Characterizing the Default Persona During Design: Mental Representations of Technology Users are Gendered

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Abstract

Technology design has historically prioritized the needs of more socially powerful groups in society (e.g., affluent white men, or the *default persona*). How technology designers come to prioritize certain groups while overlooking others is a question with real implications for design. We rely on psychological theories of prototypicality to characterize the "gendered persona," or the gender identity that comes spontaneously to mind when considering users. We conduct three studies including both non-expert convenience samples and expert samples of participants with technology design experience, exploring the gendered persona across populations and a range of technologies. We find that people are more likely to spontaneously describe users as men (across several technologies), whereas women are largely overlooked. Men represent the "prototypical user," a cultural stereotype shared by both non-experts and experts from populations whose stereotypes could impact real design decisions.

CCS Concepts

• **Social and professional topics** → **Gender**; • **Human-centered computing** → *Empirical studies in HCI*.

Keywords

bias, design, developers, psychology

ACM Reference Format:
Mattea Sim, Basia Radka, Tadayoshi Kohno, Franziska Roesner, and Kurt Hugenberg. 2025. Characterizing the Default Persona During Design: Mental Representations of Technology Users are Gendered. In *The 2025 ACM Conference on Fairness, Accountability, and Transparency (FAccT '25), June 23–26, 2025, Athens, Greece.* ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3715275.3732132

FAccT '25, Athens, Greece

ACM ISBN 979-8-4007-1482-5/25/06
https://doi.org/10.1145/3715275.3732132

1 Introduction

Tech products, systems, and models are often embedded with social biases [22, 54]. One prominent example is Amazon's 2014 recruitment algorithm trained on prior candidate data from a heavily gender-imbalanced tech industry, which unsurprisingly learned to prefer men candidates [26]. While these examples of biased systems and their consequences are increasingly common, far less research explores the degree to which people who design systems hold social biases that may permeate the design process. Of particular concern, marginalized communities (i.e., groups of people who are often excluded from mainstream social, economic, and/or cultural life because of structural and societal systems) have long been excluded from technology design and development considerations [4, 35, 38, 43, 46, 51, 55]. Designers may center the needs of a "default persona," an unmarked user represented by privileged and powerful social groups or the demographics of the designers themselves (e.g., often young, white, affluent, cisgender men [43, 55]). Open questions explored in our research are: to what extent do *people* in design prioritize some groups, while overlooking others? What are the *psychological underpinnings* by which designers come to overlook marginalized groups during design?

Research increasingly highlights the consequences of overlooking marginalized groups in technology design, with calls to critically consider what users are prioritized and what users are left out [2, 7, 8, 11, 14, 44, 50, 52, 57]. While audits of real technologies illustrate that design can center a default persona, we lack an empirical characterization of the extent to which the *people* who design systems prioritize certain social groups (i.e., the magnitude of this bias), and how or when this might occur during design (i.e., the psychological underpinnings of this bias). Our work seeks to fill this important gap. This project is a collaboration between three computer scientists (B.R., T.K., and F.R.) and two social psychologists (M.S. and K.H.). We leverage psychological theories and methods to evaluate the magnitude of the default persona during one part of the design process, or the degree to which people's mental representations of technology users (i.e., "personas") reflect more privileged and powerful social groups (consequently, rendering marginalized groups invisible).

Our research begins to characterize the magnitude of the default persona via the psychological processes by which designers may default to considering some groups and overlooking others. We focus on *gendered* representation of users (i.e., gendered personas) as a starting point for this work because women and non-cisgender people are underrepresented amongst technology designers [17, 60], and gender bias remains widespread in computing and a variety of other contexts [36–38, 48, 56]. Some of our analyses focus primarily on women and men, representing the majority of participants in our studies, but we also discuss the exclusion of non-cisgender users (e.g., people who do not identify with their sex assigned at birth, including non-binary, genderfluid, and agender people) from design considerations. We also begin to more deeply characterize the gendered persona across several variables: 1) the type of technology, spanning systems, devices, and platforms selected based on women's and men's actual self-reported interest in each technology (according to our pre-survey; see 3.1), and 2) participants own' gender identities. Here, we characterize whether the magnitude of the default persona differs across technologies and people.

We use psychological methods of *concept accessibility* — the degree to which different concepts come readily and automatically to mind — to empirically demonstrate the degree to which men or women are deemed the more prototypical technology users, in part by measuring the spontaneous use of gender pronouns (e.g., he/him or she/her) to describe a user [24].[1] We investigate this gendered default persona amongst both non-experts (a convenience sample of crowd workers) and experts (two samples of experienced software developers, software engineers, and product managers) in the U.S. to systematically characterize the culturally held gender default of technology users, and how much this cultural stereotype is shared by populations whose stereotypes might impact real design decisions and outcomes. To this end, we seek to answer the following research questions:

- **RQ1:** Is there a culturally held "gender default" that comes spontaneously to mind when people imagine users in technology design? And if so, how strong is this bias?
- **RQ2:** To what degree will experts (technology designers) share this gendered default persona?
- **RQ3:** Does the magnitude of the gendered default persona differ across technologies, and will it correspond with women's and men's actual interest in the technology?
- **RQ4:** Will participants' own gender identity affect the magnitude of the gendered default persona?

We pose two additional research questions to investigate on a more exploratory basis:

- **RQ5:** To what degree will experts embed other gender stereotypes (i.e., stereotypic traits) when imagining users in technology design?
- **RQ6:** Do people also associate other social identities (e.g., race, age, education level) with technology users?

We see this work as important for several reasons. To foreshadow our findings, we systematically demonstrate that both non-experts and experts with technology design experience are considerably more likely to spontaneously describe technology users as men, and we provide numerical evidence for the magnitude of this bias across technologies. These findings could have implications for real technology design, such that overlooking women and non-cisgender users may lead to systems and services that discriminate by design. Further, this work is the first, to our knowledge, to empirically demonstrate how people may overlook marginalized groups at a specific point in design. We find that some marginalized groups may be seen as *less prototypical* users and thus, may fail to spontaneously come to designers' minds. This novel application of psychological methods to design considerations can have both theoretical and practical implications. Indeed, future research can continue to apply these theories to investigate how and when other populations are overlooked during design. Practically, this method provides a novel bias evaluation measure — not for systems, but for people — and reveals how and when we can intervene on such biases during design.

[1]In computing, the term "accessibility" refers to whether a technology is accessible. In our work, we use the psychological definition of accessibility.

2 Background and Related Work

2.1 Psychological Theories of Prototypicality

Psychological theories of prototypicality can provide a deeper understanding of how technology design prioritizes some users and overlooks others. In fact, people from historically marginalized groups are often rendered invisible in a variety of contexts, such as dating, work, affiliation, and cultural representations [33]. According to Prototypicality Theory, people have "pictures in their minds" of who a typical group member is, for any given social group. However, this mental representation of groups often embeds other unrelated social groups. For instance, U.S. adults associate "Americanness" with white identities, more so than Black or Asian identities [13]. In other words, people might knowingly or unknowingly consider white Americans as the prototypical U.S. American.

Those who are seen as prototypical also come readily to mind, or in psychological terms, are *cognitively accessible* [24]. For example, when asked to describe "the most typical person they could imagine," respondents were most likely to spontaneously describe a man (and indeed, men have historically positioned themselves as the most prototypical people) [23, 39]. In the example of Amazon's recruiting algorithm, men made up the majority of employees at the company and thus, were the "ideal" or prototypical candidates. In contrast, women (and the overall *lack* of women) failed to come to mind, assumptions that went unchallenged until they inevitably resulted in a gender-biased system.

Importantly, prototypicality often intersects with social power and privilege. According to the Intersectional Invisibility Theory, ethnocentric, heterocentric, and androcentric ideologies regard white, straight men to be the standard, and everyone else merely deviates from this norm [39]. Those deemed prototypical also receive the most attention and consideration, while others (often, marginalized groups) are rendered invisible. For instance, prototypical people come more easily and automatically to mind [13, 23, 40], people tend to have worse memories for less prototypical group members [42], and advocacy groups may even devote fewer resources to less prototypical group members [49]. As such, it is important to understand who is seen as a prototypical user, and who is left out. Our work investigates just this question.

2.2 Gender Bias and Inclusivity in Design

Women and non-cisgender people have historically been rendered invisible in technology design [18, 27, 38, 41]. Although designers may not *explicitly* consider the gender of their users, and instead hold assumptions that products are "gender-neutral," a myriad of evidence suggests these products are embedded with assumptions, values, and ideas that can reinforce harmful gender stereotypes [14, 38, 50, 57]. Increasingly, researchers in this space are considering inclusive design broadly [29, 45], and how technology design should center the needs of women and non-cisgender users in a variety of contexts [34, 50, 52].

One method investigated in the context of gender inclusive design is *personas*, or fictitious descriptions of users that may help center people in the process of technology design. Personas via the "GenderMag" method can help designers identify gender inclusivity-related issues in software [9, 10], yet gendered personas can also bring to mind gender stereotypes and less inclusive design considerations [30–32]. Though there is mixed support for gendered personas, gendered assumptions about users may come automatically to mind [6, 23, 39], such that evaluating and addressing these biases will be integral to move toward more inclusive design.

This notion is emphasized in many critical feminist and queer theories [2, 3, 7, 8]. Some critical approaches suggest directly considering the identities that are prioritized in design (and thus, what ideas and beliefs are embedded in design) [7], and evaluating assumptions about *who* technologies are designed for, whether explicitly or implicitly [8, 11]. These approaches also shift the focus toward accountability of designers for the systems they create. Because designers may hold assumptions about who will use a product and how, which could be implicitly gendered, researchers argue that designers should intentionally challenge these assumptions and consider women and other marginalized users during design [2].

Still unexplored in this extant literature is an empirical demonstration of the magnitude at which technology designers come to overlook women and non-cisgender users across specific technologies, and the psychological underpinnings of this bias. Unlike prior work exploring the impact of gendered personas on design [9, 10, 30–32], we explore the process by which personas (or imagined users) can spontaneously *become* gendered. Our research presents a novel indirect method, using tools from psychology, to evaluate and quantify the magnitude of people's spontaneous gender bias at one point in design. We believe that this evaluation method and psychological theory may help facilitate the adoption of inclusive design solutions. Importantly, whereas this work focuses primarily on gender bias, gender is just one dimension of identity, and it will be integral to continue to investigate these questions across intersectional identities.

3 Methodology

Our methodological approach includes three stages spanning across a pre-survey and three studies:

(1) We first conducted a pre-survey to measure women's and men's interest in various technologies. We identified four technologies in which to explore gendered stereotypes of users (i.e., personas) in Studies 1–3.
(2) We investigated gendered personas across the four technologies with a non-expert convenience sample (Study 1).
(3) We investigated gendered personas across the four technologies with two separate expert designer samples (Studies 2 and 3).

Table 1: Proportion of pre-survey participants interested in each technology that are women and men. In parentheses, the within-gender proportion of women and men interested in each technology.

Technology Type	Women	Men	Total Interested
Health Watch	.490 (.790)	.510 (.797)	100
Security System	.495 (.790)	.505 (.781)	99
Social Media	.562 (.661)	.438 (.500)	73
AR Glasses	.274 (.323)	.726 (.828)	73
Participant n	62	64	

3.1 Pre-Survey

The pre-survey measured women's and men's interest in various technologies. Our goal was to identify technologies in which to explore a new set of participants' gendered representations of users (RQ1+RQ2), and whether the strength of these representations vary across technologies (RQ3).

We recruited 130 U.S. participants from Prolific (an online research platform) paid $1.25 to complete a 4-minute survey, with compensation set to match the highest minimum wage amongst the authors' respective cities at the time. We collected a representative sample distributing the survey to 65 female and 65 male participants. Participants indicated their gender identity in our survey (64 men, 62 women, 2 non-binary, 1 nonbinary and genderqueer, 1 chose "a gender not listed"). Because the sample of non-cisgender participants was small, we focus on women and men in analyses.

Participants read that we wanted to understand people's interests in different types of technologies. We provided brief descriptions of 20 technologies, predominantly adapted from Forbes and Best Products emerging technology trends for the year [25, 53], and some brainstormed amongst the authors. The full list of technologies can be found in Appendix E. Participants decided whether or not they would be interested in owning each technology in the future, if money was no issue, as a binary choice ("not interested in owning" or "interested in owning").

We assessed the proportion of women and men interested in each technology. From our findings, we chose four technologies to investigate in our studies (see Table 1 for interest across participant gender):

- **A smart watch that tracks health and biometric data** (i.e., Health Watch).
- **A smart home security system with remote light and door access** (i.e., Security System).
- **A social media platform with text, photo, and video sharing** (i.e., Social Media).
- **Glasses that overlay virtual content onto the real world** (i.e., AR Glasses).

We selected each technology to help us answer RQ3 in our subsequent studies: will the magnitude of the gendered persona correspond with women's and men's actual interest in a technology? We thus selected technologies that varied in interest across gender. We chose to investigate the Health Watch and Security System because women and men were similarly interested in both, allowing us to ask: to what extent is the default persona a man, even when women are just as interested in the technology? We also chose Social Media and AR Glasses, in which we observed the largest gender differences in either direction. This allows us to ask two additional questions. First, to what extent is the default persona a man, even when women show a greater preference for the technology? Second, is the default persona a man, and perhaps even more robustly, when men show a greater preference for the technology? In the latter case, we emphasize the importance of considering a diverse range of users *regardless* of these gender differences, which do not justify excluding women from design considerations. Failing to consider women in design may, in the short term, further marginalize women who *do* want to use the product, and in the long term, reinforce gender disparities in interest and adoption.

3.2 Studies 1–3

We quantified the gendered default persona across three samples of participants. We began by recruiting a U.S. convenience sample to explore non-experts' gendered default persona (Study 1). Here, we explore if there are widely held cultural stereotypes of technology users that may extend beyond those with technology design experience (RQ1). If true, that non-experts have a strong gendered representation of users, it is plausible that experts may hold and perpetuate this same culturally-held belief. Studies 2 and 3 allow us to explore just this question: to what extent do culturally held stereotypes about technology users persist amongst experts, or the very population whose assumptions about users might directly impact real design decisions (RQ2)? An alternate possibility is that relevant training and experience actually inhibit reliance on stereotypical representations of users. We explored these questions with two samples of participants with technology design expertise: a smaller, non-convenience sample of students in a professional master's program with prerequisites typically requiring professional software developing experience (Study 2), and a larger sample of experts from Prolific pre-screened for prior experience as software developers, software engineers, or product managers in technology (Study 3).

3.2.1 Participants.

Non-Expert Recruitment (Study 1). In Study 1, we recruited a standard sample of U.S. participants via Prolific to participate in a 7-minute online study in exchange for $2.18, with compensation set to match the highest minimum wage amongst the authors' respective cities at the time. We conducted an a priori power analysis for a one-sample test (analysis plan: 3.2.3), which indicated that 52 participants would be sufficient to detect a moderate effect size of $d = 0.40$ at 80% power. We thus aimed to collect approximately 208 participants (about 52 participants per between-subjects condition). In total, 214 participants completed the study. For this and all studies, we excluded participants from analyses who self-reported using ChatGPT or other AI systems to answer questions (or who "preferred not to answer" this question), or whose responses indicated poor attention based on the quality and relevance of open-ended responses. Study 1 included 213 participants in analyses after excluding 1 participant who indicated using AI (Health Watch $n = 52$; Smart Security $n = 56$; Social Media $n = 50$; AR Glasses $n = 55$). See Table 2 for participant demographics across studies.[2]

Local Expert Recruitment (Study 2). In Study 2, we recruited local experts for a 10-minute online study via email listservs sent to current students in a U.S. professional master's program at one of the participating institutions. Participants received a $10 Amazon e-gift card, with higher pay to increase participation amongst a non-convenience sample. Prerequisites for this program include having at least two years of full-time experience as software developers, software engineers, or similar roles. Most students also have a bachelor's degree in Computer Science, Computer Engineering, or a related field. In total, 37 students completed the study, and 34 were included in analyses after excluding 2 participants who indicated using AI and 1 participant who did not provide enough responses (Health Watch $n = 8$; Smart Security $n = 8$; Social Media $n = 9$; AR Glasses $n = 9$). The small sample size is a limitation of recruiting non-convenience samples, and we make appropriate adjustments to analyses and conclusions.

Online Expert Recruitment (Study 3). In Study 3, we recruited online experts via a 1-minute pre-screening survey on Prolific. 531 U.S. Prolific participants working in sectors related to Science, Technology, Engineering, Mathematics, or Information Technology received $0.34 for participation in the pre-screener. Participants responded to yes/no questions asking if they had prior experience as a software developer/engineer, product manager in technology, or related roles, and an open-ended question to elaborate on this work experience. We identified 266 participants who said "yes" to one or both of the experience questions and had apparently consistent open-ended responses.

We invited this sample of 266 participants to complete Study 3 and stopped data collection at 210 participants based on our power analysis. Participants were paid $10. We excluded from analyses 2 participants who indicated using AI and 2 participants who did not provide enough responses or provided inconsistent responses. In addition, we conservatively excluded 24 participants whose responses to career-related demographic questions appeared inconsistent with their pre-screening responses. This resulted in 182 participants included in analyses (Health Watch $n = 45$; Smart Security $n = 48$; Social Media $n = 47$; AR Glasses $n = 42$). Although this sample was slightly smaller than intended, we chose a conservative approach to ensure participants included in analyses had relevant experience. We also conducted a post-hoc sensitivity analysis using the condition with the smallest n (AR glasses) and found that 42 participants is sufficient to detect a minimum effect size of $d = 0.44$ at 80% power, which we determined was sufficiently close to the effect size in our original power analysis. Including all participants in analyses does not substantially change our findings.

3.2.2 Procedure. The procedure was identical across all three studies (see all materials in Appendix A), with the exception of additional career-related demographic questions in Studies 2 and 3

[2]Non-cisgender participants include participants who identified as non-binary, genderfluid, genderqueer, and agender. In Table 2, participants are counted more than once if they selected multiple gender or racial identities. We also include the frequency of participants who chose multiple identities.

Table 2: Participant demographic frequencies across all studies.

Gender	Study 1	Study 2	Study 3
Man	90	23	144
Woman	113	8	34
Non-Cisgender	8	1	5
Multiple Identities Selected	3		1

Age	Study 1	Study 2	Study 3
18-24	26	1	9
25-34	79	27	60
35-44	49	4	62
45-54	37		26
55-64	15		17
65+	6		7

Race	Study 1	Study 2	Study 3
White	156	12	123
Asian/Asian American	24	16	27
Hispanic/Latino/a/x	22	4	14
Black/African American	20		
Multiple Identities Selected	15	3	9
Another Identity/Self-Describe	5	2	4
American Indian/Alaskan Native	2		3

(Appendix B and D). Participants were told that we want to understand how people think about the users of different technologies using a process similar to Design Fiction [1, 47], in which technology designers imagine a fictional user of a technology to explore what a future with these technologies might look like. Whereas a traditional Design Fiction study might study the whole scenario created, we focused primarily on the gender identities used to describe the persona, though we did not explicitly tell participants that we were studying gender or a default persona. This part of the design process, in which people consider potential users and how they will interact with the technology (e.g., [19, 20]), is an important point to investigate because it is the start of the design process, so any assumptions made here will influence design downstream. Participants answered several prompted questions to help them imagine this user.

Participants were randomly assigned to one of four technology conditions determined in the pre-survey (Health Watch, Security System, Social Media, AR Glasses), and were told to "Imagine a person living in the U.S. who is a user of [technology]." Participants identified a first name for the fictional user in an open response (i.e., they could type any name), which was inserted into subsequent questions. Participants then answered 8 text-response questions (one per page) about the user (e.g., describe the first time [name] used the [technology] today and what [name] used it for; describe an average day for [name]; what is [name's] educational background?; list 3 traits or characteristics that describe [name]). In actuality, we used these open-ended responses to measure participants' spontaneous use of gender pronouns to describe the fictional users (adapted from psychological methods [40]).

Three final questions asked the demographic groups they imagined for the user (i.e., gender, race/ethnicity, age). We included the gender question to check apparent consistency with the pronouns used, and to rely on this response if participants used pronouns that can be ambiguous (e.g., they/them) to describe the user. Other demographic questions allowed us to investigate, on an exploratory basis, other social identities (e.g., race, age) that come spontaneously to mind when imagining a user (RQ6). Finally, participants responded to demographic questions and read a debriefing form.

3.2.3 Analysis Procedure. In Studies 1–3, two independent coders read all responses and coded the gender identity of each participant-described user (hereafter called "personas"), based on both the pronouns spontaneously used to describe the persona and the gender identified for the persona. The two coders had 100% agreement across all studies.

To analyze the magnitude of the gendered persona across technologies (RQ1, RQ2, + RQ3), we conducted one-sample proportion tests comparing the proportion of participants who described the persona as a woman to the proportion of people assigned female at birth in the U.S. population (.504).[3] In other words, we assessed if women personas are underrepresented relative to population statistics. To analyze whether the gendered persona corresponded with women's and men's actual interest in the technology (RQ3), we conducted one-sample proportion tests comparing the proportion of participants who described the persona as a woman to the proportion of women in the pre-survey participants interested in owning the technology (Health Watch = .49; Smart Security = .50; Social Media = .56; AR Glasses = .27).

3.2.4 Ethical Considerations. Study materials were submitted to the university Human Subjects Review Board (IRB) of both participating institutions, who deemed this research exempt because it poses no more than minimal risk to participants and meets a variety of other requirements. Participants could skip questions they were uncomfortable answering and could leave the survey at any time.

4 Results

4.1 Study 1 Results: Exploring the Cultural Gendered Persona

4.1.1 RQ1: Non-Experts are More Likely to Spontaneously Describe Personas as Men. We first sought to answer RQ1: is there a culturally held "gender default" that comes spontaneously to mind when laypeople imagine technology users? We observed a strong gendered default persona amongst non-experts. Overall, 69% of participants described the persona as a man, 29.6% described the persona as a woman, 0.9% described the persona outside of the gender binary (specifically, as non-binary or genderfluid), and 0.5% did not specify a gender or use pronouns. See Table 3 for the proportion of personas described as women, men, or non-cisgender in all studies.[4]

[3]We use the term "female" here to be consistent with the U.S. Census data. Comparing gender identity to people assigned female at birth in the population is not a perfect comparison, and ideally we would compare to the proportion of the population identifying as women. In the absence of these data, we acknowledge this as a limitation of our analyses.

[4]Non-cisgender personas are categorized under all specified gender identities — e.g., although some people identify with both a non-cisgender identity and other gender identities, the personas are classified as exclusively non-cisgender if no other gender identities are specified. No participants described transgender women or transgender men personas. Further, one participant in Study 1 (Smart Security condition) did not use pronouns or specify a gender identity for the persona. All other participant data are reflected in Table 3.

4.1.2 RQ3: Gendered Personas Differ Across Technology Types.

Participants most often described the persona as a man across technology types, with the exception of Social Media users (see Table 3). We investigated if the proportion of personas described as women (as compared to all other options) differed from population and pre-survey proportions described above.

Within three conditions, the proportion of women personas was significantly lower than the proportion of people assigned female at birth in the population: *Health Watch*: Z = -2.277, 95% CI [0.22, 0.48], p = .023, *Smart Security*: Z = -4.871, 95% CI [0.08, 0.28], p < .001, and *AR Glasses*: Z = -5.588, 95% CI [0.04, 0.22], p < .001. Within the same three conditions, the proportion of women personas was also significantly lower than the proportion of women amongst pre-survey participants interested in the technology: *Health Watch*: Z = -2.075, 95% CI [0.22, 0.48], p = .038, *Smart Security*: Z = -4.811, 95% CI [0.08, 0.28], p < .001, and *AR Glasses*: Z = -2.384, 95% CI [0.04, 0.22], p = .017.

Patterns in the Social Media condition differed. Here, the proportion of women personas did not significantly differ from the population proportion, Z = 0.792, 95% CI [0.42, 0.70], p = .428, nor from the pre-survey proportion, Z = 0.000, 95% CI [0.42, 0.70], p = 1.

In other words, we found that the magnitude of the gendered persona may differ across technologies (RQ3). Participants most often described personas as men across three technologies varying in pre-survey women's and men's actual interest, but this pattern did not persist for the technology in which women were *more* interested than men.

4.1.3 RQ4: The Gendered Persona Depends on Participants' Gender.

Participants' gender also played a role in the gendered persona. We investigated the likelihood of women and men describing a woman persona (as compared to any other gender), including only these gender groups because of sample sizes. A Chi-Square analysis indicated that amongst participants identified as women, there was a significant relationship between the technology condition and the likelihood of describing the persona as a woman, χ^2 = 26.277, p < .001, ϕ = .482. Amongst participants identified as men, the relationship between the technology condition and the likelihood of describing the persona as a woman was not significant, χ^2 = 3.651, p = .302, ϕ = .203. See Table 4 for the proportion of women and men who described the persona as a woman across conditions.

Women showed variability in their likelihood of describing the persona as a woman. For instance, 80% of women described Social Media users as women, and nearly half described Health Watch users as women, but only 20.8% and 22.2% of women described Security System and AR Glasses users as women, respectively.

In contrast, less than 25% of men within all four conditions described the persona as a woman. Even in the Social Media condition, which appeared more egalitarian in findings collapsed across participant gender, only 23.5% of men described a woman persona. Men may be especially unlikely to spontaneously consider women as users, regardless of the technology type.

4.2 Studies 2 and 3 Results: Exploring the Gendered Persona Amongst Experts

4.2.1 RQ2: People with Technology Design Experience are Also More Likely to Spontaneously Describe Personas as Men.

In Study 2, 76.5% of professional master's student experts described the persona as a man, whereas 23.5% described the persona as a woman. Similarly in Study 3, 75.8% of online experts described the persona as a man, whereas 24.2% described the persona as a woman. No participants in either study described a non-cisgender persona.

Answering RQ2, the magnitude of experts' gendered default persona was comparable to, if not stronger than, the gendered persona observed amongst laypeople in Study 1. We replicated the gendered default persona with both a smaller sample of student experts (Study 2) and a larger sample of online experts (Study 3).

4.2.2 RQ3: The Magnitude of Experts' Gendered Default Persona Differs Across Technology Types.

Descriptively, Study 2 experts were more likely to describe the persona as a man across three technologies with the exception of Social Media, where 55.6% of participants described the persona as a woman. In contrast, over 70% of participants within the other three conditions (Health Watch, Security System, and AR Glasses) described the persona as a man. For instance, 100% of Health Watch users were described as men. Because of the smaller sample size in Study 2, we did not statistically compare proportions within each technology condition or across participant gender. However, collapsed across all four conditions, the proportion of personas described as women was significantly lower than the proportion of people assigned female at birth in the population, Z = -3.134, 95% CI [0.09, 0.38] p = .002.

With a larger sample of online experts in Study 3, we explored whether the proportion of participants who described a woman persona across conditions differed from population proportions and pre-survey proportions (RQ3). Within three conditions, the proportion of women personas was significantly lower than the proportion of people assigned female at birth in the population: *Health Watch*: Z = -3.482, 95% CI [0.12, 0.37], p < .001, *Smart Security*: Z = -5.252, 95% CI [0.03, 0.22], p < .001, and *AR Glasses*: Z = -4.372, 95% CI [0.05, 0.28], p < .001. Within two conditions, the proportion of women personas was also significantly lower than the proportion of women amongst pre-survey participants interested in the technology: *Health Watch*: Z = -3.295, 95% CI [0.12, 0.37], p < .001, and *Smart Security*: Z = -5.196, 95% CI [0.03, 0.22], p < .001. In the AR Glasses condition, this proportion was descriptively (but not significantly) lower than the pre-survey proportion, Z = -1.508, 95% CI [0.05, 0.28], p = .131. Further, in the Social Media condition, the proportion of women personas was descriptively, but not significantly, lower than the proportion of people assigned female at birth in the population, Z = -1.076, 95% CI [0.28, 0.57], p = .282, and the proportion of women amongst pre-survey participants interested in the technology, Z = -1.857, 95% CI [0.28, 0.57], p = .063.

Notably, in Study 3, over 55% of the personas were described as men within each condition. The gendered persona was weakest in the Social Media condition, though still more than half (57.4%) of personas were described as men.

The gendered persona was particularly pronounced in the Health Watch, Security System, and AR Glasses conditions, in which over 75% of participants described users as men (Table 3). Most dramatically, in the Security System condition, 87.5% of personas were described as men and only 12.5% were described as women, in stark contrast to our pre-survey findings that men and women were near equally interested in owning this security system.

Table 3: Proportion of personas described as women, men, or non-cisgender within each technology condition and study.

		Persona Gender		
Study	Condition	Man (He/Him)	Woman (She/Her)	Non-Cisgender
1	Health Watch	.654	.346	.000
	Security System	.804	.179	.000
	Social Media	.420	.560	.020
	AR Glasses	.855	.127	.018
	Study 1 Total	.690	.296	.009
2	Health Watch	1.00	.000	.000
	Security System	.750	.250	.000
	Social Media	.444	.556	.000
	AR Glasses	.889	.111	.000
	Study 2 Total	.765	.235	.000
3	Health Watch	.756	.244	.000
	Security System	.875	.125	.000
	Social Media	.574	.426	.000
	AR Glasses	.833	.167	.000
	Study 3 Total	.758	.242	.000

Table 4: Proportion of women and men who described the persona as a woman, by technology condition.

		Participant Gender	
Study	Condition	Women	Men
1	Health Watch	.469	.176
	Security System	.208	.133
	Social Media	.800	.235
	AR Glasses	.222	.040
	Study 1 Total	.442	.135
3	Health Watch	.429	.206
	Security System	.500	.050
	Social Media	.500	.389
	AR Glasses	.556	.061
	Study 3 Total	.500	.175

4.2.3 RQ4: Men with Technology Design Experience are Unlikely to Spontaneously Describe Personas as Women. In Study 3, we also explored the impact of participant gender on the likelihood of spontaneously describing the persona as a woman (RQ4). Amongst participants identified as women, the relationship between the technology condition and the likelihood of describing the persona as a woman was not significant, $\chi^2 = 0.254$, $p = .968$, $\phi = .086$. Amongst participants identified as men, there was a significant relationship between the technology condition and the likelihood of describing the persona as a woman, $\chi^2 = 18.967$, $p < .001$, $\phi = .364$.

In general, women appeared more egalitarian in their personas, with 50% describing the persona as a woman (with little descriptive variability across conditions, though we note fairly small sample sizes of women within each condition).

In contrast, a dramatically low percentage of men described Security System and AR Glasses users as women (5% and 6.1%, respectively). Men most often described Social Media users as women (compared to the other technology conditions), though still less than half (38.9%) did so. Overall, the proportion of personas described as women varied across conditions, though men were much less likely to describe personas as women across all conditions (Table 4).

4.2.4 RQ5: Gendered Stereotypes Also Appear in Persona Traits. On a more exploratory basis, we investigated whether online experts in Study 3 may also embed gender stereotypes in their descriptions of personas (RQ5).

In particular, we explored the *traits* used to describe women and men personas, in response to the prompt asking participants to list 3 traits/characteristics to describe the user. Trait ascriptions are central to stereotyping processes and often reveal more information about the stereotype content associated with different groups [16]. We first hypothesized that people may be more likely to describe men as "tech-savvy," and counted the occurrence of this and related phrases (e.g., "tech-interested"). We counted only one occurrence of tech-savvy related traits amongst 44 women personas (2.3%), as compared to 21 occurrences amongst 138 men personas (15.2%).

Next, we used data-driven analyses to explore the most commonly listed traits describing personas. We used the 'tm' [15] and 'snowballc' [5] packages in R to clean the text and reduce words to their root form, before generating the five most frequently listed traits for women and men personas (See Table 5). "Smart" was the most common trait across persona gender. However, women personas were described with a higher number of communal traits (i.e., outgoing, fun, funny), as compared to a higher number of agentic and competence traits describing men personas (i.e., curious, active, smart, intelligent), aligning with cultural gender stereotypes [28].

We also examined gendered stereotypes indirectly by generating the most frequent traits across technology types, which themselves vary in gender stereotypicality. Notably, all five traits describing Social Media users (the most woman-stereotyped technology, according to our data) were also highly communal (e.g., kind, empathetic), and lacked competence traits (smart) present in every other condition. These results in Table 5 reveal more subtle ways that personas are stereotyped — in fact, personas are ascribed traits

Table 5: Most frequently listed traits to describe the persona in Study 3, across persona gender and technology type. Green = 12+ occurrences, blue = 8–11 occurrences, yellow = 4–7 occurrences.

Women	Men	Health Watch	Security Sys	Social Media	AR Glasses
smart	smart	smart	smart	kind	smart
outgo	intellig	healthi	kind	outgo	curious
funni	curious	activ	depend	empathet	intellig
fun	active	fit	intellig	friend	funni
intellig	kind	funni	care	social	fun

Table 6: Proportion of personas in each study described within specific demographic groups.

	White	College Ed. (+)	Ages 0-19	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50+
Study 1	.746	.681	.033	.432	.329	.127	.075
Study 2	.529	.912	.000	.471	.294	.147	.029
Study 3	.775	.824	.011	.423	.396	.110	.060

consistent with classic stereotypes of men as agentic and women as communal [28]. Broadly, experts may embed a variety of trait-based gender stereotypes in their consideration of users, beyond just the gender pronouns that come spontaneously to mind.

4.2.5 RQ6: People Associate Other Social Identities with Personas. Finally, we explored the degree to which other social identities are embedded in personas, across all three studies (RQ6). See Table 6 for the proportion of personas in each study described as monoracial white, college educated or higher (e.g., master's, PhDs), and across age.[5] Consistent with conceptual understandings of the "default persona" [55], participants' prototypical persona appears to be a young, educated, white man. The default persona also tended to have multiple intersecting privileged identities. For instance, across all studies combined, 75.9% of men personas were described as monoracial white, and 61.1% of men personas were described as white and college educated or higher. Also across all studies, 70.4% of women personas were described as monoracial white, and 51.3% of women personas were described as white and college educated or higher. Several privileged intersecting identities may be embedded in the prototypical user.

5 Discussion

The extent to which technology designers come to prioritize some groups, while overlooking others, is an important question as we strive to make more equitable technologies. Across three studies, we quantified the gendered representation of technology users. We first sought to demonstrate the magnitude of this gendered persona. We found that non-experts hold a strong gendered persona, or a tendency to associate technology users with men more so than women and non-cisgender people (RQ1; Study 1). This gendered representation of users persisted (and was strong in magnitude) amongst two samples of expert participants with technology design experience (RQ2; Studies 2–3), with possible extensions to the wider population of designers and developers whose stereotypes could impact real design decisions.

[5]Two coders independently coded the education status of each persona (94% agreement across all studies) and the primary investigator resolved disagreements.

The gendered persona was also robust, though varying in magnitude, across several types of systems, devices, and platforms (RQ3). Comparing the proportion of women personas to the proportion of women interested in the technology, women personas seem to be *underrepresented* relative to women's actual interest in the product. In other words, people tended to overwhelmingly imagine technology users as men, even when women and men showed equivalent interest in using a technology (according to our pre-survey data). We observed one possible exception to this pattern: participants more often imagined Social Media users as women than men in Studies 1 and 2. However, this finding is further qualified by more nuanced patterns of results — in Study 1, participants who were men still overwhelmingly described Social Media personas as men, and in Study 3, more than half of the expert participants described Social Media personas as men (and men participants did so even more frequently). Overall, gendered user stereotypes did *not* correspond with women's and men's actual interest in a technology (RQ3): women personas were overlooked, both when women report near equal interest in a technology (Health Watch, Smart Security), and when women report relatively lower interest in a technology (AR Glasses). We also caution against the conclusion that associating certain devices (e.g., AR Glasses) with men more so than women is appropriate if men are more interested in the technology. We believe all technologies should be designed with considerations of all possible users and stakeholders. When the centered demographic group is also a group traditionally associated with power (e.g., men), those traditionally with less power may be further marginalized.

Participants' gender identity also affected the magnitude of the gendered persona (RQ4): men were considerably more likely than women to describe personas as men, across all technologies. These results (and the study of developer bias more broadly) feel especially timely in the context of recent pushback against DEI efforts, such as Meta CEO Mark Zuckerberg's statement that corporations have become "culurally neutered" and need more "masculine energy" [21], a worrisome perspective in the landscape of an already gender–imbalanced industry where women face persistent barriers to inclusion [17, 36, 37, 56, 59, 60].

Interestingly, we also observed other indirect gender stereotypes embedded in personas (e.g., communal vs. agentic traits ascribed to different personas; RQ5). Designers may hold stereotypes about social groups that permeate technology design. These findings are relevant to the literature on personas in design [9, 10, 30, 32]. For instance, prior work found gender-neutral personas contributed to more inclusive design considerations than gender-labeled personas [30]. Our findings may further complicate this picture — even supposedly gender-neutral contexts can become spontaneously gendered, through both a persona's labeled gender *and* implicit assumptions about the persona's stereotypic traits and characteristics. In other words, gender stereotypes in design may permeate beyond just the presumed gender of a persona. Research and practice in this space should go beyond merely considering women personas to also avoid stereotypic considerations of what users across gender want or need.

Broadly, our results demonstrate how psychological theories of prototypicality can play a role in the likelihood of considering marginalized populations at a specific point in design. When prompted to imagine a technology user in a future technological landscape, men personas were more *cognitively accessible* than women or non-cisgender personas — in other words, men automatically came to mind. This automatic gendered persona is consistent with broader theories of prototypicality: people who are deemed prototypical come most readily and easily to mind [23, 39, 40]. Therefore, men are deemed the most *prototypical users*. These findings are impactful because people who are deemed prototypical not only come easily to mind, but also receive the most attention and consideration [40, 49]. Consequently, women and non-cisgender users may be overlooked in the development of new technologies, with more prototypical (and privileged) users receiving prioritization and consideration.

Importantly, this work also builds upon prior research on gender inclusivity in computing. Researchers are increasingly calling for technology designers to critically evaluate their assumptions about who will use a product and how [2, 7, 8, 11], and we contribute to this literature with both a deeper understanding of how these assumptions manifest during design and a novel method for quantifying these biases. Our findings provide empirical evidence for the idea that when gender is not made salient (i.e., in supposedly "gender-neutral" design settings), people tend to automatically default to considering men as users. Further, this novel methodological approach to *characterizing* and *quantifying* the assumptions designers make about users may have utility in applied settings, to critically evaluate gaps in design considerations.

5.1 Open Questions and Limitations

The present work raises several open questions that may motivate future work. First, our studies focused predominantly on the gendered representation of users, though many other marginalized communities are also overlooked in design, especially at the intersection of multiple marginalized identities [4, 12, 35, 43, 46, 51, 55]. We find preliminary evidence that people embed intersectional social categories into their representations of users, such as gender, race, age, and social class (RQ6). Young, white, educated men appear to come easily to mind as the typical technology users. Continuing to explore how designers overlook groups at the intersection of multiple social identities is crucial [12]. Importantly, though we predominantly investigated gender stereotypes in our studies, our work provides a foundation for continuing to empirically quantify the default persona, with many questions left to explore.

Second, the magnitude of the gendered persona varies across technologies, such that this bias may have boundaries. However, we found that people (especially men) were unlikely to describe users as women across several systems, devices, and platforms, all of which likely vary in gender stereotypicality and actual interest by gender. Our data suggest the gendered default persona is robust. Still, future work may benefit from exploring boundaries and moderators of this bias. For instance, whereas we confirm that marginalized people are not seen as prototypical users, and are therefore overlooked, there may be technologies for which marginalized people *are* deemed prototypical and are consequently subject to harmful hyper-focus (e.g., surveillance technologies targeting communities of color). Marginalized communities can be made both *invisible* and *hypervisible* by technology design, each with their own unique consequences [4]. Applying theories of prototypicality may help future research uncover how the gendered persona extends across technologies and contexts.

Third, we assessed the gendered persona across two samples of experts with technology design experience, though there may be a variety of other relevant expert populations not fully represented in our sample (e.g., UX specialists, security analysts). We believe our participants represent an important population of experts whose beliefs and decisions can affect real design outcomes. Still, future work should continue to explore these processes across expert populations.

Fourth, the technology designer samples in Studies 2 and 3 included predominantly men, and thus were not distributed evenly across participant gender. However, this imbalance reflects real gender disparities in the technology industry. We therefore believe these findings are relevant for, and may extend to, the greater population of technology designers. Further, findings replicate across both a more gender-balanced sample (Study 1) and the less balanced designer samples (Studies 2 and 3), suggesting conclusions may remain fairly consistent with more evenly distributed samples.

5.2 Implications for Technology Design

Our work reveals important insights for moving toward more equitable development and design practices. We provide a novel evaluation tool, adapted from psychological methods, that may be of practical use in real design settings. For instance, design workshops, trainings, or actual development practices may benefit from similar exercises in which designers imagine personas and later analyze and reflect on who is included across these personas and who is left out. This *indirect* assessment is particularly useful in identifying and guiding conversations around biases that may be more difficult to strategically control. Indeed, we find that gendered assumptions about users can arise spontaneously, and therefore this bias and its potential impact on design could go undetected. This method is a concrete, scalable, and valuable evaluation technique for people designing systems to improve their social impact. Whereas most auditing research focuses on biases in systems themselves, ours focuses on people, an important direction in inclusive design.

Further, our work provides empirical evidence supporting the importance of diversifying the technology workforce. Women and other marginalized groups are underrepresented within a variety of positions in the tech industry [17, 59, 60]. Notably, in our studies, women (and especially women with design experience) were more likely than men to describe users beyond the "prototypical" — i.e., women personas came more often to their minds. These findings suggest people from other marginalized groups could have more egalitarian personas, as well. Whether this is because 1) the social groups we belong to are more cognitively accessible to us, or 2) having a marginalized identity makes a variety of marginalized groups more accessible, remain open questions. In either case, including people from marginalized backgrounds (e.g., across intersections of gender, race, age, disability, education, and more) may yield more inclusive design considerations.

Importantly, our findings also reveal how we can intervene on the tendency for designers to overlook certain groups. Presumed non-prototypical users (e.g., women and non-cisgender people) may fail to come to mind in the context of technology design. However, psychological interventions can help bring to mind groups that might be initially overlooked, an area worth continued research. For example, a simple intervention providing concrete examples of how different groups are overlooked in design, and prompting people to consider users that might often be overlooked, helped computer science undergraduates consider a more diverse range of users in a threat modeling exercise [44]. Interventions that raise awareness of stereotypes can be used to train designers to intentionally consider marginalized communities.

This work is also part of a broader effort in computing to center how to design for and with diverse populations [12, 19, 20]. Researchers have put forth concrete recommendations and methodologies toward this effort. For instance, the Diverse Voices method suggests holding tech policy conversations with experts from (or advocating for) underrepresented groups, with the aim of including more diverse perspectives in tech policy that might otherwise have disparate impacts across these groups [58]. In this context, our persona methods may help identify which groups are prioritized and which groups are overlooked to move toward including more populations in design conversations.

More broadly, we recognize the importance of — as a field — changing industry norms and exploring different approaches to help developers and practitioners. Our findings empirically demonstrate that technology design can fail to account for a diverse range of user populations, underscoring the need to create and adopt normative practices across the tech industry that foster more inclusive design. We hope our findings motivate continued work in these areas on diverse stakeholder identification and consideration.

5.3 Conclusion

Taken together, we see consistent evidence that both expert designers and non-experts see men as the default user of a wide variety of technologies. The present results quantify and characterize a broader trend in technology design in which marginalized groups are often ignored during the design process. This work emphasizes the importance of studying not just biases in systems, but also biases in people who design systems, as part of the effort toward more inclusive development practices.

Acknowledgments

We thank the anonymous reviewers for their feedback that improved this paper. This work was done as part of the Center for Privacy and Security for Marginalized and Vulnerable Populations (PRISM), supported by the National Science Foundation under Awards SaTC-2205171 and 2207019.

References

[1] Naseem Ahmadpour, Sonja Pedell, Angeline Mayasari, and Jeanie Beh. 2019. Co-Creating and Assessing Future Wellbeing Technology Using Design Fiction. *She Ji: The Journal of Design, Economics, and Innovation* 5, 3 (2019), 209–230.

[2] Shaowen Bardzell. 2010. Feminist HCI: Taking Stock and Outlining an Agenda for Design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1301–1310.

[3] Shaowen Bardzell and Jeffrey Bardzell. 2011. Towards a Feminist HCI Methodology: Social science, Feminism, and HCI. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 675–684.

[4] Ruha Benjamin. 2019. *Race After Technology: Abolitionist Tools for the New Jim Code*. Polity Press.

[5] Milan Bouchet-Valat. 2023. *SnowballC: Snowball Stemmers Based on the C 'libstemmer' UTF-8 Library*. https://cran.r-project.org/web/packages/SnowballC/index.html R package version 0.7.1.

[6] Adam Bradley, Cayley MacArthur, Mark Hancock, and Sheelagh Carpendale. 2015. Gendered or neutral? Considering the language of HCI. In *Proceedings of the 41st Graphics Interface Conference*. 163–170.

[7] Samantha Breslin and Bimlesh Wadhwa. 2014. EnGendering Interaction Design. In *3rd International Conference on User Science and Engineering (i-USEr)*. 292–295.

[8] Samantha Breslin and Bimlesh Wadhwa. 2014. Exploring Nuanced Gender Perspectives within the HCI Community. In *Proceedings of the 6th Indian Conference on Human-Computer Interaction*. 45–54.

[9] Margaret Burnett, Anicia Peters, Charles Hill, and Noha Elarief. 2016. Finding Gender-Inclusiveness Software Issues with GenderMag: A Field Investigation. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 2586––2598.

[10] Margaret Burnett, Simone Stumpf, Jamie Macbeth, Stephann Makri, Laura Beckwith, Irwin Kwan, Anicia Peters, and William Jernigan. 2016. GenderMag: A Method for Evaluating Software's Gender Inclusiveness. *Interacting with Computers* 28, 6 (2016), 760—-787.

[11] Elizabeth F. Churchill. 2010. Sugared Puppy-Dog Tails: Gender and Design. *Interactions* 17, 2 (2010), 52–56.

[12] Sasha Costanza-Chock. 2018. Design justice: Towards an intersectional feminist framework for design theory and practice. In *Proceedings of the Design Research Society*. 528–540.

[13] Thierry Devos and Mahzarin R. Banaji. 2005. American = White? *Journal of Personality and Social Psychology* 88, 3 (2005), 447–466.

[14] Susan M. Dray, Daniela K. Busse, Anke Marei Brock, Anicia N. Peters, Shaowen Bardzell, Allison Druin, Margaret M. Burnett, Elizabeth F. Churchill, Gayna Williams, Karen Holtzblatt, and Diane Murray. 2014. Perspectives on Gender and Product Design. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems*. 53–56.

[15] Ingo Feinerer and Kurt Hornik. 2024. *tm: Text Mining Package*. https://cran.r-project.org/web/packages/tm/index.html R package version 0.7-14.

[16] Susan T. Fiske, Amy J.C. Cuddy, Peter Glick, and Jun Xu. 2002. A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of Personality and Social Psychology* 82, 6 (2002), 878–902.

[17] Jack Flynn. 2023. 25 Trending Tech Industry Statistics [2023]: Tech Industry Demographics, Worth And More. *Zippia* (2023). https://www.zippia.com/advice/tech-industry-statistics/.

[18] Guo Freeman, Divine Maloney, Dane Acena, and Catherine Barwulor. 2022. (Re)discovering the Physical Body Online: Strategies and Challenges to Approach Non-Cisgender Identity in Social Virtual Reality. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–15.

[19] Batya Friedman and David G. Hendry. 2019. *Value Sensitive Design: Shaping Technology with Moral Imagination*. The MIT Press.

[20] Batya Friedman, Peter H. Kahn Jr., and Alan Borning. 2002. *Value Sensitive Design: Theory and Methods*. Technical Report. University of Washington. 2–12 pages.

[21] Alyssa Goldberg. 2025. Mark Zuckerberg says companies need more 'masculine energy.' What does that even mean? *USA Today* (2025). https://www.usatoday.com/story/life/health-wellness/2025/01/17/mark-zuckerberg-meta-workforce-masculine-energy/77755286007/.

[22] Douglas Guilbeault, Solène Delecourt, Tasker Hull, Bhargav Srinivasa Desikan, Mark Chu, and Ethan Nadler. 2024. Online images amplify gender bias. *Nature* 626, 8001 (2024), 1049–1055.

[23] Mykol C. Hamilton. 1991. Masculine Bias in the Attribution of Personhood. *Psychology of Women Quarterly* 15 (1991), 393–402.

[24] E. Tory Higgins. 1996. Knowledge Activation: Accessibility, Applicability, and Salience. In *Social Psychology: Handbook of Basic Principles*, E. T. Higgins and Arie W. Kruglanski (Eds.). Guilford Press, 133–168.

[25] Meredith Hirt and Samantha Allen. 2023. 10 Smart Home Trends This Year. *Forbes* (2023). https://www.forbes.com/home-improvement/internet/smart-home-tech-trends/.

[26] Roberto Iriondo. 2018. Amazon Scraps Secret AI Recruiting Engine that Showed Biases Against Women. *Carnegie Mellon University School of Computer Science* (2018). https://www.ml.cmu.edu/news/news-archive/2016-2020/2018/october/amazon-scraps-secret-artificial-intelligence-recruiting-engine-that-showed-biases-against-women.html.

[27] Os Keyes. 2018. The Misgendering Machines: Trans/HCI Implications of Automatic Gender Recognition. In *Proceedings of the ACM on Human-Computer Interaction*, Vol. 2. 1–22.

[28] Anne M. Koenig and Alice H. Eagly. 2014. Evidence for the Social Role Theory of Stereotype Content: Observations of Groups' Roles Shape Stereotypes. *Journal of Personality and Social Psychology* 107, 3 (2014), 371–392.

[29] Calvin A. Liang, Sean A. Munson, and Julie A. Kientz. 2021. Embracing Four Tensions in Human-Computer Interaction Research with Marginalized People. *ACM Transactions on Computer-Human Interaction (TOCHI)* 28, 2 (2021), 1–47.

[30] Milena Ribeiro Lopes and Carl Vogel. 2021. The Influence of Personas' Gender in Design. In *Proceedings of the 14th Biannual Conference of the Italian SIGCHI Chapter* (Bolzano, Italy) *(CHItaly '21, 9)*. Association for Computing Machinery, New York, NY, USA, 8 pages.

[31] Nicola Marsden and Maren Haag. 2016. Evaluation of GenderMag personas based on persona attributes and persona gender. In *HCI International 2016–Posters' Extended Abstracts* (Toronto, Canada). Springer International Publishing, 122–127.

[32] Nicola Marsden and Alexander Wittwer. 2022. Empathy and exclusion in the design process. *Frontiers in Human Dynamics* 4 (2022), 1050580.

[33] Rebecca Neel and Bethany Lassetter. 2019. The Stigma of Perceived Irrelevance: An Affordance-Management Theory of Interpersonal Invisibility. *Psychological Review* 126, 5 (2019), 634–659.

[34] Anna Offenwanger, Alan John Milligan, Minsuk Chang, Julia Bullard, and Dongwook Yoon. 2021. Diagnosing Bias in the Gender Representation of HCI Research Participants: How it Happens and Where We Are. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–18.

[35] Ihudiya Finda Ogbonnaya-Ogburu, Angela D.R. Smith, Alexandra To, and Kentaro Toyama. 2020. Critical Race Theory for HCI. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–16.

[36] Hema Susmita Padala, Christopher Mendez, Felipe Fronchetti, Igor Steinmacher, Zoe Steine-Hanson, Claudia Hilderbrand, Amber Horvath, Charles Hill, Logan Simpson, Margaret Burnett, Marco Gerosa, and Anita Sarma. 2022. How Gender-Biased Tools Shape Newcomer Experiences in OSS Projects. *IEEE Transactions on Software Engineering* 48, 1 (2022), 241–259.

[37] Rajshakhar Paul, Amiangshu Bosu, and Kazi Zakia Sultana. 2019. Expressions of Sentiments during Code Reviews: Male vs. Female. In *2019 IEEE 26th International Conference on Software Analysis, Evolution and Reengineering (SANER)*. 26–37.

[38] Caroline Criado Perez. 2019. *Invisible Women: Exposing Data Bias in a World Designed for Men.* Abrams Books.

[39] Valerie Purdie-Vaughns and Richard P. Eibach. 2008. Intersectional Invisibility: The Distinctive Advantages and Disadvantages of Multiple Subordinate-Group Identities. *Sex Roles* 59 (2008), 377–391.

[40] Joanna Schug, Nicholas P. Alt, and Karl Christoph Klauer. 2015. Gendered Race Prototypes: Evidence for the Non-Prototypicality of Asian Men and Black Women. *Journal of Experimental Social Psychology* 56 (2015), 121–125.

[41] Kelsea Schulenberg, Guo Freeman, Lingyuan Li, and Catherine Barwulor. 2023. "Creepy Towards My Avatar Body, Creepy Towards My Body": How Women Experience and Manage Harassment Risks in Social Virtual Reality. In *Proceedings of the ACM on Human-Computer Interaction*, Vol. 7. 1–29.

[42] Amanda K. Sesko and Monica Biernat. 2010. Prototypes of Race and Gender: The Invisibility of Black Women. *Journal of Experimental Social Psychology* 46, 2 (2010), 356–360.

[43] Nisi Shawl and Cynthia Ward. 2005. *Writing the Other: A Practical Approach.* Aqueduct Press.

[44] Mattea Sim, Kurt Hugenberg, Tadayoshi Kohno, and Franziska Roesner. 2023. A Scalable Inclusive Security Intervention to Center Marginalized & Vulnerable Populations in Security & Privacy Design. In *Proceedings of the 2023 New Security Paradigms Workshop*. 102–115.

[45] Jaisie Sin, Rachel L. Franz, Cosmin Munteanu, and Barbara Barbosa Neves. 2021. Digital Design Marginalization: New Perspectives on Designing Inclusive Interfaces. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–11.

[46] Katta Spiel, Kathrin Gerling, Cynthia L. Bennett, Emeline Brulé, Rua M. Williams, Jennifer Rode, and Jennifer Mankoff. 2020. Nothing About Us Without Us: Investigating the Role of Critical Disability Studies in HCI. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–8.

[47] Bruce Sterling. 2005. *Shaping Things.* The MIT Press.

[48] Yolande Strengers and Jenny Kennedy. 2021. *The Smart Wife: Why Siri, Alexa, and Other Smart Home Devices Need a Feminist Reboot.* The MIT Press.

[49] Dara Z Strolovitch. 2008. *Affirmative Advocacy: Race, Class, and Gender in Interest Group Politics.* University of Chicago Press.

[50] Simone Stumpf, Anicia Peters, Shaowen Bardzell, Margaret Burnett, Daniela Busse, Jessica Cauchard, and Elizabeth Churchill. 2020. Gender-Inclusive HCI Research and Design: A Conceptual Review. *Foundations and Trends in Human–Computer Interaction* 13, 1 (2020), 1–69.

[51] Cella M. Sum, Rahaf Alharbi, Franchesca Spektor, Cynthia L. Bennett, Christina N. Harrington, Katta Spiel, and Rua Mae Williams. 2022. Dreaming Disability Justice in HCI. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts*. 1–5.

[52] Anna Szlavi and Leandro S. Guedes. 2023. Gender Inclusive Design in Technology: Case Studies and Guidelines. In *International Conference on Human-Computer Interaction*. 343–354.

[53] Stefan Vazharov, Brandon Carte, and Cat Bowen. 2023. The Best Products of CES 2023: From Tiny Accessories to Big-Ticket Appliances. *Best Products* (2023). https://www.bestproducts.com/tech/a42419066/best-of-ces-2023/.

[54] Madalina Vlasceanu and David M. Amodio. 2022. Propagation of societal gender inequality by internet search algorithms. *Proceedings of the National Academy of Sciences* 119, 29 (2022), e2204529119.

[55] Sara Wachter-Boettcher. 2017. *Technically Wrong: Sexist Apps, Biased Algorithms, and Other Threats of Toxic Tech.* WW Norton & Company.

[56] Yi Wang and David Redmiles. 2019. Implicit Gender Biases in Professional Software Development: An Empirical Study. In *2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Society (ICSE-SEIS)*. 1–10.

[57] Gayna Williams. 2014. Are you sure your software is gender-neutral? *Interactions* 21, 1 (2014), 36–39.

[58] Meg Young, Lassana Magassa, and Batya Friedman. 2019. Toward inclusive tech policy design: A method for underrepresented voices to strengthen tech policy documents. *Ethics and Information Technology* 21 (2019), 89–103.

[59] Zippia. 2024. Software Developer Demographics and Statistics in the US. *Zippia* (2024). https://www.zippia.com/software-developer-jobs/demographics/.

[60] Zippia. 2024. Software Engineer Demographics and Statistics in the US. *Zippia* (2024). https://www.zippia.com/software-engineer-jobs/demographics/.

A All Study Materials

A.1 Instructions

In this study, we want to understand how people think about the users of different technologies. Technology designers and researchers sometimes use a process similar to "Design Fiction" to imagine a fictional user of a potential technology and describe how this user might interact with the technology. This process of imagining a user allows us to more deeply explore how a future with these technologies might look.

In this study, you will be randomly assigned to imagine a fictional user of a specific technology. You will then answer several prompted questions designed to help you build a sort of character profile for this user to more deeply imagine who they are as a person and how they will interact with this technology. This fictional user should come from your imagination — that is, you should not describe yourself or someone you know.

Imagine a person living in the U.S. who is a user of [technology type]. Answer a series of questions about this user. [Participants are randomly assigned to one of four technology conditions]

(1) A smart watch that tracks health and biometric data
(2) A smart home security system with remote light and door access

(3) A social media platform with text, photo, and video sharing
(4) Glasses that overlay virtual content onto the real world

A.2 Measures

A.2.1 Persona Questions. [All responses are open-ended text boxes and each question is answered before moving on to the next page]

- What is this fictional user's first name? (you can refer to this name as you answer more questions) [this name is piped into the following questions]

"[name] is a user of [technology type]." [this line appears at the top of every page]

- In a few sentences, describe the first time [name] used the [technology type] today and what [name] used it for.
- Describe an average day for [name]. For instance, what does [name] do after first waking up? What does [name] usually eat? Where does [name] go?
- Describe where [name] lives.
- What does [name] like to do for fun?
- Describe the nature of [name]'s romantic life.
- What is [name]'s educational background?
- In the spaces below, list 3 traits or characteristics that describe [name].
- Describe what [name] looks like.

Now, indicate the demographic groups you imagined for this user.

- What is [name]'s gender?
- What is [name]'s race and/or ethnicity?
- What is [name]'s age?

A.2.2 Attention Checks. Which type of technology were you asked to imagine a user for?

(1) A smart watch that tracks health and biometric data
(2) A smart home security system with remote light and door access
(3) A social media platform with text, photo, and video sharing
(4) Glasses that overlay virtual content onto the real world

We want to know your honest response to this following question. Your response to this question will have no impact on the payment you will receive for completing this study. Did you use ChatGPT or other AI systems to answer any questions in this study? (again, you will receive full payment no matter how you answer this question)

(1) Yes
(2) No
(3) Prefer not to say

B Study 2 Career-Specific Demographic Questions

Do you have experience as a full-time professional software developer, software engineer, or a related role?

(1) Yes
(2) No

Do you have experience with advanced computing and hands-on programming?

(1) Yes
(2) No

How many years of professional software development, software engineering, or related experience do you have? (enter value below) [open-ended response]

What was your undergraduate degree? [open-ended response]

C Study 3 Pre-Screening Materials

C.1 Instructions

Questions in this study will determine your eligibility for another study. You will be paid for your responses to this survey regardless of your eligibility.

C.2 Measures

Do you have experience as a professional software developer, software engineer, or a related role?

(1) Yes
(2) No
(3) Not sure

Do you have experience with advanced computing and hands-on programming?

(1) Yes
(2) No
(3) Not sure

Do you have experience with product management in technology?

(1) Yes
(2) No
(3) Not sure

Tell us more about your work experience related to software development/software engineering/product management or a related role, if applicable: [open-ended response]

D Study 3 Career-Specific Demographic Questions

Do you have experience within the last ~3 years as a software developer, software engineer, product manager, or a related role?

(1) Yes
(2) No

If your experience as a software developer, software engineer, product manager, or a related role was more than ~3 years ago, please indicate when you last worked in this role (skip this question if not applicable) [open-ended response]

How many years of software development, software engineering, product management, or related experience do you have? (enter value below) [open-ended response]

E Pre-Survey Materials

E.1 Instructions

In this study, we want to understand people's interests in different types of technologies. We will provide brief descriptions of different technologies that may exist now or in the future. You will report whether or not you could see yourself owning these technologies in the future, assuming money was not an issue.

E.2 Measures

For each of the following technologies, please rate whether or not you would be interested in owning it in the future, if money was no issue. [binary response: Not Interested in owning; Interested in owning]

- Smart refrigerator with a Bluetooth speaker and customizable screen
- AI oven with remote monitoring camera that recommends cook times, temperatures, and meals
- Toilet scanner that analyzes and sends health metrics to your phone
- Fitness mirror that streams workout classes and provides real-time feedback on form and other metrics
- Head-mounted virtual reality device for gaming
- Glasses that overlay virtual content onto the real world
- Smart video door lock with face recognition and a fingerprint sensor
- Privacy browser extension that blocks tracking, cookies, and fingerprinting
- Virtual reality social media platform
- Smart thermostat with remote temperature adjustment
- AI smart home that proactively adjusts temperature, lighting, and other environmental preferences
- Sleep machine that changes lighting and audio with the sun
- Smart watch that tracks health and biometric data
- Smart watch with a camera for photos and video calling
- Wireless earbuds with touchscreen audio and calling controls
- Smart home security system with remote light and door access
- Virtual private network that hides user's IP address and encrypts data
- Social media platform with text, photo, and video sharing
- Baby foot monitor that detects oxygen levels
- Augmented reality mirror that lets users virtually try on clothes while online shopping
- Select "not interested in owning" for this question [attention check]