.



nurse: sir... you've been in a coma since Saturday night

ME: Oh boy, can't wait to get my travel reimbursement



Figure 28 Hackathon attendees comment in the event through memes

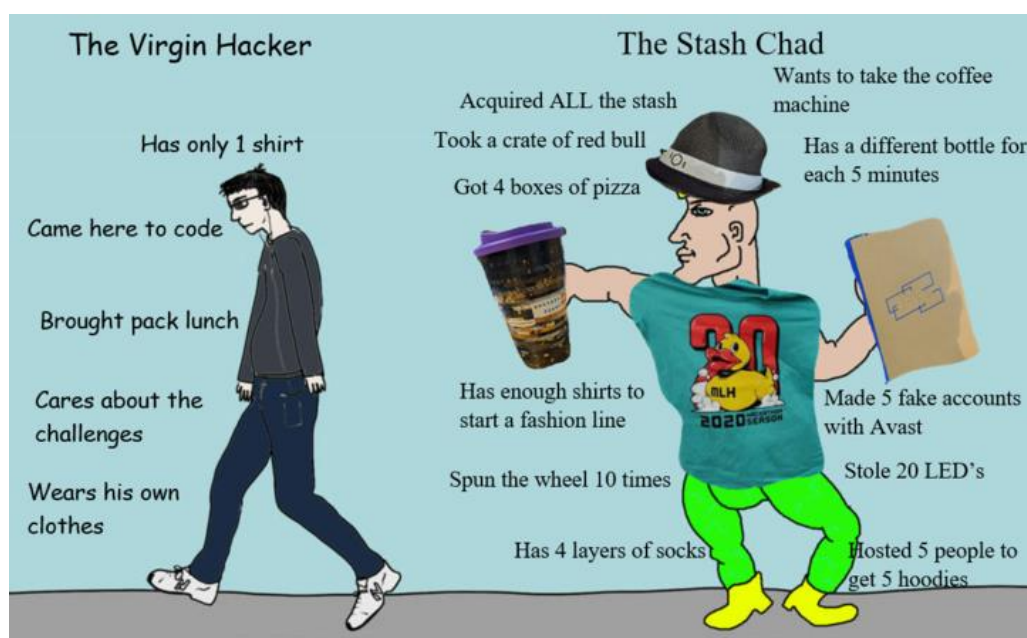
These memes show a shared experience of the event, and create in-group belonging as the experiences they narrate make sense within a particular context, posted in real time with the experiences of attendees and immediately distributed through an online instant messaging platform.

In addition to the branded fedoras being a reference to memes, there were physical humour jokes that were memetic in origin. The most common examples were dabbing, flossing and the T-pose. First, dabbing originally refers to a type of hip-hop dance, where one arm extends outward, and the other is bent – covering the face. In a similar vein to “dank”, dabbing refers to ironic coolness within online cultures. Similar to dabbing, “flossing” is a dance move popularized by the game Fortnite. In the game the dance is largely used to celebrate a victory or to goad opponents, which simply involves moving your arms from side to side and alternating one behind your back. The final embodied meme that was enacted across events was the T-pose, which is the default unanimated stance of video game characters, their legs together and their arms directly outwards. It is heavily associated with Super Smash Brothers game, due to a glitch in the version for the Wii U. Flossing and the T-pose are clear indicators of the geek masculinity associated with computer games and ironic joking. Though dabbing is more widely known, hip-hop traits are often adopted by geek masculinity made humorous by their self-awareness that they are “white and nerdy” (Kendall, 2011). Individuals are able to gain social standing by referencing culturally shared images in embodying memes. Memes here are profane, they are the common units of interaction both online and offline that define and bound the culture in terms of gendered competency.

### ***“The Virgin Hacker and the Stash Chad”***

Indicative of the irony that is common thread in geek masculinity and associated cultures, memes also reflected the attendee’s own identity. The images posted to the hackathon with the meme challenge were often more reflective than the more general memes shared across all events. Due to this particular event having a competitive element with a not insignificant prize, memes were more original, using popular formats to express the attendee’s experiences and understandings. Memes here are a reflexive identity resource, with the sole purpose of being objects of sensemaking in the cultures they are intended to be consumed in. A particular differentiation of masculinity that was visible to me as a researcher was perfectly encapsulated in a meme that was entitled “Virgin Hacker vs. Stash Chad”, highlighting a dichotomy between geek masculinity and

the more hegemonic gender performed by the representatives of sponsors at events. In general, the Virgin vs. Chad meme originated from 4chan and refers to a series of illustrations drawn in Microsoft Paint, in which a “Virgin” man with low self-confidence is compared to their “Chad Thundercock” counterpart.<sup>204</sup> It is worth pointing out that what underscores the memes is that the intended audience identifies with the characterised Virgin and not the Chad.<sup>205</sup> Virgin here encapsulates both the literal meaning, but also a reference to people (men) who maintain activities that are time-consuming and may be deemed unattractive to the opposite sex. As such, the meme in Figure 29 reflects this self-parody.



*Figure 29 The Virgin Hacker vs. The Stack Chad*

<sup>204</sup> Chad Thundercock is a nickname for any attractive, popular men who are sexually successful with women. “Chad” refers to a popular name used in American media for athletic men, which Reddit refers to as “alpha douchebros”.

<sup>205</sup> The virgin identity and Chad label are closely associated with “incel”, a now colloquially well-known term which is a portmanteau of “involuntary celibate”. Although it is not the topic of this project, the incel is a particularly toxic trope that falls in the purview of geek masculinity. It has been proven to be dangerous and warrants further engagement and critical consideration.

“Stash” is a word used to refer to branded merchandise of any description, and is produced by a range of institutions from start-ups, to banks and universities. The “Chad” in hackathons is not the athletic alpha male type that is typically the subject of the meme; he is even wearing the branded fedora. Rather, the Chad is a culturally-specific depiction of undesirable masculinity. He is seen to attend hackathons for the purpose of free clothing, food/drink, and accessories. The Chad also unfairly accrues technological resources, such as “5 fake accounts with Avast” (an Internet security application) and “stole 20 LED’s” (light emitting diode - hardware). By contrast with the Chad, the Virgin Hacker “cares”. He came to the event to write code, and even brought his own lunch. As stated, hacker is the standard descriptions of attendees of hackathons, and is indicative of the Virgin being the in-group and the negative associations of being a Chad. The implication is that those who consume stash and the freebies at the event with too much vigour are not real hackers. Sex, or lack of it, is repeatedly a defining factor of geek masculinity (Kendall, 2011). What is absent in this playful approach to masculinity is any representation of femininity or women. Whilst these memes poke fun at masculinity, they mark the space as gendered. One meme simply involved the following text on a plain white background “Day 977 without sex. Still studying computer science”. In heteronormative joking about male virginity, women are outsiders in a toxic framing of masculinity. The absence of women is confirmed in heterosexual, male virginity.<sup>206</sup> In this masculine narrative those who are competent with technology are incompetent at sex in an equal measure, as if it the two are mutually incompatible.

Masculinity is not contested by these two representations of Virgin and Chad; we are just debating the terms. Women’s absence is so apparent that masculinity itself is dichotomised into types. Multiple masculinities are present in hackathons not as tensions, but as discrete characterisations.

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<sup>206</sup> Chang (2019) points to how women at tech companies will make jokes about how working in programming removes them of their sexual appeal. Technology is masculine, but associated with the heterosexual incompetence of Kendall’s (2000) geeks.

The depictions of masculinity are not sincere, and instead are intended to reflect stereotypes of hackathon attendees. The joke is that even within the un-cool culture of geek masculinity there are still “Chads”. They are ironically portrayed against the Virgin Hacker, in an expression of irritation at their accumulation of resources. Overall, there is an ironic commentary on the masculinities of hackathons.

### ***Stack Overflow Memes***

Another cultural artefact that appeared in memes was references to Stack Overflow (SO), the subject of Study II. This reference was expected, and ratifies the choice to include the analysis of the forum in this project. Memes that focus on SO usually focus on the indispensable nature of the site for programmers of all abilities, fields, and purposes. References would appear in a range of meme formats: a popular example from one meme channel is shown in Figure 30. The genre is referred to here as “Meme Man”, a poorly drawn 3D head that was the mascot for the Facebook page, “Special meme fresh”. It is known as a surrealist meme as it’s a form of irony that is artistically bizarre and where the humour is derived from its absurd style.<sup>207</sup> The format is especially popular among programming communities, where it incorporates purposeful misspellings. Purposeful misspellings are common across several genres of memes, most notably LOLCats (For a more in-depth discussion, see Miltner, 2014). Examples for the Meme Man include “tehc” (tech), “data siens” (data science), “codd” (code/coding). The misspelling accompanies a caption which references a tech in-joke or practice. The image in Figure 30 is an example of this format, where the joke is the indispensable nature of SO. Note that C.S. stands for Computer Science.

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<sup>207</sup> Although not directly relevant to its usage here, Meme Man is frequently used in a practice known as “shitposting” in which a conversation is intentionally derailed by nonsensical or insubstantial comments. It is low effort content that is intended to derail a conversation through noise, rather than antagonism.

When all the code you submit for  
ur C.S. projects is actually just a  
bunch of stackoverflow snippets



*Figure 30 Stack Overflow Meme Man from the dedicated meme Slack channel*

As before, the central characters of these memes are referenced as masculine. Though the meme is less context-specific than the Virgin vs. Chad meme in Figure 29, it highlights the default masculinity that is perpetuated in memes (Brooke, 2019a). As well as referencing the use of SO, some of the memes shared also referenced the culture of the site as hostile. Figure 31 features the *They're the Same Picture* two-panel meme based on a scene from the American sitcom *The Office*.<sup>208</sup> In the top pane, there are two images and the point is that the right picture is either derogatory or complimentary. In the image below (Figure 31), Stack Overflow is shown next to an image from the videogame *DOOM: Eternal*, picturing a battle scene that takes place in hell. The meme is making the point that SO is hostile and antagonistic, indistinguishable from a hellish scene.

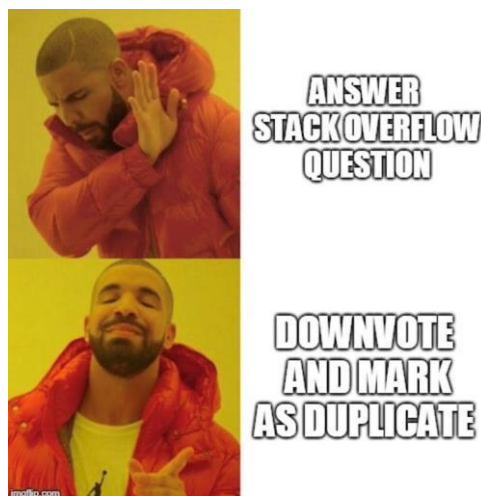
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<sup>208</sup>The Office was originally British, but was remade for an American audience.



*Figure 31 They're The Same Picture: Stack Overflow as Hellscape*

It is also worth noting that the meme is yet another reference to the inseparability of technological culture from memes and video games. Another submission that was of particular interest in demonstrating the interpretation of SO by event attendees is displayed in Figure 32. The meme is known as Drakeposting or Drake Reaction, and originated from the Canadian music artist Drake's music video Hotline Bling. The top pane references disgust at the image displayed to the right, and the bottom pane is satisfaction or approval. The typical usage is sarcastic or ironic, or at least not literal.



*Figure 32 Drakeposting: Stack Overflow*

Taken together, Figure 31 and 32 show that SO is hostile and unwelcoming. Figure 32 adds another dimension to this, highlighting the specific behaviour of downvoting and marking user's contributions as duplicate. These activities, along with the comments to "check the documentation" and "we're not here to do your homework", examined in Study II, are typical aggressive behaviours on the site. In general, SO is referenced as indispensable but tainted by hostile and unhelpful behaviour, which is a strong material link with Study II of this project.

### ***Conclusion: Internet Culture Offline***

Hacker culture is characterised by its manifestations online and offline. These are not diverging spaces, but rather the hackathon is a ritualised, condensed expansion of creative coding culture. Rather than reflecting a divergence of culture, in which the body is re-membered, offline spaces represent a continuation of the culture and structures of gender that are so pervasive online. Not only are memes shared simultaneously to the event, bounded in the spaces of purpose-built instant messaging platforms, they are physical and tangible objects. Memes are no longer panelled images and impact font captions, but are ironic and embodied. Dabbing, flossing, and T-pose are typical of this transference. Rather than considering the mode of communication as the unit of analysis, it is sensible to focus on the boundedness of the culture. Technology cultures are mediated by gender as a social structure, meaning that understandings of gender are present across forms of communication. The ritualism of gender at hackathons is inseparable from the everydayness of memes.

## **Section IV: Hackathons, Inclusion, and Exclusion**

The following section serves to align the themes that emerged from first-hand observation to the wider context of scholarly research. In doing so, I will first outline the concept of ambivalent irony, and how this propagates prejudicial interaction. Next, I will examine the materiality of hackathons, aligning my work with Cheryan et al.'s (2009) framework of ambient belonging. This paves the way for an examination of hostile and benevolent sexism, and the distinct forms these take in masculine technical culture. I will then propose that the tendency of technology culture to describe sexism as a phenomenon that exists at an individual level is part of the reason it is able to continuously propagate, agile in its movements between modes of communication. I will conclude with the contribution of this study to the wider project of this thesis.

### **Ambivalent Irony**

A common theme throughout the sociability of hackathons was irony, palpable in vocal comments, clothing, memes, and fedoras. Irony is a contested term for scholars, used and defined in a myriad of ways and subtypes (Colston & Lee, 2004; Davis et al., 2016). Broadly, irony is when meaning is expressed in communication that indicates the opposite of the surface interpretation. Irony is amusing to those who get-the-joke and the full significance of irony is for the interpretation of the audience. When irony is ambivalent it is indistinguishable from earnestness. In his study of humour online, Milner (2016) refers to how the legitimate expression and satirising of identity are indistinguishable, unless the author states their intent. This ambiguity defines the antagonism associated with online anonymous communities (Milner, 2013). The uncertainty is clear in the hackathon branded fedoras, the humour of which was never clarified.

Irony is used for a number of pragmatic functions, including: to be humorous; to express surprise; to express mastery; to diminish/enhance criticism; to highlight a deviance from expectations, or to show negative emotion (Colston & Lee, 2004). Such narratives of irony reflect an ambiguity -

an ambiguity of masculinity, oscillating between approval and disapproval thereof. Irony can thus be used to destabilise the notion of a coherent and visible masculinity, a prime example of which is the “Virgin v. Chad” meme. The irony functions to reference the cultural knowledge of the fedora-wearing “nice guy”, aiming to highlight a disjunction between the memetic reference and the attendees of these events. Although the authorial or original intention of irony is evasive, one may presume that it was not the intention to paint the event attendees as misogynistic, involuntary celibates, who hate women. Rather, it was an ascertaining of a cultural boundary, a situational in-joke, and a translation of an Internet joke into the material world. Irony thus works to encompass the contradictions and tensions of masculinity at hackathons. It serves to bring together hegemonic norms and geeks, oscillating between depictions in a boundary-setting ironic knowingness.

More than a vehicle of cultural knowledge, irony is a fundamental part of online communication that favours distanced critique. In his work on Internet memes, Milner (2013) points to how the ironic logic of anonymous online spaces antagonises the core identity categories of race and gender. In mocking these categories, the irony-laden communicative practices reinforce their essentialism. The playful nature of satire and parody can disguise the antagonisms that replicating this humour offline entails. Here the boundary is blurred between the earnest sexism and misogyny of the fedora-wearing “nice guys” and the ironic use of this concept by hackathon organisers and attendees. As with Milner’s (2013) analysis of memes, the joke reflects the banal standard and irony can shelter bigotry. As the description of hackathons shows, irony was not only present in the fedoras. Ironic inflections of masculinity were present in references to “Chads”, “lvl 99 wizard ... mother of dragons” (Dungeons & Dragons and Game of Thrones references), to “being a man” and “alpha”, and even in the ironic (cringe) coolness of dabbing and flossing. The default masculinity of online spaces is translated into the satirical joking at hackathons. The ironic lingua franca of anonymous online spaces illustrates how the sexism of

Internet spaces is equivalent to the culture of hackathons, with sufficient ambiguity to negate responsibility.

In his work on memes, Reddit, and 4chan, Milner (2013) refers to “antagonistic irony”. Here, the dominant discourse can be sexist or racist in its irony, but as the banal standard it shelters bigotry. In these cultures, ironic commentary reinforces negative stereotypes and “the blur between irony and earnestness makes room for discourse otherwise impermissible”. In hackathons this blurring is key, and any retorts or countering perspectives are quelled with claims to joking. Irony, and the cultivation of the ironic, are fundamental to Douglas’s (2010) enlightened sexism. Douglas’s (2010, p.13) argument is that it’s a joke on the men: “it’s silly to be sexist; therefore, it’s funny to be sexist”. This perspective is particularly prominent in the fedora joking and m’lady comments that reference these ideas. Irony serves to deflect and negate the stakes of falling short of hegemonic norms. In the same manner, by ironically referencing the fedora, the hackers are showing that they also fall short of the toxic, predatory “nice guys” stereotype. The fedora is a joke on men. They are defining their identity in rejecting hegemonic and toxic masculinity, but both tropes paint women in sexualised and romantic terms. In propagating these stereotypes through the vehicle of humour and irony, one is propagating sexism and the idea that men and women are fundamentally different.

## **Objects and Ambience**

The importance of objects is demonstrated in the research carried out by Cheryan et. al. (2009) into Ambient Belonging. As discussed in Chapter I, Section II, ambient belonging is generally the feeling of fitting into an environment, specifically referring to the material objects and structural (layout) components, as well as the people seen to be occupying the space. Cheryan et al.’s (2009) research shows that objects that signify geek-masculine culture can deter women from participating in technical spaces, even when the spaces are populated by women. Hackathons are overwhelmingly populated by men and objects associated with geek masculinity. Although there

are artefacts such as tampons that indicate a non-masculine body, without the presence of women at events they go unnoticed.

Adolescence is also perceptible in the hobbyist collecting of objects, the most prominent of which was stickers.<sup>209</sup> Stickers are an intricate part of the culture, a personal story of interactions and meaning - a record of an individual's involvement in coding culture and hackathons. The assertion of the otherness of femininity was encapsulated in the political statements of "girls can write code". Even in writing code, women were acutely associated with practices denoting relative ease and simplicity. Coding practices were dichotomised into the mastery of men and the inability of women. Building on the discussion of feminine "coders" in Ensmenger's (2003, 2010) history of computing (discussed in Chapter I, Section I), hackathons show how lower level languages are more masculine and higher level languages are feminine. Being feminine and competent at a hackathon was a political act, outside of the ordinariness of creative coding culture. Masculinity here is materiality, physicality, and closeness to the machine.

## **Benevolence and Hostility**

Whereas hostile manifestations of sexism were more present in online spaces, benevolent forms were omnipresent at hackathons. Benevolent sexism is affectively positive but is still patronising and condescending in that it encourages women to embrace traditional gender roles (Glick & Fiske, 1996). In their study of STEM classrooms (Chapter I, Section II), Kuchynka et al. (2018) propose that increasing institutional pressure and raising awareness of discrimination may hamper more overt, hostile expressions of sexism. However, in a non-traditional environment, the potential social and legal sanctions may constrict manifestations of sexism to its more benevolent forms. The point of hackathons is collaboration and working with others to create a project or

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<sup>209</sup> The collecting of stickers appeared adolescent as it was reminiscent of early-teenage preoccupations with trading cards, such as Pokémon or Match Attax Football cards.

artefact. Fundamental to this is collaborative problem-solving, working together to develop new knowledge in a temporary organisation structure complete with a CoC.<sup>210</sup> As was evident in the team selection procedure, at hackathons, the different expertise of potential team members forms an element of the selection process. However, the benevolence of hackathons means that geek masculinity is the arbiter of technical knowledge. Women have no right to expertise, and their every choice or assertion is frequently Questioned, doubted, and ignored. Even when they show competence directly or indirectly through joking, they are treated as illegitimate. Benevolent sexism is manifested in condescension. This “white knighting” creates a position of power, a Mertonian (1961) status set in which the woman is a damsel, waiting for her male saviour. As the dominant group is authored, the feminine is implicitly defined. This misogynistic process of classification is the product of the Madonna-whore complex, which is the inability for women to be visible as anything other than “mothers” or “whores”. This dichotomy stems from the reinforcement of gender norms, fundamental to ambivalent sexism (Glick & Fiske, 1996).<sup>211</sup> Sexism thus creates a cast of characters. Each role for masculinity is strong or capable, whereas the feminine is subjugated.

## **Hacking and the Individual**

Gender in hackathons and hacker culture is understood at the level of the individual. This understanding of gender means that success and discrimination are always understood in individual terms. The success of an individual woman is taken as proof against the pervasive nature of sexism, and discriminatory behaviour of an individual is seen as a one-off. This is typical

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<sup>210</sup> Like Bechky (2006), I find that temporary organisations use a role-based structure in order to maintain coherency across events. Although Bechky’s work into film sets looks at the professionalization of roles, the nuances of which are negotiated in context, my work examines the emergence of gender roles. These roles are not named positions, but rather the norms and expectations of women based on gendered identity categories.

<sup>211</sup> The role of dichotomisation in establishing scientific norms is discussed in the Introduction to this project.

of the geek-revenge fantasy, where the geek gains prestige and social capital through a start-up. The start-up culture and the geek mix into Hick's (2013) programmer. Gender as structure is embedded in the capitalist networks of start-up culture, and hegemonic masculinities play an important role in attracting capital investment (Plante & Maurer, 2018). As technological development is a humongous industry, the structure of gender in capital and banking feeds into creative coding culture. At hackathons, an ideal outcome of the events was seen as the formation of a start-up, with many of the prizes reflecting capital investment in the idea produced at the event. The idea is that hackathons are the spaces in which geeks take risks in the projects they create, with the opportunity to receive financial investment.

## **Conclusion: Invisible Women**

This study illuminates how gender assigns technical knowledge at hackathons. Like Stack Overflow (Study II) hackathons are male-by-default, in which multiple forms of masculinity compete for status and recognition. Aligned with the findings of Study II, I find that gender structures dictate legitimacy across in-person and online interaction. The presence of Stack Overflow at hackathons was not only a validation of the multi-sited approach of this project, it also supports my claim that the focus of research should be culture and not form of communication. Sexism was found at each site, not because sexists happened to be there but because sexism is a feature of technology culture.

My participation in hackathons showed how gender norms are reinforced by ironic joking. This playful interaction acknowledges culturally masculine hegemonies, whilst maintaining the plausible deniability of its "just a joke". In joking about prejudice harmful stereotypes are permitted. All rebuttals and protestations are condemned as "social justice", as the speaker is ostracised for not participating in the boundary making. To engage with technology culture women must consent to their subjugation, accept being explained to and relinquish their femininity. In this context the feminist is once again a "killjoy", dispelling the collective myth of

equality (Ahmed, 2010). Whilst femininity is only permissible in terms of technological incompetence, masculinity thrives. Programmers and geeks compete for validation, vying for domination over technology. The status of a particular skill shifts with associations of gender; the masculine hardness and closeness to the machine is constantly defined in opposition to femininity. As gendered dichotomies define desirable skills, the masculine is ratified as superior. Whilst femininity is always the undesirable, the particular skill association is fluid. One moment a particular programming language might be more masculine than another, based on it being a more abstract and complicated. The next moment, the same language is feminine, when used for “pretty” user interface design. To associate with femininity is to deprecate and dismiss. Even in ironic joking the pejorative connotation of femininity is repeated and remixed, all opposition is dismissed as not “getting the joke”. Python, after all, is for *girls*.

Sexism is found in the details, in the everyday ordinary interactions at hackathons. My work extends Cheryan et al’s (2009) ambient belonging, show how *belonging* is not just indicated in objects but in how culture is reproduced in lived experience. Women are made invisible, they are not accounted for in both literal and figurative terms. It is one thing to not be provide clothing and “stash”, but it is another entirely to not even be seen. To be in the bustling and intense enviroment and fight to merely have your gaze returned. To be walked into, jostled and stepped on; a reminder that you are taking up space not intended for you. To experience this, to feel as if you are haunting the hackathons, to be an unwanted and unwelcome presence, is how sexism works. Women’s mere attendence is simply not enough if they do not participate or return to such events. Sexism is in implicit assumptions of feminine emotionality, diametrically opposed to geek social ineptitude. Femininity is opposed to the anti-social masculine traits associated with technological knowledge. Women are expected to be care givers, constantly enacting emotional work whilst accommodating the fragility and social awkwardness of the geek troupe. The ordinariness of sexism in technology is what has allowed it to survive, thriving in associations of technical knowledge.

Overall the combination of methods in this project shows that gender and culture exist outside the modes of communication that shape them. In this structure, the gender roles and power structures are apparent online and offline, across platforms, and even in sharing memes. Broader cultural norms of sexism and masculine dominance are expressed through expectations of knowledge, who gets to know about software/hardware or who uses Python/C. In seeking legitimate participation, hackers re-enact tropes leading to the reproduction of broader sexism, which is fundamentally exclusionary. For the typically isolated, anti-social geek, engaging in practices of exclusion reinforces in-group social bonds and belonging. This perspective is most representative of how users interact with each other and the culture at large. What I find at hackathons is that sexism exists in the details; small instances of dismissible prejudice. But these apparently small experiences are tributaries. They flow into power structures that are carved by gender, forming the norms of interaction. Each instance is disregarded as inconsequential, but to understand sexism in this individualistic fashion is myopic. Rather, it trickles into each interaction, and in technological culture it serves to burst the pipeline.

# CHAPTER V

## CONCLUSION: BREAKING THE GENDER CODE

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*“You can always tell ambitious women by the shape of our heads, they’re flat on the top from being patted patronisingly.”*

- Dame Stephanie Shirley<sup>212</sup>

In writing this thesis I, a woman, learnt to code. This project originates in my own experiences, the research is grounded in a formal investigation informed by personal narrative. In much computational work, code is discussed in value-neutral terms, without acknowledging how it is imbued with the values of its creator (Latour, 1999). As such, this project problematizes methodological (quantitative/qualitative) and theoretical (data science/gender studies) binaries, to present an analysis of gender social structures. My enquiry takes place, not only in ethnography, but also in every line of code. In my methodological design I embedded non-binary understandings of gender as value into my code. In the wider project, I dismantle claims to fairness and meritocracy in programming, showing how gender dictates the evaluation of technical knowledge. In Study III, the lived experience of coding was visible in my literal, physical, positioning within the culture. My participation in programming at hackathons was an original contribution to the literature, as I was able to be immersed in the hacker’s story of creation

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<sup>212</sup> Fittingly, Dame Stephanie Shirley is the founding donor of the Oxford Internet Institute.

and competition; a participant in the fullest sense. Moreover, in Studies I and II, I was similarly ideologically situated in the practice of a woman learning to code. I was building my skills in R and Python and debugging my scripts on Stack Overflow.

My research design, then, was informed by my experiences as a computational researcher interested in gender, as well as by the literature. Outside of hackathons I often experienced sexism, most commonly in the assumption that I didn't possess the necessary skill set to undertake a computational project.<sup>213</sup> Furthermore, as I used Cross Validated, Data Science Stack Exchange, and Stack Overflow, the condescension and masculinity of the platforms created tiresome everyday problems that required troubleshooting from the very beginning.<sup>214</sup> Through my interactions with computational researchers and others with technical skill sets, gender assumptions continued to be a part of my daily experience. Those who employ computational methods within the academy are not immune from the masculinity of creative coding culture. At the same time as my research revealed the rampant nature of sexism in computational culture, these findings were reflected in my own experience of this culture, where women were ostracised at every level. I thereby had the ironic misfortune of becoming the subject of my own investigation. As such, the entirety of this project is participatory research, situated in the experience of a woman learning to code.

## **Where do we go from here?**

Prior to summarising my findings, I wish to highlight the absence of intersectionality in my writings. Whilst this project does not aim to obscure disparities that are the result of racism or pro-Western bias, its focus on gender alone may tacitly do so. By acknowledging this omission,

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<sup>213</sup> This is not to imply that computing was my first experience of sexism in academia by any measure.

<sup>214</sup> Both hosted on the Stack Exchange network that arose from Stack Overflow, *Data Science* focuses on the problems and doubts that data scientists encounter on a regular basis while *Cross Validated* is more statistically focused.

it is my hope to point the way to future avenues of investigation and activism. Based on my research into how gender mediates creative coding cultures, Appendix V details concrete measures to advance women's inclusion. I had intended to pilot some of these measures as part of my research. However, the opportunity to do so was removed due to COVID-19. I welcome initiatives that develop these recommendations, that pilot them in practice and that further advance the political project of promoting women's inclusion in creative coding. Although I cannot claim that these recommendations will necessarily also foster inclusiveness in terms of intersectionality, I hope that they will assist in this conversation. Intersectionality needs to be a fundamental part of the dialogue on where we go from here.

### ***Technical Solutions***

In the course of passing conversations on inclusion in technology culture, I was often presented with two simple solutions to the problem of prejudice in online forums. The first was to *just make everyone anonymous*, the premise being that women cannot be discriminated against if no one knows their gender. This misses the point. Sexism is not just a comment on your own gender identity (“you can’t do that, you’re a woman”), but on how wider culture enacts gender (“women can’t do that”). A person’s gender does not exist only when it is overtly recognised by another; it is the result of cultural processes and the internalisation of norms and expectations. In anonymity, assumptions about gender are reduced to the simplest form, homogenised into a singular dominant category.<sup>215</sup> Research has shown that gender is never perceived as absent or neutral, as the dominant category is seen as the norm (Brooke, 2019a; Nakamura, 2013; Tanczer, 2016). In technology culture the norm of competence is the anti-social, white, man.

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<sup>215</sup> This homogenisation is an instance of Bayesian rationality. See Chapter I, Section II, *Statistics or Stereotypes?*

The second solution people often offer is in direct contrast to the first; *make everyone use their real names*. Debates on the “realness” of given names aside, this strategy also falls short of understanding the pervasive nature of the problem involved. Real names do not erode cultural prejudice. Besides exposing those whose names signal identity categories to bigotry, real name enforcement allows sexism to propagate in subtler forms. At best, institutions condemn gender hostility, doing little to counter sexism’s adoption of benevolent or obfuscated forms (Kuchynka et al., 2018). Sexism survives because it is adaptable, evolving with context to reinforce gender power structures.

What is evidenced here is that identity regimes are not enough to effect change.<sup>216</sup> The enforcement of anonymity or real names does not negate cultural norms, but is merely the impetus for shifts between hostile and benevolent sexism. In thinking about where we go from here, we need to understand that sexism is coded into technology. In understanding sexism as a cultural process we ultimately depose the technical authority of masculinity, breaking the gender code. This thesis contributes to a wider feminist project, not only by problematizing the current state of gender in creative coding culture, but also through an activist dimension, as the research directly informs proposed concrete solutions, detailed in Appendix V.

## **Theory as Activism**

As part of a wider feminist project, my contribution in this thesis is to expose and dismantle the narrative of “natural” masculinity in creative coding culture. I have shown that the construction of naturalness is a historically situated political project of exclusion. In the history of technology, the masculine attraction to technology is seen as an innate predisposition, warranting no further

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<sup>216</sup> There is a tension in the gendered implications of identity enforcement regimes. Many platforms justify their adherence to real names with the promise of “minimising inappropriate content” and claim that they help to “create a more just society” (Hogan, 2013, p. 2). Yet, pseudonyms are justified by providing an affordance by which women’s work can be creatively recognised, albeit reinforcing the legitimacy of masculinity. See Chapter I, Section II, *Women do not like Star Trek*.

explanation. Through the narratives of masculine affinity, femininity is rendered incompatible and defined in opposition to technology. When we *see* or *remember* women in technology, their presence is emphasised as a moralising project. Through remembering forgotten women in technology we congratulate ourselves for our feminist efforts, thanking institutions for permitting such brilliant women to succeed (Dunbar-Hester, 2019). By casting our gaze backwards in this manner, we blind ourselves to the current inequalities of women and non-men in technology.

Technology itself is often presented as unbiased and externally situated, and the dogma of progress sees improved capacity as akin to a natural law. As outlined by Mackenzie and Wajcman (2006), this assumption of progress is deterministic, as technological systems are seen as predestined to follow a mathematical (usually linear or exponential) trajectory. By telling the story of “natural” programmers, we allow ourselves to forget that computers were not *discovered*, but *constructed*. Technology is embedded; it is not external to relations and social structures. Technology is not without history: it is created by individuals, their social interactions, and the cultural contexts in which they are embedded. As shown in Chapter I, *How did we get here?*, the development of technology is a history of gender power, of contested fields of knowledge and legitimate expertise.

### ***Gender as Social Structure***

Using Risman’s (2004, 2009) framework of gender as social structure, I have shown how gender operates simultaneously on (1) individual, (2) interactional, and (3) cultural levels to perpetuate the natural masculinity of technology. I have explored how a tautology has emerged in scholarship where gender performativity is discussed in the terms of Bem’s (1974) functional sex roles theory (Chapter I, Section II). Computational studies are particularly guilty of equating what a group of men or women do, with *doing gender* (Deutsch, 2007). Such efforts in operationalisation itself are treated as “inevitable”, justifying the simplification of gender into a binary. Equating expressions of gender with gender as an ascribed quality pays lip service to the social construction of gender. It is often well meaning, but ultimately fails by embedding tautological and essentialist

assumptions in the design and operationalisation of studies of gender; we cannot understand how gender intervenes if we start with binary gendered categories prior to our investigations. We can only reinforce and potentially magnify differences.

The conception of gender as social structure shows how explorations of sexism on a singular level miss much of the story. Examinations of gender in technology cultures typically focus on the individual as the sole unit of analysis. Here, interaction is the assembly of one or more individuals, and culture is then defined merely as an aggregation of individual behaviours. This, too, is how sexism in technology is talked about. By concerning ourselves *only* with personal stories and statistics on the frequency of harassment, we fail to capture the cultural norms that sexism represents. Assumptions of the natural masculinity of technology inform the methodological decisions that researchers make, from binarising gender to defining femininity in its deviations from (normative) masculinity, or codifying success in masculine terms. In each of these choices we miss how gender defines the terms of creative coding culture.

### ***Sexism as Politics***

Sexism is colloquially discussed in terms of examples, of experiences, and personal narratives of adversity and hostility. Each case is used to indicate the presence of a larger phenomenon – but the whole is greater than the sum of its parts. The system of gender and technology has properties beyond specific instances of sexism that non-masculine individuals experience. Sexism is not grassroots, bottom-up, phenomenon but is a hostile manifestation of gender structure and the norms that perpetuate it. It is useful here to refer again to the scholarship of Deleuze and Guattari (1989), whose work on micro-politics shows how it is the “minority” that is politically saturated.<sup>217</sup> The (masculine) “majority” is insensitive and unencumbered by its gender and thus only perceives gender in micro organisations of sexism. In discussing the micro organisation of

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<sup>217</sup> In terms of the acquisition of power, not numerical size.

fascism, Deleuze and Guattari (1989) argue that it is in the micro, everyday interactions that fascism is at its most dangerous. The same is true for gender structures. Sexism is a macro level manifestation, and viewing it on an individualised level diminishes the need to fight wider cultural processes. Sexism resists system-wide activism as it has the potential to make those on the receiving end of systems of oppression feel as if it is their responsibility alone to change. In the next section I revisit how the findings of each study characterise the operating of gender as social structure in technology culture. I return here to Ahmed’s (2010) characterisation of the killjoy feminist, and I dismantle the notion of meritocracy and achieved equality, showing that feminism’s work is far from done.

## Summary of Chapters

This thesis has shown that gender intervenes in technology culture, as it dictates perception, reception, and expectations of women in technology. Below, Table 36 revisits the research questions for each study. By addressing these questions, I show how gender *intervenes* in creative coding culture. Study I explored how gender mediates perception by dictating gender roles, legitimate claims to technical knowledge, and associations of hostility. Building on these findings, Study II showed that gender also alters how users are received on programming forums, as their contributions and questions are evaluated from a masculine standpoint. Study III examined gendered expectations of an individual’s ability within hackathon culture, identifying masculine notions of whose participation is valid.

*Table 36 Research Questions*

<b>Study I:</b> Perceptions of Gender and Hostility	<b>RQ1</b>	Does the gender majority of a platform affect perceptions of hostility?
	<b>RQ2</b>	Do gender-based stereotypes affect perceptions of hostility?
	<b>RQ3</b>	What are the gender assumptions of technical knowledge in anonymous spaces?
<b>Study II:</b> Reception to Gender on Stack Overflow	<b>RQ4</b>	How salient is a user’s gender on Stack Overflow?
	<b>RQ5</b>	Is there a gendered difference in Answer effort?
	<b>RQ6</b>	Is there a gendered difference in users’ interactions on Stack Overflow?
	<b>RQ7</b>	Is condescension gendered?
<b>Study III:</b> Gender Expectations at Hackathons	<b>RQ8</b>	How is gender visible at hackathons?
	<b>RQ9</b>	What does communication at hackathons look like?

As illustrated in the Introduction, the narrative of the “leaky pipeline” focuses efforts to address gendered inclusion on problems existing in formal institutions. By contrast, my emphasis has been on the informal avenues of technology, the culture that permeates universities, entrepreneurial enterprises, and specific platforms. In summarising this project I show how sexism is *hardcoded* into coding, fixed into technology culture by its very design.

### ***Chapter I: Literature Review***

At the start of the literature review, I emphasised the importance of storytelling as a means of understanding the processes of sense making. My objective was to illustrate how we build conventional wisdom. The “wisdom” of gender and technology is that there is a natural difference in technical ability: masculine affinity contrasts with feminine ineptitude, and that this difference is inevitable. Defining *natural* is an expression of political ideology. In justifying inequality, it describes one group as those who are distinctively skilled and those who are not. In Section I, *How did we get here?* I showed that the propensity to prefer a simple story of innateness is a narrative fallacy. Enduring hegemony is facilitated by simple stories, as one can justify a group having a privileged position based on a meritocratic framing of their natural ability and talent. In highlighting the path-dependency of sexism and technology, I accounted for both a formal and informal history of creative coding, showing how its development inside as well as outside of institutions has been shaped by masculinity. I charted how technical competence became associated with anti-social white men due to a potent cocktail of flawed research and future profit seeking.<sup>218</sup> I charted how this history situates the “brogrammer” in a position of power in technological development, as geek masculinity takes on the entrepreneurial, frontier spirit. Building on Dunbar-Hester (2019), the section concluded with a discussion of diversity and a cautioning against promoting diversity for economic reasons, in order to widen a consumer base.

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<sup>218</sup> See discussion in Section I, *Born, not Made* on the Cannon-Perry test developed by hiring experts, and an IBM study that emphasised the efficiency of programmers with masculine personality traits.

Building on the historical outline earlier in the chapter, Section II breaks down gender power in operation. This discussion was supported with a framework of Goffman's (1961) role sets, as gender stereotypes are interactional and indicative of a pragmatic interest in demarcating gender hierarchies. The "Gender Code" comprises the norms and expectations that dictate anticipated and possible behaviour. Referencing Cao et al. (2018), I outline how statistics of representation, and the associated inferences, are not apolitical. Perceptions of competence are ultimately informed by an understanding of who is most likely to be capable. Under the heading *Women do not like Star Trek*, I turned the discussion towards technology and computing culture. A foundational study here was Cheryan et al.'s work (2009) on *ambient belonging*, discussing how the physical environments and objects associated with computer science can deter women from taking part in the field. Cheryan et al. (2009) argue that a lack of ambient belonging can preclude women from ever taking an interest in these environments, even without having directly experienced prejudice and hostility themselves. Crucially, they also found that the presence of stereotypes and stereotypical objects did not repel men. Applying theories of ambient belonging to Computer Mediated Communication (CMC), I examine Schwartz and Neff's (2019) theory of *gendered affordances*. They assert that a user's gender identity alters how that individual perceives a space, and their capacity for action within it (Schwartz & Neff, 2019). Together, ambient belonging and gendered affordances show how gender shapes action.

From discussing the operating of gender in anonymous (and pseudonymous) spaces, I then move to a review of scholarship on the topic of gender in programming forums. On Stack Overflow, Ford et al. (2016) highlight that women are deterred from participating by argumentation/blunt responses, masculine dominance, and large community size. The affordances of anonymity are shown to be more beneficial to an in-group, as the features that signal belonging to the dominant group are simultaneously barriers for an out-group. In this context Ford et al. (2017) develop the concept of *peer parity*, or the importance of seeing "someone like me" in participatory spaces. However, some studies doubt the very existence of gender-based categorical discrimination in

online spaces. Vedres and Vasarhelyi (2019) argue that it is behaviour associated with “femaleness” that adversely affects women, not the reception given to people who identify as women. However, the grounding of these claims is questionable since features of “femaleness” are extracted from categorically defined accounts (Vedres & Vasarhelyi, 2019). My research highlights the importance of contextually defining success. It is problematic, for instance, to define women's success in a coding culture merely in terms of survival and tenure.<sup>219</sup> Online status systems are too often seen as value-free meritocratic mediators of success.<sup>220</sup> Moreover, returning to the impact of stereotypes that Section II began with, gendered perceptions of ability are seen to adversely affect an individual's own perception of their abilities, and consequently their outcomes.

Through a summary of historical and academic accounts I concluded that work in the field has done much to contribute to women's invisibility in creative coding cultures. The masculinity of computing has firm roots in the obscuring of women in accounts of the history of technology. Epitomised in IBM's marketing of a compiler being “So easy a woman could do it!”, femininity is authored as fundamentally incompatible with technology.<sup>221</sup> In computational research, operationalisations of “success” and gender have propagated the story of men's dominance. The literature review served not only to outline relevant scholarship, but also to show how this project was motivated by the lack of prominent accounts of women's exclusion.

### ***Study I: Perceptions of Gender and Hostility***

The first study of this project drew on the Ambivalent Sexism Inventory (Glick & Fiske, 1996, 1999) to explore perceptions of gender and hostility in anonymous forums. Building on the

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<sup>219</sup> If a woman has to “put up with” sexism and hostility in order to function in a community, this cannot really be considered successful participation.

<sup>220</sup> Particularly in reference to the online voting systems of platforms like Reddit, which Massanari (2015b) argues propagates racist and sexist content due to power law effects.

<sup>221</sup> The IBM example is discussed in Chapter I, Section I, *Born, Not Made*.

stereotyping literature outlined in Chapter I, Section II, this study addressed the following research questions: (RQ1) Does the gender majority of a platform affect perceptions of hostility?; (RQ2) Do gender-based stereotypes affect perceptions of hostility?; (RQ3) What are the gendered assumptions of technical knowledge in anonymous spaces? The function of this study in the wider thesis was to test assumptions of gender, hostility, and role-based expectations of competence. Model 1 looked at perceptions of hostility, Model 2 examined assumptions of gender in technical help seeking, and Model 3 explored gender norms in technical help offering. Together, the models represent the linear collection of experiences involved in taking the first steps into creative coding culture.

Platform was an insignificant predictor across all models, which supported my premise of a cross-platform approach where the subject of analysis is culture, rather than the functioning of a particular social network. Gender was excluded as a significant predictor in Model 1, which was contrary to the hypothesis informed by the literature. Looking to RQ1, the gender structure (*GenderBalance*) of a platform was significant, which suggests that *perceived* gender dominance predicts assumed hostility, not the gender of the individual making the judgement.<sup>222</sup> Belief in sexist stereotypes towards women (ASI) and men (AMI) was a strong predictor of perceived hostility, addressing RQ2. This implied that *perception is reality*, and that it is social-gendered assumptions that dictate belonging. Model 1 showed that an increase in masculine hegemony was associated with an increase in perceived hostility, regardless of the gender of the respondent.

Turning to gender roles in technical knowledge seeking (RQ3), Model 2 indicated that the salience of stereotypes (ASI and AMI) was a strong predictor that a user seeking technical help will be seen as a woman. Across platforms, Model 2 shows that men are much more likely than women to attribute technical help seeking to a man. Nonetheless, the results of the model are somewhat

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<sup>222</sup> *Gender* was also insignificant as an interaction term on *GenderBalance*.

unclear.<sup>223</sup> I argue that this is likely to be due to the tension between the attributes of feminine incompetence and masculine acquisition of technical skills embedded in the role of “help seeking”. The exploratory results of Study I informed the research design of Study II. In formulating Study II, I included Questions and Answers as contextual pairs (RQ6/RQ7), and Study III also enquired into sensitivity towards competitive knowledge and seeking answers in teams (RQ9).

In Model 3, I aimed to characterise the perceived gender of a user offering technical knowledge. This model was the only instance where the sexism inventories were not significant. There was, however, a continuation of in-group bias, where men were nearly twice as likely as women to presume that a user offering a technical help was a man (RQ3). Model 3 explored the relationship between hostility and the perceived gender of users who possess technical knowledge. Where there was a unit increase in the hostility rating of the platform, there was also a sizable (162%) increase in the likelihood that a competent user was seen as a man. This speaks to the culture of programming forums, such as Stack Overflow, which is strongly associated with masculine hostility (Brooke, 2019a), and highlights how visibility of gender is as important as assumed masculine dominance in affecting the perceived hostility of a space.

In aligning the findings with the research questions set out in Table 36, I first find that it is the *perceived* gender majority of a platform, and not respondent (possessed) gender, that affects assumed hostility (RQ1). Furthermore, I find that faith in gender stereotypes, as evidenced in AMI and ASI, is also a significant predictor of perceptions of hostility (RQ2). Looking to the gendered assumptions of technical knowledge, I find that a strong belief in stereotypes contributes to

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<sup>223</sup> I also wish to make the point here that in academic research the acknowledgement of potential missteps in the research design process is extremely valuable. If scholarship is concerned with advancing a field, particularly in political projects, the authors should be clear about where weaknesses (and strengths) lie so that future researchers can be attuned to them.

perceptions of gender roles in technical help seeking and offering (RQ3). In addition, Study I also shows how assumed masculinity is a strong predictor of perceived hostility. This finding was counter to a hypothesis informed by ambient belonging, which found no change in perceived hostility for men between neutral spaces and those associated with technology culture (Cheryan et al., 2009). Therefore, Study I took an exploratory approach, quantifying perceptions of gender in creative coding culture.

### ***Study II: Reception to Gender on Stack Overflow***

In the second Study, I focused on Stack Overflow (SO). I examined gendered differences in experiences, perception, and reception on the forum. Ford et al. (2016) note that SO is colloquially referred to as “programmers’ paradise”, indispensable to complete novices and seasoned veterans alike. Study II starts with a more in-depth discussion of the few studies into gender on SO and their methods, and sets out how my project contributes to this scholarly conversation. This review then leads to a series of questions. How salient is users’ gender on Stack Overflow (RQ4)? Is there a gendered difference in Answer effort and reward (RQ5)? Is there a gendered difference in users’ interactions (RQ6)? And finally, is condescension gendered (RQ7)?

One of the contributions of Study II lies in the operationalisation of gender beyond a binary, using a modified *genderComputer* algorithm (Vasilescu et al., 2012). This multi-label characterisation is itself a step towards dismantling a discrete binary account of gender. Here I found that a user’s gender was highly salient, with only 2.5% of my sample identified by my algorithm as “anonymous” users (RQ4). Whilst Study I relied on perceptions of a gender binary, Study II encompassed more nuanced understandings. All of the statistical procedures in the chapter are conducted using the five-category understanding of gender. Consequently, the language used to discuss gender also shifts to accommodate this distinction.

I first investigated the conception of a masculine insider and non-masculine outsider. I found that feminine users have significantly less reputation than any other gender identification.

Unsurprisingly, the more masculine a user was perceived to be, the higher the reputation they accrued. In delving into this result further, I found that the relationship between user tenure (time active) and reputation was mediated by gender, which indicates that the reputation system is not a simple function of time. Nonetheless, I also showed that feminine users are less active on the platform than more masculine users, which is in line with the findings of Ford et al. (2016). Informed by these results, by the storytelling approach (Chapter I, Section I), and by causal attributions (Section II), I look into differences in features of Answer effort and the score that these Answers receive. This adds a caveat to gender salience (RQ4), as reputation systems also dictate visibility. The novel conclusion here was that feminine users receive lower scores for their Answers which, based on the basic operationalisation, are generally characterised by higher effort. This finding levels a challenge at the narrative of a just world, and discredits arguments that use meritocracy as a basis to explain and justify women's lower participation on SO.

Moving to the connectivity of SO users, I presented evidence of gender homophily and reciprocity. This supports the scholarship of Ford (2017) and Mishkin (2019) on the importance of seeing "someone like me" (RQ4) as a prerequisite for women's participation in creative coding. Nevertheless, the *k*-core degeneracy showed that the proportion of feminine users holds for the most connected users (RQ5). Whilst a small proportion is not a particularly positive finding, it shows both that there are feminine power users and that SO is not a closed system. I argued that SO is not only hostile to "new users" but that women's lack of representation holds across levels of connectivity. Taken with the earlier results on user tenure, this shows strong evidence of a gendered barrier to women (and non-men) getting into coding. Their perception of programming forums and the way they are initially received create an active gender filter, as the masculinity of technology becomes internalised in stereotypes and ratified in interaction.

The final aim of Study II is to predict a user's gender based on how they are received on SO. The findings here show that there is a marked difference in the level of hostility and condescension that users of different gender salience experience across the platform. What is remarkable here is

that gender can be predicted based on how someone is spoken to rather than how they speak to others (RQ7). I reflected on the consequences of my findings, discussing how on SO a user is shamed for not knowing an apparently “easy” Answer, through references to Google or homework. In this way condescension serves to define such recipients as an out-group, attracting stigma for their attempted foray into coding culture. Because of the affordances of SO, a user does not need to be the recipient of a personal condescending comment to be very aware of the prevalence of such discourses on the platform. Study III reflects on this cultural understanding of the platform, as SO’s hostility is the subject of satire at hackathons. As Study I shows, an increase in masculine dominance leads to a large increase in perceived hostility even before the content of an interaction is taken into account. The perception of SO as a masculine, hostile environment means that it can largely only maintain much of the same - masculine, hostile programmers. Given that SO is a “paradise” for programmers, this antagonism undermines the conjecture that it is only the good programmers that survive. There is trouble in paradise as the elitism of SO creates a self-perpetuating system of hostility and masculinity.

Returning to the research questions that directed the study, I found that a user’s gender was reasonably salient in usernames, but that this visibility was mediated by the reputation system on the platform (RQ4). I also found that there is a significant difference in Answer effort, but feminine users are unfairly evaluated on the basis of their gender (RQ5). In terms of interaction I found strong evidence for peer parity (homophily, assortativity, reciprocity) across levels of gender, but that men on average are more active (RQ6) which is likely due to a comparatively positive reception to their interactions on the platform. This conclusion is supported by the prediction of gender using features of context-specific condescension (RQ7). Study II shows that visibility of gender dictates reception in programming forums of creative coding culture.

### ***Study III: Gender and Expectations at Hackathons***

The ethnographic approach of Study III complemented the broad strokes of the statistical methods of Studies I and II. The culture of hackers does not exist merely in the interactions on online

platforms, but also in local, embodied manifestations. As shown in Chapter I, programming is situated in hobbyist culture, associated with anti-social “genius”. In participating in the events as a hacker I had a hitherto unique experience as a researcher; coding alongside my informants. I was able to engage with the materiality of coding together through signals, smells, and socialisation. I could experience the tumultuous excitements of the competition, the exhaustion of the marathon, and the frustrations of being a woman. As a *girl* at a hackathon I became the subject of my own research. I was reflexive in evaluating my labour and contributions to my team, analysing how gender intervened in embodied practices of creative coding. The questions that this study answered were: (RQ8) How is gender visible at hackathons?; (RQ9) What does communication at hackathons look like?

Stereotypes are not just the product of a social world, but have the power to affect it. The hackathon organisers and attendees are aware of the geek-nerd-hacker cast of characters, which is the subject of playfulness in the form of “ambivalent irony” (RQ8). In expressions such as memetic physical humour, sharing memes, and even clothing, irony is fundamental to creative coding culture. This is a practice of boundary making, in the creation of context-specific discourse. In Chapter I, Section II, I discussed discursive communities of practice, how language and mixed meaning are fundamental to geek culture's obsession with niche knowledges. As play, irony disguises how the identity antagonisms of gender are central to coding culture. In parodying the characterisations of “nice guys” and “brogrammers”, the masculinity of technology is asserted by the men it favours. By using the vehicle of humour and the vagueness of multiple meanings, hostile sexism is able to propagate across hackathons with impunity.

Study III shows how gender norms are reinforced by ironic joking, as hackathon attendees acknowledge that their culture is saturated with multiple narratives of masculinity. My observation of hackathons found that masculinity exists in many forms, but the geek stereotype reigns (RQ8). These stereotypes communicate belonging through the use of objects. Geek masculinity dominates the artefacts central to the culture, but the presence of sanitary products

and preferred pronouns on name badges shows that objects can also be sources of inclusive politics (RQ9). Additionally, the innovation and start-up tenants of technology culture, the industry representatives, express hegemonic masculinity. But these representatives are largely untarnished by the toxic sexism that Hicks (2013) observes in the USA (RQ9). The gender social structure determines whose technical ability is deemed legitimate. Here gender essentialism is recreated in knowledge binaries, such as software/hardware, where the more “complex” or technical is associated with masculinity. In this context, personal effort is seen as the sole cause of individual success and failure. This individualised granular framing fails to account for the systemic barriers presented to those trying to break into the masculine dominated field of technology.

## **From Pipelines to a Feminist Project**

This project dismantles the “natural” masculinity of creative coding. In the Introduction, I posed the question: *how does gender intervene in creative coding culture?* I formulate gender as a social structure to encompass a situatedness and a lived experience, but also to acknowledge how gender can constrain or alter a course of action. The intervention here adversely impacts on women’s inclusion in technology culture. There is an active gendered barrier, not a *passive* leak from a *lifeless* pipeline.

Each study focuses on a particular manifestation of boundary-making practices, addressing the individual, interactional, and cultural workings of gender structure. Through these studies I show how stereotypes prescribe individual capacity for action, how interaction dictates who can possess legitimate knowledge, and how culture perpetuates notions of exclusively masculine competence. I show that the communities of Reddit, Stack Overflow, and hackathons are aspects of a wider technology culture. The gender structure permeates technology culture, dictating the terms of interaction in each instance. Deep cultural knowledge of geeks and stereotypes shapes how gender is performed and responded to. In anonymous spaces and embodied competitions, the same

culture defines legitimate participation and knowledge. This culture, the culture of technology, is characterised by gender structure. It is defined by its gendered power relations, troupes, and ultimately it's sexism.

In addition to these theoretical contributions, my work is political in its very research design, which confounds binary stereotypes of gendered knowledge. Discussions within the academy are orientated around what data science and computational methods can offer to investigations into the social world. We should also consider what cultural methods can add to computational studies. Interdisciplinary work is only truly “inter” if it's mutual, not favouring one over the other. Such work requires a reciprocal symbiosis. From this perspective, I counter the objectivity attributed to computational methods. Like an interview or observation schedule, an algorithm is broadly a set a rules. Both require structure, conditions, and competent researchers in order to empirically engage with the social world. Like such schedules, computation is a tool, invariably coded with the values of its creator, most obviously in the decision processes of research design. Moreover, I counter the argument that *objectivity* is desirable in research. In claiming objectivity, researchers are denying the wealth of context that motivated and informed their decision making practise. In Haraway's (1988) terms, to claim objectivity is the “God trick”, to see the researcher as split from the subject of their enquiry. Research across disciplines is often motivated by a personal, subjective relationship with the topic. Tauting objectivity is to wash our hands of the responsibility for our claims to truth. By approaching knowledge making from an embodied perspective we are forced to take responsibility for our research. In the practise of identity inference, it is particularly important that researchers acknowledge their responsibilities. By brandishing objectivity sexist and racist implications of research become naturalised, *discovered* by value-neutral scientific inquiry.<sup>224</sup> Computational research embraces a first-person

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<sup>224</sup> An example of computational research with potentially dangerous implications can be seen in a study by Wang and Kosinski (2018) who use a deep neural network to classify individuals sexual orientation

methodological account (“I validated the model”) yet remain opposed to subjectivity and situatedness. The incorporation of computational methods into a critical, feminist, project is novel. However, this contribution is not solely a matter of methodological novelty, as it also has wider political implications. This project demonstrates the need for computational methods to acknowledge their own situatedness, and I propose that in the emancipatory project of the social sciences we must dismantle claims to objectivity in methods.

To refer to this thesis as multi-sited or mixed methods is to misconstrue its contribution. This project has one site; it is exclusively focused on technology culture. It is not mixed method, but embeds critical understandings of gender in computational approaches and empirical practises of programming in an ethnography. Instead, this project is radically multidisciplinary in its epistemology. Throughout this work I have made an argument for academic inquiry to reorientation to culture as the unit of analysis, away from a quasi-deterministic approach that concentrates on the modes of communication. Platforms do not radicalise programmers to sexists, they merely quantify existing prejudice into scores and reputation systems. As platforms do not create sexism, it follows that sexism can not be dismantled by changing how we measure success on platforms. In technology culture success is heavily mediated by gender. In Chapter I of this project I introduced the “geek revenge fantasy”, how entrepreneurial success in the technology industry is closely associated with the white, male, anti-social stereotype. I showed how academic research has qualified success in masculine terms (Vedres & Vasarhelyi, 2019), blaming *feminine behaviour* and pardoning technological culture from accusations of categorical discrimination.

This feminist project discloses how gender dictates visibility, power, and thus entry into creative coding cultures. It conducts a social structural analysis of technology to culture to show how

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from facial images. The ramifications of automatically determining a person’s sexuality from a limited selection of photos are enormous. It puts LGBTQA+ people at risk worldwide in places where they remain a repressed minority.

sexism defines interaction and legitimate knowledge. To define our offline and online lives as distinct and different is to neglect the extent of gender's permeation and the ubiquitous nature of communication. Considering each platform and space to possess their own unique culture is not representative of how technology and the internet are used. Culture is not bounded by the forms of communication that it transmits and receives. It is bounded by sociability and the visibility of its participants. The culture of hackathons is also the culture of Reddit, the culture of Stack Overflow, and ultimately the culture of technology. To box this culture into distinct platforms and occasions is to miss the larger picture - technology culture is hostile to women and the symptoms are everywhere. As a work of feminist scholarship and activism, the conclusion of this thesis is inescapable: *it is time to break the gender code.*



# Appendix I: Survey Screenshots

---



SpaceCat  
@Anon00761698

I made 22 free Python tutorials on YouTube and wanted to share them with you all!

[googl/YNS2D](https://www.google.com/search?q=googl/YNS2D) #TechHelp



Python Programming

Best Book on Python :  
<http://amzn.to/1NxiML> Beginner Python Tutorial :  
<https://www.youtube.com/playlist?list...>  
youtube.com

12:42 PM - 14 Dec 2016



reddit

LEARNPROGRAMMING

comments

other discussions (0)

show images (0)

I've taught 30,000 students how to code. Now I'm offering my course for free, forever. (self.learnprogramming)

I've decided to make my course on complete full-stack web development [free forever, here!](#)<sup>[1]</sup>. It's a massive amount of content. Please let me know what you think of the course!

0 comments source share save hide give gold report hide all child comments

>>

Anonymous 12/14/16(Wed)20:25:17 No.58001532 ▶ [>>58001606](#)

I want to learn python but I'm an idiot and do not know which versions and what to install. Please help me.



InvisibleHat @Anon00761698 · 2m

I'm scared I'm not smart enough to learn programming to a hire-able level. Is it really possible to learn this skill online?

[#TechHelp](#)



# Appendix II: Stack Overflow Screenshot

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## Extracting all Nouns from a text file using nltk

Asked 4 years, 3 months ago Active 5 months ago Viewed 35k times

Ask Question

Is there a more efficient way of doing this? My code reads a text file and extracts all Nouns.

```
14 import nltk
File = open(fileName) #open file
lines = File.read() #read all lines
sentences = nltk.sent_tokenize(lines) #tokenize sentences
nouns = [] #empty to array to hold all nouns
for sentence in sentences:
    for word,pos in nltk.pos_tag(nltk.word_tokenize(str(sentence))):
        if (pos == 'NN' or pos == 'NNP' or pos == 'NNS' or pos == 'NNPS'):
            nouns.append(word)
```

How do I reduce the time complexity of this code? Is there a way to avoid using the nested for loops?

Thanks in advance!

python nltk

share improve this question edited Nov 7 '15 at 21:10 asked Nov 7 '15 at 20:54 Rakesh Adhikesavan 6,691 ● 9 ● 34 ● 57

Replace the if condition with `if pos.startswith('NN')`; also use a `set` or `collections.Counter`, don't keep a list. And do some `map/reduce` instead of a list comprehension. Otherwise, try shallow parsing, aka chunking – [alvas](#) Nov 7 '15 at 21:10

add a comment

6 Answers active oldest votes

If you are open to options other than NLTK, check out [TextBlob](#). It extracts all nouns and noun phrases easily: **Post: Accepted Answer**

```
21 >>> from textblob import TextBlob
>>> txt = """Natural language processing (NLP) is a field of computer science, artificial int
actions between computers and human (natural) languages."""
>>> blob = TextBlob(txt)
>>> print(blob.noun_phrases)
[u'natural language processing', 'nlp', u'computer science', u'artificial intelligence', u'cor
```

share improve this answer edited Nov 10 '18 at 5:15 answered Nov 7 '15 at 21:53 Aziz Alto 10.8k ● 3 ● 52 ● 48

You say "It extracts all nouns and noun phrases easily" but I don't see the option to extract nouns only. How could I get nouns alone in your example such as "computer" or "science"? – [Sulli](#) Feb 3 '17 at 21:58

you could use `blob.tags` to filter out NN only something like `[n for n,t in blob.tags if t == 'NN']`. – [Aziz Alto](#) Feb 4 '17 at 5:54

1 Personally, I have found that `TextBlob` doesn't perform nearly as well as `nltk` – [austince](#) Nov 7 '17 at 23:53

1 The code may be simpler, but `textblob` calls the NLTK to tokenize and tag. This cannot reduce the "time complexity" of the OP's code. – [alexis](#) Mar 2 '18 at 10:17

add a comment

import nltk

```
19 lines = 'lines is some string of words'
# function to test if something is a noun
is_noun = lambda pos: pos[:2] == 'NN'
# do the nlp stuff
tokenized = nltk.word_tokenize(lines)
nouns = [word for (word, pos) in nltk.pos_tag(tokenized) if is_noun(pos)]
print nouns
>>> ['lines', 'string', 'words']
```

Useful tip: it is often the case that list comprehensions are a faster method of building a list than adding elements to a list with the `insert()` or `append()` method, within a 'for' loop.

share improve this answer edited Nov 9 '15 at 2:40 answered Nov 7 '15 at 21:18 Boa 2,056 ● 13 ● 30

1 The answer is a correct train of thought. Using this is cleaner: `is_noun = lambda pos: True if pos[:2] == 'NN'`. Note: List comprehension is not necessarily faster than for loop. It's just that you don't have to

Blog

- Sharing our first quarter 2020 community roadmap
- What's behind the hype about Blazor?

Featured on Meta

- The company's commitment to rebuilding the relationship with you, our community
- The Q1 2020 Community Roadmap is on the Blog
- Planned maintenance scheduled for Saturday, March 7, 2020 at 14:00 UTC (9AM...)
- What is the mission of Meta, as a community?

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- 1 Tokenizing and POS tagging in Python from CSV file
- 0 Creating a function to count the number of pos in a pandas instance

Related

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- 629 open() in Python does not create a file if it doesn't exist
- 3474 How do I list all files of a directory?
- 1043 Find all files in a directory with extension .txt in Python
- 1286 Importing files from different folder
- 742 Extract file name from path, no matter what the os/path format
- 4 NLTK extracting terms of chunker parse tree
- 2 NLTK - joining proper nouns after tagging
- 0 Extracting/Parsing Pronoun-Pronoun and Verb-Noun/Pronoun Combinations from a Sentence
- 1 python text processing: identify nouns from individual words

Hot Network Questions

- Apex HttpMethod with two possible returning types
- Can someone intuitively explain the reason for the units of entropy (J/K)?
- A shocker in soccer, pt. 2
- How could humans reach distant stars and still stay as a united government if you can't use faster than light travel
- Summing a sub-square of a quarter of an infinite chessboard
- Why do stars get bigger and brighter when older?
- Single Digit Representations of Natural Numbers
- Feeding a newborn throughout the night without letting him cry
- I make big structures look marvellous
- What are examples for the phenomenon that more (or better) information makes everybody worse off?

# Appendix III: Hackathon Observation Schedule

<b>Hackathon: Date:</b>		
<b>Event information:</b>		
<b>Narrative Focus</b>	<b>Primary</b>	<b>Secondary</b>
<i>Prior to Attending</i>	Are teams arranged in advance?	Over what networks [platforms] are teams made up? Do participants know each other prior to attending?
	Does registration require gender?	What demographic factors are collected?  Is pre-event socialising encouraged?
<b>Notes:</b>		
<i>Fist Arrival</i>	How do participants greet each other?  Are there any hierarchies or 'known' figures present?  Are there signifiers of ambient belonging?  What are their reactions to my research and questions?	Are greetings gendered? i.e. displays of 'brogrammer' behaviour  Are people wearing signifiers of geek or nerd culture?  Are there overt displays of gendered identity?
	What do participants think of the event schedule?  Are there comments about sleeping arrangements?	Are women more likely to relate and socialise with each other?  Are there woman speakers who insight comment? Is the representativeness of the hackathon discussed?  Are people nervous/anxious?
<b>Notes:</b>		
<i>Forming Teams</i>	Are there any obvious dictators of team membership?	Are there indicators of homophily in team members?

	Is hostile behaviour observed?	Are women working in teams of only women?
	Are boundaries set?	Is appropriate behaviour talked about?
<b>Notes:</b>		
<i>Working in Teams</i>	How does the team work together?	How are roles set? Are group hierarchies emerging?
	How is the physical space used? Are platforms discussed?	A programming forums used during the hackathon?
<b>Notes:</b>		
<i>Communicating in Teams</i>	Is life outside of the hackathon discussed?	
	Is sexist behaviour observed?	Is sexist behaviour corrected? or encouraged?
	Is hostility observed?	How do women interact with other women? How do they interact with men? and vis versa
<b>Notes:</b>		
<i>Leaving the Hackathon</i>	Are bonds formed?	Do participants plan to stay in touch? Are goodbyes friendly?
<b>Notes:</b>		

# Appendix IV: Supplementary Materials

## Submitted with Hackathon CUREC 1A

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### 1. Information to Hackathon Organisers: Email Template

Dear [*Organiser Name*],

I am writing to you to discuss the possibility of conducting academic research at your Hackathon. The event I am interested in researching is [*Hackathon Name*] on the [*Hackathon Date*].

The project forms part of my doctoral thesis at the Oxford Internet Institute, University of Oxford and examines how gender affects participation in informal programming events. I will examine what barriers are being created to women entering technical coding spaces.

I will aim conduct myself as a participant, as I am competent in several programming languages and data science techniques. But I will make myself as a researcher known to my team members and other participants. If it would be beneficial to you, I can provide you with a report on the current level of gender-inclusivity of your hackathon, and potentially provide recommendations for how your event can be more open and welcoming. Please let me know if you believe you would benefit from such a report.

Please find attached two documents for your consideration (1) provides more information on the project and (2) an information slip we will provide to participants at the event. I will be happy to engage in a discussion about my research and related topics via email, phone, or skype. Thank you for your time and I look forward to your reply.

Best wishes,  
Siân

**Siân JM Brooke** | *DPhil Information, Communication, and the Social Sciences*  
*Oxford Internet Institute*  
*St Edmund Hall, University of Oxford*  
07802751993 (mobile)



## 2. Information to Hackathon Organisers: Information Sheet



**Drafted:** 11<sup>th</sup> February 2019

### **Study Title:**

**Breaking Gender Code: Visibility, power, and performing gender in creative programming cultures**

You are invited to take part in a research study on how a person's gender effects their participation in hackathons and other programming events in the United Kingdom. Before you decide whether to let us participate and observe your hackathon, it is important that you understand why the research is being done and what it will involve. Please take time to read the following information carefully. If there is anything that is not clear, or if you would like more information please get in touch with the research team. The contact details are at the end of this information sheet.

**Researchers:** Dr Bernie Hogan, Siân JM Brooke

### **What is the purpose of this project?**

This study will investigate the effects of a person's gender on their participation in hackathons, looking at how people interact and work together in a team at these events. We aim to see if gender stereotypes put people off taking part. Observing how people interact at these events and participating in the hackathon itself is the best way to study them and get a fair understanding of the event.

### **Why has this event been chosen?**

We are looking at several events to see the similarities and differences across hackathons. We are selecting events with a focus on programming, but varying motivations across the United Kingdom.

### **Do I have to take part?**

It is up to you to decide whether or not to take part. We will be giving out slips that are a condensed version of this information sheet at the hackathon. We will not be putting off competitors and will be taking part in the event as an ordinary participant. If you decide to take part, you are free to withdraw at any time and without giving a reason.

### **What will taking part involve?**

If you decide to participate, we will observe and participate in the hackathon event that you are coordinating. The purpose is to observe competitors and participants in the hackathon as they socialize, organize, and delegate among their team and others. The researcher will participate in the hackathon, as they are competent in R and Python, and their application in data science. Notes will be taken by the researcher in a notepad as they observe the hackathon. Observations do not judge the capability of participants outside of this setting. Although, if unsafe or harmful behaviour is observed the procedures laid out by you as the event organizers will be followed. The notes will be stored in a safe place and only the research team will have access to them. The notes will be destroyed in accordance with University regulations and/or if you should decide to

withdraw from the study. That participants will not be identified by name or any other person specific details, only their self-identified gender will be recorded. Ms. Siân Brooke will undertake the observation.

**What are the possible benefits of taking part?**

We can directly provide a report to you as the event organizers which can provide a survey of our findings of gender and openness at your event. If requested, we can provide recommendations for inclusivity and ideas for how they may encourage diversity in their competitors. Please note that you will need to directly request this report and it will not be provided by default.

**What are the possible damages or risks of taking part?**

There are no foreseen disadvantages or risks to taking part. However, if as a result of the study, issues are raised for you which you wish to discuss further, please contact the research team. If you wish to make a complaint or have any concerns about any aspect of the way you have been approached or treated during the course of this study, please contact Dr Bernie Hogan at [bernie.hogan@oii.ox.ac.uk](mailto:bernie.hogan@oii.ox.ac.uk).

**Would taking part in the study be confidential?**

Whilst the event will be identified, unless directly specified, competitors and participants will be given a pseudonym for the research and only the researcher will have access to the computer records where real names may be stored. All information which is collected about you during the course of research would be kept confidential and destroyed after three years, in accordance with the Data Protection Act 1998 and GAP.

**What would happen with the results of the study?**

Pseudonymised findings will be used for a final report, academic papers and for dissemination via user networks.

**Who has reviewed the study?**

The study has been granted by ethical approval by the Ethics Committee, Oxford Internet Institute, University of Oxford.

**Contact for further information**

Any concerns relating to this study can be addressed to the Research Team:

Name: Siân Brooke

Tel: +44 7802 75 1993

Email: [sian.brooke@oii.ox.ac.uk](mailto:sian.brooke@oii.ox.ac.uk)

Address: Oxford Internet Institute, 1 St Giles, Oxford, OX1 3JS

### 3. Information to Hackathon Participants: Information Slip

#### **Hackathon Research Information Slip**

**About:** We are researching how people participate and work together in hackathons in the United Kingdom. We are observing the event that you are attending. The purpose is to observe how you work in a team and navigate the hackathon. I will be taking notes on a notepad, but I will not be judging your ability or capacity outside of the task at hand. Research at this event has been approved by the hackathon organisers.

**Confidentiality:** Your identity will be kept entirely confidential. If you are featured in the final report, you will be given a pseudonym and will not be referred to by your real name. All information which is collected about you during research will be kept confidential and destroyed after three years, in accordance with the Data Protection Act 1998 and GDPR.

At any point, you can withdraw from the research and not be featured in the project. I can provide you with more information on request.

**Contact:** Siân Brooke, Oxford Internet Institute, [sian.brooke@oii.ox.ac.uk](mailto:sian.brooke@oii.ox.ac.uk)

## Appendix V: Recommendations

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The masculine dominance of technology is acknowledged even by those who support it. These proponents see a natural order in women's exclusion in programming, attributing "differences" to innate ability. Also referred to as "the elephant in the valley", the rife nature of sexism is so rarely recognised by the central institutions of technology culture (Madansky, 2018). The lack of women in computing is seen, but it is not attributed to sexism. In touting the pipeline metaphor, institutions deny their responsibility in dismantling inequality through hiring practices and company culture. Instead, they blame the leaks further up the pipeline, predominantly in education. By placing focus on women's lack of representation in formal computer science classrooms, companies are able to paint gender equity as out of their control. But classrooms aren't the only places that people learn to code, and often are not the skills that the vast majority of Software Developers are hired on.

Stack Overflow (SO) and the League contextualise the underrepresentation of women and non-men in terms of wider, formal, statistics. In its most recent *Developers Survey* (2020), SO "corrects" its 12% response rate of women to a weighting 20%, attributing the shortfall to "systematic sampling issues".<sup>225</sup> Contrary to their adjustments, what is "systematic" here is the marginalisation of women from SO, not a methodological issue of sampling. To report otherwise is to mask the problem. In collecting information on user gender when signing up for the platform, SO would be better able to ascertain the reality of its "gender problem".<sup>226</sup> As such, 20% is treated as a gold standard of success, a threshold for inclusiveness that fails to account for all the other spaces, disciplines, and backgrounds in which women code.

Whilst Stack Overflow admits "sampling error" the League goes a step further advertising its 24% female identifying attendees as an accomplishment. This "success" is framed in comparison to the 21% representation of enrolment in Computer Science university departments in the USA. This figure is immediately problematized if we consider that not all those who code are computer scientists. Many other STEM disciplines have technical training, even extending across social sciences. Moreover, as many more are learning outside of traditional certifications on forums, such as Code Academy or Udemy, statistics of STEM enrolment are a biased metric.

For both the League and SO, 20% is seen as a satisfactory proportion of women's representation. It simply is not. The quantification of "acceptable representation" should not be maintenance of a status quo. This low threshold creates a margin by which institutions may justify their efforts as sufficient, even marketing their achievement as noteworthy. What is needed from such institutions is a declaration that representation is falling short of where it should be. Before progress can be made towards inclusion, the current state of exclusion needs to be recognised as impermissible. Silence is validation of women's outsider status, and the secret of sexism in technology is long since out.

Once women's lack of representation is problematized by institutions, they can begin to make pledges to correct it. A step that could be taken by both SO and the League is a visible commitment to their respective Codes of Conduct. In each instance, the CoC do define unacceptable behaviour in gendered terms.

---

<sup>225</sup> In line with statistics in the USA for the number of women who work as "Software Developers".

<sup>226</sup> This information could be chosen to be displayed on profiles or not by the user.

*“We don’t tolerate any language likely to offend or alienate people based on race, gender, sexual orientation, or religion — and those are just a few examples. Use stated pronouns (when known).” (SO)*

*“Harassment includes but is not limited to offensive verbal or written comments related to gender, age, sexual orientation, disability, physical appearance, body size, race, religion [...]” (League)*

In tackling culture of sexism what is required is (1) visibility of commitment (2) action.<sup>227</sup> As argued in Study III, A CoC means very little if its contents are not known and breaches are not seen to have consequences.<sup>228</sup> The League can promote the visibility of its CoC in several ways, three of which are outlined here, but a more complete list can be found in the Table 38. Recommendations for Stack Overflow are in Table 37.

Firstly, they can simple name what constitutes unacceptable behaviour, and state that there is no tolerance for sexism, racism, and bigotry in any form. Secondly, posters and other printed materials featuring the CoC can be distributed around the venue, this will allow attendees to see a commitment to these principles. Additionally, in reporting violations, the League provides three phone numbers and email address, delineated by North America, Asian-Pacific, and Europe. This broad sweeps reporting, that doesn’t even directly contact the League representative at the event signals inaction through such a broad geographic umbrella. An alternative could be a “anonymous tip system”, commonly used on University campuses, where instances of sexism and harassment can be reported namelessly in real time. In addition to providing sufficient harassment and first responder training to League representatives, and stating that violators of the CoC will be asked to leave the event. Considering the Leagues partner include companies which programmatically allow developers to receive and send SMS/phone calls, this should not be a technical or logistic challenge. By integrating these simple measures, the League signals that it understands the problems of sexism and hostility in coding culture, and makes tangible steps towards an inclusive environment.

My recommendations to SO follow much the same pattern; the CoC needs to be visible in order to have an impact. A simple technical solution for this could be in having a fixed banner on Stack Overflow which reminds users of the CoC and has a briefly outline of unacceptable behaviour. In addition, in the same manner when one is writing a Question or Answer they are provided with criteria. As users are encouraged to “Avoid ... (1) Asking for help, clarification (2) Making statements based on opinion” what should be included here is the commitment against prejudicial comments.<sup>229</sup> Moreover, the language of “likely to offend or alienate” is unhelpful. By framing bigotry as “offense” the onerous is on those who such comments are directed at. “Offense” is not productive language in addressing systemic inequality. Outlined here is the rationale behind just a few steps that can be made to articulate a practical commitment to tackling the white masculine dominance of technology.

---

<sup>227</sup> The Me Too (#MeToo) movement (started in 2006) is an example of how high visibility (from 2017) can motivate action to be taken. The movement gained momentum when high profile names publicised allegations of sexual harassment and assault through social media platforms, eventually leading to the trial and imprisonment of film producer Harvey Weinstein.

<sup>228</sup> The League, does promote their CoC at the start of the event, but without detail and typically just showed a URL on a PowerPoint slide

<sup>229</sup> This is a quote from a box that appears when a user chooses to submit an Answer to a Question.

**Table 37 Recommendations for Inclusivity of Platforms**

<b>What</b>	<b>How</b>
<i>Code of Conduct</i>	(1) Banner of CoC across the platform. (2) Show users specifics of the CoC when writing an Answer/Comment.
<i>User Gender</i>	(3) Collect users gender (4) Give users the option to show it on their profile, or “woman” flair
<i>Voting</i>	(5) Do not show score on Posts. Prevent power law effects (herding)
<i>Posts (Reputation)</i>	(6) Equal reputation awarded for Questions and Answers (7) New users gain higher reputation
<i>Sexism Flag</i>	(8) Allow users to specifically flag a comment as sexist. (9) Allow users to report condescension (10) This can be expanded to include racism.

**Table 38 Recommendations on the Inclusivity of Hackathons**

<b>When</b>	<b>What</b>	<b>How</b>
<b>Prior to the Event</b>	<i>Branding / Advertisement</i>	(1) Do not go for gendered marketing. Either machismo or juvenile “girly” (2) Market the event with visible diversity (3) Explicitly state that attendees do not need to be able to code, and it is an opportunity to learn
	<i>Language</i>	(4) Avoid “hacker” and “hack” (5) Avoid geek masculine terms such as “ninja” (6) Make the humour available to all
	<i>Team Building</i>	(7) Set up all teams in advance, put all team members in their own slack channel with a mentor (8) Only allow single tickets or pairs and form these into teams of four (9) Gender equal teams (50/50) (10) Match from different backgrounds/Universities
	<i>Ticketing</i>	(11) Allow attendees to choose women’s sizes, or even smaller sizes (12) Personal pronouns on badges (13) Feature the CoC or tip line on participant badges
<b>Event Set Up</b>	<i>Code of Conduct</i>	(14) Have the CoC read aloud (15) Posters of the CoC around the venue (16) Anonymous tip system (number to text) (17) Ensure League representatives have sufficient harassment training
	<i>Project Planning</i>	(18) Encourage a planning phase (19) Provide stationary and paper on tables (20) Encourage each team member to take on responsibility, different skill sets compliment
	<i>Encourage Good Hygiene</i>	(21) Make shower facilities available (22) Provide deodorant and dental products (23) Hand wipes and sanitiser (24) Encourage attendees to keep the venue clean

	<i>Food Options</i>	(25) Multiple food options, including healthier food (26) Limit alcohol consumption, if any.
	<i>Hosting / Overnight</i>	(27) Set up a system where attendees can host one another (28) Gender matching hosts (29) Reward hosts with additional “stash” to motivate (30) Several (seperate) sleeping areas
<b>Representatives</b>	<i>Mentors / Coaches</i>	(31) Mentors available to attendees (32) Diversity in mentors (33) A range of backgrounds and specialisms, not just identity characteristics
	<i>Affinity Groups</i>	(34) Invite organisations such as “Girls Can Code” to have a stand at the event (35) Feature stickers and merchandise from these groups
<b>Workshops</b>	<i>Introductory Sessions</i>	(36) Have an introductory session on a widely used programming language that introduces terms etc.
	<i>Tier System</i>	(37) Create a tier system for ranking the difficulty of workshop (38) Indicate what sort of background is needed (38) Have more advanced workshops nearer the end of the hackathon
	<i>No Experience Necessary!</i>	(39) Mark workshops where no coding is necessary clearly on the schedule (40) Workshops on point-and-click AI, where interest can precede ability
<b>Teamwork</b>	<i>Emphasis</i>	(41) Place emphasis on diversity of skillsets (including design) (42) Emphasise creativity in solutions
	<i>Antisocial</i>	(43) Do not allow teams of one (44) Encourage teams to share tables
	<i>Games</i>	(45) Ice-breaker, social games available around the venue (46) Multiplayer video games
<b>End of the Hackathon</b>	<i>Presentation</i>	(47) Have a science fair set up, with multiple stands demoing rather than presenting to the whole hackathon
	<i>Prizes</i>	(48) A variety of prizes, including ones that are available to complete beginners

## Appendix VI: Form 2D

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# This information is to be attached to all scripts of candidate number .....

### Candidates with Specific Learning Difficulties

This candidate has been diagnosed with a Specific Learning Difficulty ('SpLD' e.g. dyslexia, dyspraxia, dysgraphia, working memory deficit and attention deficit (hyperactivity) disorder (AD(H)D)).

**Please mark the script or submitted work as it stands, but indicate to yourself in your notes that the candidate has a SpLD and record any factors you consider to have a particular bearing on his or her performance. The Board will later consider what account to take of the candidate's condition when adjudicating his or her classification.**

'Specific Learning Difficulties' is an umbrella term given to a range of conditions which affect a person's ability to learn. These are commonly characterised by impaired concentration and problems with information processing and recall, and may also cause difficulties with reading, writing and spelling.

Candidates with these conditions may be awarded extra time in examinations to allow them to read the examination paper slowly, consider their responses to the questions, plan out their work, and read it over at the end.

Amongst Oxford students the most common of these disorders is dyslexia, the symptoms of which include:

- omission, repetition, transposition or substitution of words or punctuation
- particular difficulty in interpreting the Question
- simplified vocabulary and language structure (to avoid making errors)
- spelling and grammatical errors
- errors in sentence structure, word ordering and organisation
- poor or immature handwriting
- poor short-term memory
- particular difficulties generalising, or acquiring and applying rules

Students with dyslexia often think in non-verbal, non-linear patterns, with the result that their work may appear disjointed. It is recommended that examiners first read the work through quickly in order to obtain an initial sense of the candidate's overall argument and understanding of the Question.

Examiners should discount errors in spelling, grammar and sentence structure as these are considered to derive from the candidate's disability (though this does not apply in examinations where to do so would compromise the academic standards of the assessment, or where fitness to practise regulations apply). This is the case regardless of whether candidates have opted to take their examinations with extra time. Where a word processor is used, the spelling and grammar checks are enabled.

Examiners should not make extra allowance for remaining deficiencies in planning, content and logical argument, as this would constitute double compensation (even if extra time has not been taken).

## **Form Code No.2D**

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