Beyond a Neutral Tool or Teammate: Envisioning AI Interventions for Women's Equity in Male-Dominated Teams

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Abstract

Artificial Intelligence (AI) is rapidly reshaping team collaboration in workplaces. Meanwhile, women only represent 22% of the global AI workforce, raising questions about whose perspectives drive AI design. This dual reality makes the stakes high: without critical attention, AI may entrench existing gendered dynamics; but with deliberate design, it may open new avenues for equity. Through in-depth interviews with 30 AI professionals (22 women), our work both confirms gendered challenges in male-dominated teams and offers a novel contribution: how those who directly experience these dynamics envision AI's role in mitigating them. These practitioner-informed design visions reveal AI's potential of offering multi-level support and empowering women to navigate these teams, and its risks of reinforcing stereotypes and surveillance. We call on the HCI community to explore this emerging design space for equitable human-AI teaming while critically attending to gendered power dynamics.

CCS Concepts

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

Keywords

Gender, Women in STEM, AI professionals, Male-dominated teams, Human-AI teaming

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1 Introduction

The rapid advancement of Artificial Intelligence (AI), particularly large language models (LLMs), has drawn increasing attention to the ways gender bias becomes embedded in these systems [23, 51, 52]. Research has shown that training data and model outputs frequently reproduce stereotypical and discriminatory patterns, reinforcing rather than challenging gender inequities [26]. Addressing these issues is not simply a matter of technical curation, but also requires diversifying who builds and governs AI [53]. However, women remain underrepresented, making up only about 22% of the global AI workforce [97]. This underrepresentation results from social [11, 89], historical, organizational [88], and team-level [3, 13, 47] barriers that discourage women's participation and advancement in the AI field. These patterns not only limit women's opportunities in the present, but also contribute to their decision to leave, or never enter the field [89]. To ensure the responsible and equitable design of AI systems that foster rather than undermine gender equity, it is critical to support the participation and influence of women in AI, who often find themselves in male-dominated teams.

Indeed, HCI and CSCW researchers have long been at the forefront of designing technologies to support collaboration, inclusion, and equity in workplaces and teams [24, 40, 92]. Significant efforts have been made to develop interventions to support underrepresented populations, from accessibility tools [18, 98] to cross-cultural collaboration platforms [28, 38]. However, one group that has received comparatively little explicit design attention is **women working in male-dominated teams**. Decades of organizational research show that gender minorities in such contexts face unique challenges, including marginalization [25], stereotype threat [85], and exclusion from informal networks [68, 76], which persist even as overt discrimination has declined. Despite this, few HCI or CSCW studies have directly addressed how technology could support women in navigating these male-dominated team environments, such as those found in STEM and AI.

To address this critical knowledge gap, we conducted semi-structured in-depth interviews with 30 AI professionals (22 women) to unpack women's gender-related challenges working in male-dominated teams and the potentials and perils of AI interventions in addressing such challenges. We focus on **women AI professionals** because they work in teams in which gendered dynamics unfold alongside the development of AI technologies that increasingly shape organizational and societal practices. This makes women's experiences in these teams particularly consequential beyond their immediate workplaces. We investigate **AI as a potential intervention** because it offers unique capabilities beyond humans facilitation: (1) providing consistent, adaptive feedback at low interpersonal risk [28, 44], (2) detecting subtle interactional patterns that often escape human notice or are intentionally ignored due to social discomfort or bias [57], and (3) operating longitudinally across contexts and modalities [29]. Driven by these motivations, we aim to answer the following research questions:

- **RQ1:** What challenges do women AI professionals experience in male-dominated teams?

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- **RQ2:** How do AI professionals envision the potential of AI to mitigate these challenges?
- **RQ3:** What concerns and limitations do AI professionals identify regarding AI's role in mitigating these challenges?

Our work contributes to HCI and CSCW scholarship in three interlinked ways. First, we link women AI professionals' first-hand experiences of gendered challenges in everyday work practices to their own visions of how AI might mitigate or exacerbate inequity. This effort moves beyond just documenting and understanding bias as an empirical phenomenon to articulating a new design space for equity-oriented AI in HCI, where AI is examined as an active social actor embedded in team culture. These practitioner-grounded visions extend existing HCI research on gender in computing by revealing how women AI professionals' team experiences directly inform design possibilities for future AI systems, which in turn impact society at large. Second, our work extends CSCW theories and research on computer-supported collaboration by bringing feminist HCI principles [7] into the design space of AI-mediated collaboration, imagining AI not just as a neutral facilitator or a tool, but also as a power-laden social actor capable of shaping and shifting team norms. Third, our work outlines a concrete set of AI-mediated strategies for addressing gender inequities in male-dominated teams, while also identifying potential harms. In doing so, we highlight design tensions and propose measures to inform responsible AI design by leveraging equitable collaborative technologies.

2 Related Work

2.1 Gendered Reality in AI Development and Workforce

Bias in large language models (LLMs) typically originates in the data they are trained with, which can cause models to reproduce and sometimes amplify gender stereotypes [70, 96]. Empirical studies show this across levels of granularity: at the sentence/decision level, LLMs are three to six times more likely to pick an occupation that matches stereotypical gender expectations and then "rationalize" that choice in their explanations [51]; at the discourse level, models echo patterns that over-credit "male-coded" contributions [23]; and at the task level, even neutral prompts can drift toward male pronouns for certain software-engineering activities (e.g., "he tests" occurs 100% of the time under back-translation in one setup) [94]. These findings align with broader critiques that uncurated web-scale corpora encode historical inequities and that post-hoc alignment alone does not reliably uproot group-exclusive harms [52]. Together, they underscore that bias shows up in who is depicted as competent, whose ideas are credited, and what roles are considered "fitting". Broader cultural critiques such as *Brotopia* [17] and *The Authority Gap* [83] further contextualize these inequities, showing how masculine norms and credibility gaps continue to shape technical culture.

Mitigating gender bias requires better measures. Within HCI/CSCW, work has contrasted lexicon flagging with end-to-end classifiers [23], while domain–specific audits reveal stereotypes that generic tests miss. Frameworks like GenderCARE propose inclusivity, robustness, and realisticity criteria, showing counterfactual augmentation plus fine-tuning can reduce gender gaps with little performance loss [90]. Yet recent analyses caution that "alignment" can mask rather than eliminate harms [53].

Ethical curation of datasets also requires diverse perspectives within the workforce, particularly the inclusion of more women, whose lived experiences can surface hidden biases and reframe design priorities. Foundational feminist scholarship has long argued that technology design is never neutral but reflects the positionalities of its creators [23]. Feminist HCI in particular emphasizes the importance of participatory, situated, and inclusive practices to ensure technologies reflect marginalized voices [7]. Unfortunately, women remain significantly underrepresented in AI, comprising only 22% of the global workforce [97]. Compounding this inequity, recent audits of AI-assisted hiring demonstrate that such systems often disadvantage women even further [4], creating a reinforcing cycle in which women's contributions and values are systematically excluded from shaping AI's future.

2.2 Women in STEM and Male-Dominated Teams

The underrepresentation of women in AI workforce [19, 36, 61] is not only a result of systematic exclusion, many are pushed to consider leaving due to negative experience in STEM and male-dominated teams [14, 15, 80, 99–101]. For instance, research on women in engineering shows that masculinized norms force women into a double bind of assimilating into male-coded behaviors or being marginalized, often driving attrition [9]. Qualitative accounts highlight how women's professional and leadership identities are eroded through persistent microaggressions, such as devaluation of competence, dismissal of bias experiences, and pathologizing of character, which trigger burnout and turnover [48]. Interactional analyses of mixed-gender research groups further demonstrate that women's contributions are more frequently ignored or overridden, forcing them to strategically negotiate floor time and assert authority through multimodal cues like tone, gaze, and laughter [87]. Similar patterns are evident in cybersecurity, where women experts encounter resistance, hostility, and undervaluation of their recommendations, slowing adoption and pushing many out of the field [103]. Studies of software teams and open-source software (OSS) communities further illustrate these challenges: while women's presence improves collaboration [16], women remain severely underrepresented in OSS, facing toxic cultures, biased peer review, and impostor syndrome despite contributing at equal or higher quality [95]. Beyond software engineering, persistent gender disparities and cultural barriers have been documented across AI and computer science research [19, 36, 61].

In teams where men outnumber women, gendered dynamics systematically undermine women's participation and amplify negative experiences. Classic studies of group interaction show that men interrupt women more frequently and with greater success, and mixed-gender groups see fewer supportive and more disruptive interruptions compared to all-male groups, reinforcing women's marginalization in discussion [84]. Experimental evidence further demonstrates that in mixed-gender work groups, women become less task-oriented and less talkative, whereas men become more dominant and vocal, highlighting how gender composition alters behavior in ways that disadvantage women [65]. At the structural level, women in male-dominated workplaces face gender stereotyping and policy-based discrimination, with discretionary enforcement of seemingly neutral rules used to exclude, penalize, or expel them [12]. Beyond these structural barriers, women who act assertively or display leadership behaviors often encounter a "double bind", in which competence leads to social backlash rather than credibility. Such prescriptive stereotypes position agentic women as violating gender norms, resulting in penalties in evaluation, hiring, and promotion decisions [73, 77]. These studies reveal how skewed gender ratios not only silence women's contributions but also entrench inequities through interactional dominance and institutionalized bias.

2.3 Computer-Supported Solutions to Regulating Team Dynamics

HCI research has long explored ways to balance team participation, from visual feedback to embodied interfaces. Early systems showed that public participation visualizations and linguistic feedback could reduce dominance but only modestly empower quieter members [24, 54]. Later tools such as Meeting Mediator used sociometric sensors to equalize turn-taking across teams [49], while real-time language feedback systems targeted information exchange and engagement, benefiting struggling groups but risking overload [91]. Gamified approaches like ScoringTalk incentivized quieter voices and restrained over-talkers, sometimes at the cost of richer contributions [2]. Embodied systems like TurnTable embedded feedback into physical space to nudge more organic participation [37].

Beyond participation balancing in general teams, CSCW has also developed technologies tailored to marginalized groups, from accessibility systems for deaf and blind collaborators [18, 62, 98] to cross-lingual tools that aid nonnative speakers through awareness displays [38], task rebalancing [71], and real-time feedback [27, 28, 56]. These systems redistribute communicative effort and demonstrate how design can foster more equitable collaboration. However, strikingly, no comparable interventions confront the gendered inequities women face in male-dominated teams.

As such, more research is urgently needed to explore technologies that can better support women's participation in such contexts. We focus on **AI as a promising intervention** as it offers distinctive and evolving capabilities. Unlike general tools that are more rigid and static, LLMs allow for more nuanced and context-aware conversational understanding and generation [1], real-time adaptivity [44], personalization [104], and longitudinal tracking [43]. These qualities make AI a uniquely promising avenue for addressing the subtle interactional dynamics that sustain gender inequities in collaborative work. Additionally, a recent systematic review on diversity and inclusion in AI [82] highlights that gender remains the most frequently discussed axis of inequity in AI development, while concrete operationalizable solutions for improving inclusion in AI teams remain limited. These insights further point to a persistent gap between recognizing gendered challenges and designing interventions that meaningfully address them.

In summary, prior work shows that gender inequities in AI are shaped by biased technical infrastructures, underrepresentation within the AI workforce, and interactional barriers faced by women in male-dominated teams. While HCI and CSCW research has explored tools for balancing participation, no existing systems directly confront the gendered dynamics underlying these inequities. These gaps motivate our study to focus on how women AI professionals draw on their lived experiences to envision AI systems that can meaningfully support gender equitable collaboration.

3 Method

Our approach follows feminist HCI traditions that use qualitative inquiry to foreground participants' lived experiences and values in socio-technical systems [7, 50]. Semi-structured interviews were chosen for their capacity to elicit situated, reflexive accounts of gendered work experiences, while allowing participants to direct the conversation toward what they found most salient.

3.1 Recruitment and Participants

Following approval from Clemson University's Institutional Review Board, we recruited participants through three channels: the authors' professional networks, social media (LinkedIn), and a crowdsourcing platform (Prolific). To cast a wide net while maintaining relevance, we intentionally set broad eligibility criteria in the advertisement: participants qualified if they *currently work or have previously worked in an AI-related field, including but not limited to machine learning, data science, human-AI interaction, AI policy, and other AI-related areas.* Interested individuals first completed a prescreening survey that asked about their educational background, job title, employment sector, how their work relates to AI, and the gender composition of their team(s). We prioritized participants who reported working regularly (several times a week or more frequently) on teams where men outnumber women. We also aimed to ensure diversity across AI-related professions, including a balance of women in technical roles (e.g., software engineers) and research roles (e.g., HCI researchers who study AI policy and/or design AI systems). This diversity allowed us not only to capture a wide range of experiences of gender dynamics across different roles in functionally diverse AI-related teams, but also to gather multiple perspectives that can inform technical development, design, and policy aimed at empowering women in male-dominated teams and fields.

A total of 30 participants completed an interview, among whom 22 self-identified as women, 7 as men, and 1 as non-binary/third gender. We included the perspectives of men and non-binary participants because understanding gender dynamics in male-dominated teams requires examining not only the experiences of those most affected by marginalization, but also how others perhaps contribute to, perceive, and respond to these dynamics. Their insights help contextualize the structural and interpersonal patterns that shape team interactions. The average age was 30.43 (SD = 3.61). Participants were mainly based in the U.S., with P18 and P19 located in Pakistan and Bangladesh respectively, and several U.S.-based participants reflecting on prior work experience in other cultural contexts (e.g., South Korea, Bangladesh, China). While these reflections offer some cross-regional insight, we acknowledge that the sample is largely situated in the Global North. Full demographic information is provided in Table 2 in the Appendix.

3.2 Semi-Structured Interviews

We conducted in-depth semi-structured interviews with participants over Zoom. At the beginning of the interview, we obtained oral consent for audio recording (the full informed consent document was viewed and checked at the prescreening stage). The interviews lasted between 47 and 125 minutes (61 minutes on average), and the participants received $10 per hour in the form of an Amazon gift card or equivalent Prolific compensation after completion of the interview. Compensation procedures adhered to IRB and platform guidelines for fair hourly payment.

To minimize priming bias during data collection, the interview guide used open-ended, non-leading prompts, and was pilot tested with two AI professionals to ensure neutrality and clarity. The interview protocol consisted of three main parts: (1) general views on how AI impacts gender equity and a description of their daily work; (2) experiences or observations of gender dynamics and gender-related discomfort; (3) reflections on the potential and constraints of AI to address gender-related challenges. Specifically, participants were asked to describe a typical workday, including their job responsibilities, interactions and collaborations with others, and the gender composition, power dynamics, and expertise distribution within their team. These accounts often led to a natural transition into eliciting instances of gender dynamics, issues, or discomfort experienced or observed specifically in team meetings, asynchronous communications, or collaborative tasks. For each instance described, participants were further probed for elaborations on aspects such as participation, decision-making, disagreement/conflict resolution, (mis)communication, etc., for identification of any gender patterns. They were also asked to reflect on how the situation may have played out differently if they (or their collaborators) were of a different gender, or if the team's gender composition had been different. For each account of the concrete issues they had experienced or observed, participants were prompted to consider how AI might (or might not) be able to address the challenge, informed by their professional expertise and direct engagement with cutting-edge AI technologies.

3.3 Data Analysis

The interview recordings were automatically transcribed using Otter.ai. We conducted an inductive approach to analyze the data, as it is well-suited for understanding "how people interpret their experiences, how they construct their worlds, and what meaning they attribute to their experiences" [63]. Following the guidelines for qualitative analysis in CSCW and HCI practice [60], our analytical methods were oriented towards identifying recurring concepts and themes of interest, establishing relationships among them, and organizing them into more complex groups and overarching themes, rather than specifically targeting inter-rater reliability.

Following Clarke and Braun [20]'s guidelines for thematic analysis, we analyzed all collected interview data in the following steps. Two of the authors closely read through all the transcripts to identify information relevant to the research questions by highlighting them and taking notes. Then, the same two individuals conducted iterative coding processes independently, during which they assigned initial codes to information relevant to the research questions, developed emergent themes based on codes, categorized the responses into higher-level themes, and highlighted distinctions, comparisons, and connections among the themes. During this process, the authors explored boundaries of the codes and themes by paying attention to and actively looking for discrepant data [58]. Our approach combined deductive attention to the research questions with inductive sensitivity to emergent concepts, resembling a hybrid between Clarke and Braun [20]'s thematic analysis and Thomas [93]'s general inductive method. Next, the two authors collaboratively and iteratively discuss and refine the themes and sub-themes, in which initial codes were merged, broken down, or modified by identification of alternative interpretations and cases that did not fit [59]. Finally, the two authors extracted and further examined quotes in their context, and uncovered the connections among the constructs of themes. As such, they were able to use the quotes to construct a comprehensive narrative that amalgamated the responses to the research questions.

Positionality Statement. Before proceeding, we want to provide context about how our identities may influence our analysis and interpretation of the data [8, 79]. All authors are researchers in human–AI interaction, and two identify as women who have extensively studied gender in computing and AI development. These backgrounds informed our sensitivity to participants' gendered experiences and AI visions, while also prompting reflexive consideration of how our own perspectives might shape interpretation.

In the following sections, we present our findings on gender-related challenges faced by women AI professionals in male-dominated teams **(RQ1)**, participants' envisions of AI interventions to mitigate them **(RQ2)**, as well as their concerns and perceived limits of such interventions **(RQ3)**, as summarized in Table 1.

4 RQ1 Findings: Gendered Challenges Women AI Professionals Face as Both Team Members and AI Builders/Researchers

Women AI professionals described a range of gendered challenges in their teams, many of which echo well-documented patterns in STEM and other male-dominated fields (e.g., [48, 100]) and recent feminist critiques of the AI industry, which highlight how AI systems and tech cultures can entrench misogyny [10] and exclusion [42]. While these challenges are not unique to AI, understanding how women in AI teams experience them has distinct sociotechnical consequences and is therefore essential for HCI research, as inequities in these teams can shape whose perspectives, needs, and values are reflected in the AI systems they design. For the women in our study, these challenges were experienced not only as barriers within their immediate teams but also as conditions shaping how they imagined AI could intervene in or potentially amplify gender inequities, providing essential grounding for the interventions envisioned in Sections 5 and 6.

4.1 Barriers to Participation and Influence in Team Meetings

4.1.1 ***Difficulties of speaking up.*** Our analysis revealed two factors that made it difficult for women AI professionals to speak

RQ1: Gendered challenges women AI professionals face as both team members and AI builders/researchers	RQ2: Envisioned AI to mitigate the challenges	RQ3: Concerns, trade-offs, and limits of AI in mitigating the challenges
• Barriers to participation and influence in team meetings – Difficulties speaking up – Frequent/selective interruptions or being spoken over – Struggle for ideas to be acknowledged, weighed, and acted upon • Multi-level gendered exclusion – Microaggressions and subtle discrimination – Stereotypes and double standards of competence, autonomy, authority – Structural barriers and lack of support	• Team-level interventions addressing contextually shaped gender disparities – Gender-aware meeting analytics – AI to actively support equitable participation in meetings – AI as representation and cultural counterweight • Personal-level interventions to build confidence and assertiveness – AI coaching for communication and assertiveness – AI mentor to test and validate skills/abilities	• Cautions around surveillance, transparency, and anthropomorphism • Tensions between social appropriateness and effectiveness of AI interventions • Limits in shifting entrenched stereotypes and team norms

Table 1: Summary of Key Findings.

up: first, women's own self-doubt, lack of confidence, tendency toward self-monitoring and cautious communication; second, men's dominant participation and fast-paced team dynamics left little room for women's voices.

Women's self-monitoring and cautious communication. Women described holding back in male-dominated team meetings due to low confidence (e.g., P4F, P25F), fear of judgment (e.g., P1F, P6F), and heightened self-monitoring (*"more cautious or nervous about every sentence"* -P3F). Even women who admitted to be dominant with other women admitted to be *"subdued"* (P20F) in male-dominated teams. Such dynamics were exacerbated in the AI domain, where some women felt stereotype threat (e.g., *"one of us represent all of us"* -P4F) and reported receiving less adequate technical training (P4F, P17F, P23F) compared to men perceived as more *"naturally tech-savvy"* (P18F).

Male-dominated conversational dynamics. While women participants tended to blame themselves for not speaking up (*"it's less about gender but more personality"* -P3F), men admitted that the loud (P9M, P10M, P13M), fast-paced (P9M, P10M, P12M), and highly assertive style in male-dominated teams often left little room for quieter and softer voices (*"men tend to speak more quickly, assertively, with strong opinions… she communicates more thoughtfully, inviting discussion rather than pushing a stand, but in a fast-paced, male-dominated environment, forceful voices dominate"* -P9M). This dynamic is intensified in the AI domain, where rapid technological change is coupled with a cultural stereotype of "talking fast", as P12M noted, *"We are software engineers, we talk fast."*

4.1.2 ***Being frequently and selectively interrupted or spoken over by men.***
Almost all women reported having experienced frequent interruptions or being spoken over, noting that these are subtle enough to be dismissed as unintentional, yet persistent enough to undermine their participation. As P4F noted, *"they wouldn't normally speak over you if you are a male counterpart, but they feel more comfortable doing that."* Men also admitted that *"when women speak more softly or cautiously, some teammates seem quicker to cut in... but men even if they're junior, don't get interrupted as much."*-(P15M). P7F emphasized how these subtler forms of disrespect (i.e., interrupted or *"shushed"*), *"are not enough for men to get in trouble, but it's enough to make you feel uncomfortable in the workplace."*

4.1.3 ***Struggling for ideas to be acknowledged, weighed, and acted upon in decision-making.***
Women described how their contributions in team discussions were often "overlooked", "downplayed", or overshadowed by men's dominant voices. As P7F noted, *it was hard to have my voice heard… men are more likely to put themselves in front of a group and be very definitive in their viewpoints."* Male participants echoed this pattern, describing how women's suggestions could be *"brushed off"* until repeated by men (e.g., *"a female developer suggested tweaking a model input, it was brushed off quickly, and 10 minutes later, a male engineer brought up a similar idea, and the team discussed it seriously"* -P15M). In some cases, women's contributions were subtly re-appropriated through "last control" behaviors, where men would restate women's ideas to claim authority (e.g., *a guy would still want to validate, give a summary, take the last control of the idea recommended by the female"* -P12M).

Over time, such experiences could discourage women from raising points in group settings, leading them to shift their input to private channels, which further reduces their influence on collective decisions. P14M shared an example of a female QA engineer whose urgent safety concern was dismissed in a meeting but later validated when she escalated it one-on-one. He reflected that *"if a male brings up this issue, it's less likely it would've been ignored… people are used to having men as the technical expert, so their concerns come out louder."* This shows how entrenched expectations of male authority and technical expertise shape whose contributions are taken seriously, reinforcing women AI professionals' marginalization in collective technical decisions.

Furthermore, in asynchronous communication, women's more polite and collaborative communication styles (e.g., phrasing requests as *"just checking in"* -P14M or *"if it's not much trouble"* -P12M) also led to their requests being acted on more slowly than that of men's more direct style (P6F, P27F). While participants acknowledged such styles reflected emotional intelligence, they also noted it could reduce perceived urgency or authority, leaving women's requests overlooked or delayed (P6F, P13M, P27F).

4.2 Multi-level Gendered Exclusion

4.2.1 ***Microaggression and subtle discrimination.*** Participants described how gendered disrespect often appeared in small but persistent behaviors that undermined women's standing in male-dominated teams. These microaggressions (e.g., nicknames like "honey" used only for women -P4F, being "snapped at" -P25F, or "eye-rolls" signaling dismissal -P23F) rarely crossed the line into overtly sanctionable harassment. Instead, they operated on the margins of professional interaction, making it difficult to challenge them without incurring social costs. P7F recalled in her complex systems class that *"anytime a woman answered a question, young men would start whispering and scoffing and they only did it when women answered."* Such nonverbal cues and dismissive reactions devalued women's contributions publicly, but male peers rarely intervened. *"I have so rarely seen a man correct another man, they don't even notice the sexism."* This lack of accountability normalized subtle exclusion, reinforcing unequal power dynamics and discouraging women's participation.

4.2.2 ***Stereotypes and double-standard of competence, autonomy and authority.*** Women AI professionals described being subject to gendered double-standard that questioned their competence, autonomy, and authority. Even when leading projects, their technical expertise was overlooked in favor of men (*"I developed everything but the co-PI asked where the male students were, saying they can solve this, not me."* -P6F). Similarly, P17F noted that women were routinely assigned male supervisors, implying they *"aren't competent enough to do things on [their] own."* Such assumptions extended to leadership evaluation, where assertive leadership behaviors praised in men were disparaged in women (*"While male leaders were seen as charismatic, women showing the same style were judged as 'not knowing what [they're] doing'."* -P5F). Likewise, communication acceptable from men is criticized in women (*"if such thing (sounding commanding in emails) comes from a male, I don't take it personal. But from a female leader, I take it as being disrespectful."* -P11M).

4.2.3 ***Structural barriers and lack of support.*** These biases were compounded by organizational practices that limited women's advancement. Participants described being excluded from leadership opportunities (P17F, P19F), denied training resources (P17F), and lacking access to female mentors or role models in their workplaces (P17F, P24): *"Being the only woman in the team, I didn't have any female figure to look up to or learn from"* (P19F). When women raised concerns about bias or exclusion, their experiences were sometimes dismissed by male leaders (P18F, P26F) as "emotional" or attributed to overthinking (e.g., *"Women are emotional. Men hardly feel intimidated or unvaluable, even if their contribution is not taken seriously."* -P12M). Men often framed interruptions or dismissals as neutral behaviors (P12M, P15M), further invalidating women's perspectives. The combination of exclusion, lacking mentorship, and dismissal of lived experiences created a reinforcing cycle: women had fewer opportunities to demonstrate expertise and authority, less institutional support, and greater barriers to recognition, advancement, and leadership.

In summary, the gendered interactional and structural challenges described in this section reflect broader inequities documented across male-dominated technical fields, yet they take on particular significance in AI work because team practices intersect with decisions that shape sociotechnical systems. These dynamics show how participation and influence are unevenly distributed within AI teams, and how these patterns impact whose perspectives and values become embedded in the systems these teams create. Understanding these dynamics is therefore essential for HCI, as it provides the contextual grounding needed to design interventions that address inequity at both the team and personal levels. Building on this foundation, the next section presents how participants envision AI itself as a potential means for transforming gendered collaboration norms.

5 RQ2 Findings: Envisions of AI to Mitigate Women's Challenges in Male-Dominated Teams

Based on their own perspectives of women's challenges in male-dominated teams, participants reflect upon how AI could be designed to mitigate them and reshape gendered collaboration norms in their everyday work. The intervention ideas they proposed are necessarily speculative. In HCI, such speculation is not only acceptable but methodologically grounded [81, 102]. Speculative design thinking uses imagined futures to surface values, reveal design tensions, and guide the development of emerging technologies [5, 74]. We present these envisioned interventions as contextually informed design probes rather than predictive claims, and use them to identify opportunities and constraints for equity-oriented AI in collaborative work. This framing positions participants' visions within established HCI traditions and provides a scaffold for the analytical themes that follow. Their ideas clustered around two levels of AI-based intervention. At the **team level**, they envisioned AI could reveal gender disparities, actively foster equitable participation, and serve as a symbolic ally and cultural counterweight. At the **personal level**, they suggested AI could help women prepare for high-stake interactions, adapt communication styles, and build lasting confidence through coaching and evidence-based validation.

5.1 Team-level AI interventions mitigating contextually shaped gender disparities and discrimination

In this section, we detail how participants envisioned AI could support equitable collaboration by shaping interactional processes in meetings. Their visions centered around three pathways: using AI-driven meeting analytics to make inequities visible; designing AI as an active facilitator that regulates turn-taking and amplifies marginalized voices; and imagining AI as a symbolic ally that models and legitimizes alternative communication norms. Interpreted through an HCI lens, these visions emphasize not just what AI could do but how AI would interact with users, raising design considerations around timing, tone, modality, and the social sensitivities of intervening in real-time team dynamics.

5.1.1 *Gender-aware meeting analytics for revealing gender patterns of interruptions, participation, and contribution.*

Making bias visible without triggering defensiveness. Participants saw AI-generated quantitative metrics not just as data, but as an interactional aid that could make conversations about bias less defensive. Metrics like speaking time or interruption rates could validate women's lived experiences, so people can't *"shy away from it"* (P4F). This reframes AI's role from merely detecting imbalance to mediating how such insights enter team dialogue and raises design questions about when and how feedback should be surfaced to avoid triggering defensiveness. As P7F noted,

> "AI identifies tonal voice and say in this meeting, men are comprising 80% of the conversation when they only comprise 20% of the room. AI can bring to light things that people know are happening, but validated quantitatively. Because people get defensive. They're like, this isn't happening. But it is happening."

Unlike traditional technologies that can only capture surface-level metrics, AI, particularly with advances in LLMs, can integrate multimodal signals (e.g., voice tone, lexical patterns, conversational dynamics) and adapt in real-time. Participants imagined these capabilities not just as technical detection, but as interactional support. AI-generated evidence could help teams surface patterns that women experience but struggle to legitimize. In this sense, the key design challenge is not only what AI detects, but how such insights are introduced into team processes in ways that validate experience without creating tension.

Participants also acknowledged that analytics alone cannot dismantle the underlying cultural norms and power imbalances driving these disparities. But they can serve as an intermediate step by making inequities visible and actionable while deeper systematic biases remain harder to confront, as P12M cautioned,

> "AI can create awareness but it can't fix the culture. AI can identify that a woman on the team get interrupted 50% more often than her male peers. This creates a data that we can't easily dismiss.But AI can't influence the real bias, which is embedded in people already. But this can reveal the bias."

Fairly crediting idea contributions. Beyond counting participation and interruptions, AI could help teams negotiate credit more equitably by tracing how ideas evolve. By highlighting when contributions are overlooked or re-appropriated, AI could make teams recognize the original source and the eventual uptake of an idea, especially when women's input is only acknowledged once repeated by others.

> "AI could flag when similar ideas are repeated and show who said it first, give credit where it's due; track patterns over time, whose suggestions are usually ignored and picked up later by someone else." (P25F)

Unlike traditional systems that count turns or speaking time, LLMs can analyze semantic content and conversational context, distinguishing genuine novelty from repetition. This capacity positions AI to surface inequities in attribution. Participants wanted such analytics to be sensitive to differences in communication style, to ensure that credit is not disproportionately assigned to long-winded contributions while undervaluing brief but incisive ones. As P24F observed,

> "Men sometimes go on and on about a point, and do mansplaining, but may not contribute anything new. AI should be able to recognize that and translate that into little insight."

Male participants also admitted how women's input is often concise, efficient, and well-thought, whereas men feel free to simply *"throw out big ideas just to get the momentum going"* (P12M). P13M also noted,

> "She keeps her points brief and straight to the point. While the males might go into lots of details, she usually sticks to a sharp and efficient point."

These reflections emphasize that equitable analytics must recognize the value of brevity and clarity, rather than conflating verbosity with meaningful contribution.

Diagnosing why interruptions happened. P27F proposed using AI not only to record interruptions but also to analyze linguistic cues that might make interruptions more likely. This moves analytics beyond simple detection to diagnosing interactional dynamics that reflect confidence, status, and gender norms.

> "AI can be used to analyze sentence completion rates, how often someone starts speaking and does not finish her sentence, understanding why people get interrupted. AI can infer if it's due to a confidence gap, power imbalance, or if someone uses more hedging language. AI can detect if it's driven in a gendered pattern."

The emphasis on hedging language highlights how gendered norms of cautious self-presentation may interact with power dynamics to invite interruption, and sentence completion rates could serve as a measurable proxy for conversational dominance. By revealing these, AI can provide teams with diagnostic insights that shift the focus away from blaming an individual to broader interactional patterns, which reframes interruptions as a systematic rather than personal issue.

Equipping team lead to intervene. Participants envisioned such AI meeting analytics as an assistant to meeting leaders by surfacing participation gaps and bias patterns in real-time or through private follow-ups. By prompting facilitators rather than calling out individuals publicly, AI could help create space for underrepresented voices while minimizing social risks.

> "This might be shared privately with the facilitator during or after the meeting, sending discreet forms to the team lead to ask if they would like to hear from the females on the team." (P24F)

> "It can also help with training. AI analysis can be used in rituals or team debrief to talk about communication equity." (P29F)

P29's suggestion reflects a broader vision of AI not just as a situational assistant but as a long-term partner that helps teams build shared awareness and integrate equity reflection into routine practices such as debriefs or retrospectives. Importantly, feminist HCI cautions that such support must avoid turning inclusion into a procedural "check box" handled by automated prompts. The value participants described lies *not* in AI replacing facilitators, but in *scaffolding* their interactional work in offering discreet cues, prompting reflection, and supporting norm-setting in ways that keep human judgment and cultural responsibility at the center of the process.

5.1.2 ***AI to actively support equitable participation in meetings.*** Participants envisioned AI not only as a passive tracker of participation, but as an **active facilitator** that *"shepherd[s]"* (P2N) and regulates equitable turn-taking, pauses conversations to address interruptions, and prompts quieter members. P3F connected her suggestion to a strategy she had learned from teachers in her research to address early gender disparities in classroom participation:

> "Every kid has 'chalk chips'. They give each student several and when they speak they use one. Some use a timer. AI could serve such a meeting management role."

Others imagined AI stepping in more directly during interruptions:

> "AI can help step in more actively, gently pause a conversation when it detects repeated interruptions, giving the interrupted person a chance to finish." (P25F)

P14M proposed a more discreet, personalized approach:

> "AI as an augmented assistance in live meetings, in smart glasses or air-boards that can whisper cues during meeting to the females that they haven't spoken up yet, they might want to rephrase what someone just said, or if they want to follow up."

P14's vision reframes AI as a personal participation coach, offering subtle, private prompts that encourage quieter members to enter the conversation at moments that feel natural to them. This approach reduces the social risks associated with public calls for input, potentially empowering participation without embarrassment.

Beyond regulating participation, some (P12M, P26F) also highlighted the role of AI as a **voice amplifier**, addressing how vocal tone and volume can influence perceived authority, noting that women's contributions were often overlooked when delivered more softly. AI could equalize these dynamics by amplifying women's voices and enhancing their presence in virtual meetings:

> "a voice amplifier that make women's voice stronger, so it carries authority. It shouldn't be that only male voices are heard just because they have a deeper, more baritone tone. AI can help women claim their voice. Women tend to speak more softly, which might contribute to ideas getting over if the voice don't signify confidence. In virtual meetings especially, if these voices could be amplified, people would know it's a serious point and should be taken seriously."(P14M)

Together, these accounts depict AI as a meeting facilitator that not only regulates equitable participation but also ensures women's voices are amplified and taken seriously.

5.1.3 ***AI as representation and cultural counterweight.*** Participants also envisioned AI as more than a facilitator of participation. They framed it as a symbolic ally and cultural counterweight that could redistribute the burden of gender imbalance in male-dominated teams and legitimize alternative communication styles. Several participants described female-coded AI as offering a sense of solidarity, diversifying leadership models, and reducing the pressure on any single woman to represent her gender, analogous to the benefits of having more human women on the team. As P30F reflected:

> Dropping some female-coded AI on the team might feel like more people on my side automatically. We can work together at equal wavelength. It will reduce the burden on me, so I won't be the only one to carry the weight of male dominance. It will also create a model of female voice and leadership, make it feel more equal."

Extending this vision, P22F imagined AI not only as a symbolic ally but as a role model for leadership,

> I would feel more comfortable if a female-coded AI intervenes and calls on the person (who interrupted), or put the power in women's hands to decide if they want to expand. This resembles a good leader that young women might emulate to become and advocate for next generation of young women.

Here, a female-coded AI is seen as both empowering women in-the-moment and demonstrating leadership behaviors that young women can model. As such, AI is framed not just as a technical tool but as a sociotechnical agent of representation and mentorship, which suggests alternative possibilities for authority and advocacy.

Rather than superficially "gendering" AI through voice or appearance, participants emphasized **embedding alternative communication norms**, such as collaborative tone (P25F), deliberate delivery (P13M), and crediting behind-the-scenes work (P23F) into AI's interaction style. This approach could challenge the dominance of male-coded patterns in AI training data and in team culture. By valuing substance over volume or aggressiveness, participants imagined AI that could actively reshape what counts as a credible contribution in technical teams. As P23F put,

> "AI can help the team see who is quietly driving the debugging and not just talking the most, ensuring credit for contribution, not volume... creating a model for females on the team, and when I say 'model,' I don't just mean slapping on a human voice or labeling it as such, but something deeper, like a model of behavior, intelligence, and interaction that reflects the strengths and realities of how women communicate. Most AI tools are trained on dominant communication patterns, which are often male-coded: learning from the loudest contributors, and historically, those have

> often been men who project confidence and dominate. So if there's a female model, it could reduce this risk."

This vision positions AI as more than a neutral facilitator, but as a cultural counterweight that legitimizes communication styles traditionally marginalized in male-dominated settings. By legitimizing collaborative and less assertive styles of interaction, female-coded AI could act as both a corrective to biased training data and a role model that redefines the range of acceptable team behaviors. As such, AI could help normalize diverse styles of communication, such that confidence is not necessarily associated with competence, opening space for alternative ways of leading and contributing.

5.2 Personal-level AI interventions to help women AI professionals build confidence

At the personal level, participants envisioned AI 1) helping women prepare communication through rehearsal, scenario simulation, and code-switching assistance; and 2) providing constant mentorship by validating skills, tracking growth, and offering judgment-free learning opportunities. Through an HCI lens, these visions highlight interactional considerations such as how AI should deliver feedback, how directive or supportive it should be, and how users retain agency in shaping their communication norms. They frame AI not as a replacement for human mentorship but as an interaction partner that supports confidence, competence, and equitable participation over time.

5.2.1 *AI coaching for communication and assertiveness.*

Meeting preparation. Participants envisioned AI as a personal coach that could help women prepare for high-stakes interactions, respond confidently under pressure, and strengthen their assertiveness over time. They emphasized that such preparation through scenario simulation could help counteract power imbalances in male-dominated settings.

P3F described AI as a rehearsal partner to help women enter meetings with well-formed questions and stronger presence.

> "AI could simulate a conversation with the female employee before the meeting, generate questions to get women prepared more, that would build up confidence."

P5F reported that she had already been using ChatGPT to prepare before meetings, especially when anticipating situations where she might struggle to respond on-the-spot. She reflected that in previous meetings, she always felt dissatisfied with her responses, especially in a project where she retrospectively realized that she was the only woman. She regretted *"(missing) the chance to raise key points in time"*, or *"failing to take a strong stand"*, resulting in her clients *"pushing [her] to share source code"*). She saw strong potential for AI to provide scenario-based simulations, to offer guidance on how to react to anticipated scenarios, and project leadership and assertiveness.

Similarly, P4F suggested that gendered AI could help women navigate male-dominated environments.

> "It's easy to make AI present in different genders. That could help move organizations away from old cultures. In male-dominated companies, women might perform poorly in interviews due to anxiety. If they rehearse with a group of male AI beforehand, they might communicate better before talking to humans."

Code-switcher. Women in male-dominated teams often adapt their language to appear more "professional", toning down expressiveness. AI was envisioned to play a role in assisting this process, as P20F noted,

> "Using AI as a code-switcher in your language, because being a woman in a male-dominated team, there are language differences. I use a lot of exclamation points... women often type the way they talk, very expressive, smiley faces, while men do that less. Based on the way I talk, they underestimate me or are reluctant to give me more responsibilities."

To address the issue of women's messages getting delayed in action, participants (P12M, P23F) imagined that AI could rephrase messages to maintain politeness while adding *"directness"* and *"urgency"*. Others suggested that code-switching could also work on the receiver's side, nudging them to interpret messages equitably. As P14M put, such a system could prompt colleagues to *"treat a 'soft-spoken' message from a female colleague with the same priority as one from a male"*, thereby countering unconscious bias in how communication is interpreted and valued.

5.2.2 *AI mentor who tests and validates women's skills and ability.*

Women frequently attribute their lack of confidence in speaking up in meetings to a fear of judgment, yet they often rely on external validation to build confidence. They envisioned AI to be a validator of their competence and skills, helping them build confidence by providing specific, evidence-based feedback rather than generic praise. As P21F explained, *"concrete validation, such as recognizing growth in knowledge and skills, solving increasingly complex problems, or tracking milestones over time"*, would give her *"proof I can hold onto"* to counter self-doubt. Here, unlike human mentorship, AI was imagined as offering continuous, accessible support that is always available and free from social judgment.

Participants also connected this need for validation to the structural barriers they faced in skill development. For instance, P17F recounted that she was denied training opportunities that were exclusively provided for men in her previous organization. She therefore envisioned AI mentorship to offer women-in-tech a safe, judgment-free space to develop skills, gain confidence, and prepare for leadership without relying on organizational gatekeeping:

> "In technology fields, you need constant practice and training to sharpen your skills because things change so fast. I've been denied those opportunities, while men are given them. Without that chance to practice, there's no point in being here so I quit. AI could support continuous learning, keep your skills sharpened, even if you can't attend in-person training."

These highlight how women's envisions of AI mentorship went beyond emotional reassurance. They framed AI as an ally for building sustainable competence and confidence, through validating women's growth, archiving their achievements, and providing continuous learning opportunities to counter both self-doubt and systematic exclusion from training.

6 RQ3 Findings: Concerns, Trade-offs, and Perceived Limits of AI-Driven Gender-Based Interventions for Male-Dominated Teams

While participants saw AI as a promising intervention for supporting women AI professionals in male-dominated teams, they also raised cautions about its risks. Concerns centered around surveillance, transparency, anthropomorphism, social appropriateness, and the limits of AI in addressing deeply-entrenched gender dynamics.

6.1 Cautions around surveillance, transparency, and anthropomorphism

6.1.1 Surveillance. Participants voiced concerns that AI designed to monitor meetings and workplace interactions for discriminatory or diminutive language could easily slip into unwanted surveillance. For instance, P7F cautioned that *"there's some potential to become like Big Brother to grade people's language."*

P2N warned against overzealous "AI watchdogs" in addressing sensitive issues such as verbal harassment targeting women, noting that *"People might feel like cancel culture is getting way so out of control that now even AI agents are telling them that they're gonna get cancelled if they say the wrong thing"*. P2N further pointed out that automated moderation systems on social media platforms have shown how *"algorithms that trawl for community violations often wind up harming minorities and underrepresented people inadvertently and protecting people that it's supposed to target."* These reflections highlight AI professionals' unease with AI surveillance. While it could in theory detect microaggressions and harmful behaviors towards women, it risks fostering a culture of censorship and mistrust that may ultimately disadvantage the very groups it intends to protect.

6.1.2 Transparency. Male participants generally supported AI monitoring team communication, but stressed clear framing, consent, and purpose. P13M, for example, emphasized that transparency matters, *"if everyone on the team knows that the conversations are being analyzed, the goal is clear, to support inclusion, not evaluate individuals secretly."* For him, AI tracking of speaking time and interruptions could be valuable, but only if positioned as helping the whole team rather than policing individuals.

Others echoed this need to frame AI as a collective support, not a "gender fix". As P15M put, *"they should make it about the team, frame the AI as a support, not a supervisor, so we won't feel watched"*. P12M elaborated that effective deployment should be grounded in team values and professional norms, *"I wouldn't frame it as a gender equity fix. I will tie it to engineering principles, I want to use the AI to track system performance and normalize it as a team tool, not as a surveillance device"*.

Even among those open to the idea, concerns about misuse were salient. P9M explained that while he would feel "mostly comfortable" with AI monitoring if done "transparently and ethically," safeguards were critical: consent from all participants, clarity on what data is analyzed, and strong privacy protections. Most importantly, he insisted the tool must not be used punitively, *"The AI should be used to support learning and improvement, not to discipline or blame individuals, like tracking speaking time or interruption frequency to rank people's performance, that is punishment."*

These reflections show men's willingness to accept AI monitoring if it is carefully framed as an inclusive, team-level support system. But they also highlight a key tension: the same tools that can promote fairness risk creating feelings of surveillance or punishment if not handled with transparency and consent.

6.1.3 Anthropomorphism. While female-coded AI was envisioned as an option to make male-dominated teams feel gender-balanced, participants captured the tension between short-term user comfort and long-term societal consequences of gendering AI. On one hand, a female-coded agent might make some women feel supported in male-dominated settings. On the other, defining what counts as "female-coded" AI risks embedding stereotypical ideas of femininity, especially given the "fractured nature of feminism" today. This highlights a design dilemma: while anthropomorphism may offer immediate relational benefits, it also risks normalizing objectification or amplifying harmful stereotypes if not critically examined. P20F captured this dichotomy in her reflection,

> "As a researcher, anthropomorphism causes more problems and issues than it helps. But as a user, if there was an AI who was acting like a Girly Pop, I would feel better about working in a team that is otherwise male-dominated. It's the dichotomy between the individual woman versus the larger societal impacts. The problem is who's deciding what female-coded means. To some it can feel empowering, to others offensive. We exist in a time where femininity, womanhood, feminism in general is super fractured. We don't have a clear narrative of how to characterize women well. What feels sex-positive to some may look like objectification to others. That's what makes gendering AI so difficult, the line between empowering representation and reinforcing harmful stereotypes is so thin."

Her concern is by no means unreasonable. In fact, another female researcher cited an example that demonstrated the very concern actually happened during her experiment where a female-coded AI agent was implemented for team collaboration.

> "I've had male participants straight-up making sexist jokes on the agent during the experiments. Maybe we made her voice pitch a bit high." (P27F)

This illustrates how gendering AI, even with good intentions, can unintentionally elicit sexist behavior, as small design choices like vocal pitch can reinforce and reproduce the very biases that female-coded AI is intended to counter.

6.2 Tensions between social appropriateness and effectiveness of AI interventions

AI professionals envisioned AI as a meeting facilitator, but their reflections revealed a core tension between social appropriateness and effectiveness. To prevent women from being interrupted or their ideas from being overlooked, AI would ideally need to intervene in-the-moment. However, participants emphasized that such real-time interventions risk backfiring, as they could be socially awkward, embarrassing the interrupter and making women feel overly protected. As P13M noted:

> "if the AI points out directly at that moment, it will be embarrassing for the person being interrupted, and also shaming for the person doing the interrupting. This might create a tension and resistance."

For this reason, participants preferred post-meeting summary of interruption patterns that *"allows for reflection without shame"* (P14M), or *"nudge the manager to check in with the interrupted person afterwards"* (P9M), to real-time interventions.

However, some women also pointed out that such post-hoc approaches may not be effective or even counterproductive. As P29F noted, *"If guys can reflect upon those things and correct, they wouldn't be doing it in the first place"*, suggesting that those most responsible for interrupting may be least likely to change based on post-hoc feedback. Another highlighted that delayed interventions do little to bolster women's standing in-the-moment, *"I will still be viewed as the quiet one that doesn't have her own opinion in my male teammates' eyes, and next time they still don't expect my input"* (P6F). While post-hoc approaches provide socially less disruptive solutions, they are limited in addressing the real-time dynamics that shape women's influence and recognition.

6.3 Limits of AI Interventions in Gendered Team Dynamics

While participants envisioned various ways AI can support and empower women in male-dominated teams, they also acknowledged limitations and identified areas where AI can help little. The biggest challenge is that **AI cannot uproot entrenched stereotypes**. For instance, P6F expressed skepticism that AI could meaningfully uproot gender bias, arguing that those who discriminate are unlikely to change even if AI flags their behavior. In her view, lasting change requires individuals' willingness to reflect and transform, not external nudges:

> "I don't think AI is going to change people's perspective. People who want to change and reflect they could make discrimination usually don't do those things. If someone is discriminating people by gender, even though they got an alarm, they will not change."

A male participant's own biased remark underscored P6's concern,

> "It's going to take a very long way for that (AI fundamentally changing stereotypes) to happen. because I'm sorry to say this, but men are more authoritative in technical discussions, and women being better communicators, but not the core engineers. These are things that have been crucially learned over many decades. What AI can do is to just recognize these patterns, but I don't believe it can change anything." (P12M)

One potential way to gradually shift such bias is through repeated exposure to AI modeling gender-swapped behaviors. For instance, P20F reflected on how communication styles coded as relational or expressive are often seen as incompatible with competence. She suggested that AI could help challenge this bias,

> "if AI, which people already view as competent, used that same communication style, it could normalize it. Over time, more exposure would help people value that style as competent."

Another recurring concern among women was that in male-dominated teams, gender-based microaggressions, bias, and discrimination can surface *"anywhere, anytime, in any subtle forms" (P23F)* that escape others' notice and are felt only by the woman affected. Therefore, the fundamental limitation of AI interventions is that **AI cannot be omnipresent**. Regarding this practical limit of AI coverage, P20F noted,

> "I'm also hesitant to say full on workplace monitoring, because that gets really tedious, and when something is tedious, people just find workarounds so they don't have to deal with it. "

Similarly, P25F emphasized the limits of AI intervention to virtual spaces and work-related interactions, *"AI can't force social behavior or rebuild the office culture overnight, in physical, real-time presence, it might not be able to detect much."* These reflections highlight how AI may provide useful nudges in limited contexts, but cannot function as an omnipresent safeguard against gender bias.

Participants also highlight that **AI cannot easily change established team norms**. P3F spoke about the limits of AI intervention in teams where norms and expectations are already established, stressing that the timing of AI support matters:

> "It's hard for AI to have an impact if a team is built for a long time. In the beginning when team members are getting to know each other, I do think AI could help encourage new female members more, help build her role in the team. But later on is going to be hard to change the dynamic and atmosphere."

She argued that AI is most effective during team formation, when dynamics are still fluid. At this stage, AI can play a role similar to that of supportive leaders, offering extra encouragement to new female members who might otherwise struggle to establish their voice. Once team norms and hierarchies solidify, she believed AI would have little power to shift entrenched dynamics.

7 Discussion

So far, our findings show that women AI professionals face challenges consistent with those in other male-dominated teams **(RQ1)**, which in turn shapes how AI professionals envision AI's role in addressing these gender issues **(RQ2)**, and the concerns they raise about such interventions **(RQ3)**. Together, they highlight the opportunities and challenges of designing AI to support gender equity and empower women in such settings. In this section, we synthesize and interpret these findings in light of HCI, organizational, and critical theories, and put forward potential design principles for gender equitable team collaboration.

7.1 Extending AI as a Social Actor in Male-Dominated Teams: Promises and Perils

The CASA (Computers as Social Actors) paradigm [66, 67] shows that people apply social characteristics and stereotypes to computers, treating them as if they were social actors. Our findings extend this work in several ways. First, we show that treating AI as a social actor can operate at both **the team- and individual-level, serving distinct but complementary needs**. At the team-level, participants envisioned AI as capable of shaping team norms and creating more balanced gender dynamics, for example, by redressing skewed gender ratios in male-dominated teams or by modeling equitable turn-taking. The former has been tested in most recent work [45] that shows the presence of a same-gender voice agent can bolster minority women's participation in gender-imbalanced teams. At the personal-level, female-coded AI was imagined as a mentor or role model for women who lack such human support in male-dominated environments. Participants also saw potential for AI to act as a training partner for men with little prior experience working with women, helping them acclimate to and normalize non-masculine communication styles that are often undervalued in technical workplaces. In this way, our findings extend CASA paradigm from dyadic interaction into the team/group domain, showing how AI identity cues can influence both collective and individual experiences in teamwork.

Second, our findings highlight the **potential dangers and social consequences of positioning AI as social actors, and identify ways to mitigate them**. Several participants worried that gendered AI could inadvertently reinforce the very stereotypes it was meant to counter, or even invite sexist behaviors toward the agent and, by extension, toward women. To mitigate these risks, a synthesis of our findings reveals a more nuanced design strategy: avoid reproducing stereotypical gender coding in highly visible, collective contexts such as team meetings, where it could normalize bias at scale. Instead, gendered AI might be more safely deployed in private or individualized contexts, where users can benefit from stereotype-conforming support (e.g., for "nurturing" (P19), comfort (P20) or mentoring (P17) functions) without reinforcing those roles in public organizational life.

Finally, we extend CASA by situating it within feminist HCI [7, 8] and feminist data studies [50]. Rather than treating anthropomorphism as an intellectual curiosity, our findings suggest that researchers and designers must be mindful of **how gendered projections onto AI may reproduce or disrupt inequities in teams**. A feminist extension of CASA shifts the focus from how people stereotype AI to how AI might be designed to challenge rather than mirror these stereotypes, aligning with broader calls in CSCW for equity-centered groupware and interventions that reshape norms rather than adapt to them [40, 41]. As such, our work pushes CASA beyond dyadic HCI. Not only do humans treat computers socially, but those "social rules" are selectively and unequally distributed. By linking CASA to feminist HCI, our findings suggest that AI as social actors must be theorized not just as generic teammates, but as carriers of gendered and power-laden roles within teams that have the potential to shape team power dynamics in both beneficial and harmful ways.

7.2 Making Gender Power Dynamics Visible Through AI

Our findings on women's ideas being overlooked, interrupted, or subject to double standards echo tokenism dynamics [46], which suggests that underrepresentation amplifies visibility while reducing authority. As a minority in AI/technical teams, women are hyper-visible but under-heard. Critical mass theory suggests that once women (or other underrepresented groups) reach a threshold of roughly 15–30%, they are no longer treated as tokens [78]. At this tipping point, individuals gain collective support and can shape group norms, reducing hyper-visibility and enabling meaningful cultural change. Our participants' envisioned AI interventions (e.g., female-coded AI to balance participation) can be understood as attempts to create a form of socio-technical "critical mass" by proxy. Rather than replacing representation, these interventions reduce the burden on tokenized members by making inequities visible, ensuring women's contributions are consistently recognized, and supporting more balanced participation until structural representation improves.

It is impossible to discuss gender-based interventions without drawing on critical theories. Women described how it is through the "little things" (e.g., selective interruptions, overlooked ideas) that accumulate to hinder their participation and influence in male-dominated teams. These micro-practices exemplify Foucauldian perspectives [35] on how power is enacted through everyday discourse rather than overt domination or exclusion. As participants envisioned AI as a mediator of discourse that could track who interrupts whom, credit contributions, or flag gendered asymmetries in participation, our findings extend these theoretical insights into the socio-technical domain. By making visible such gendered micro-practices, AI has the potential to reveal the otherwise hidden power dynamics. This suggests a new direction for discursive theories of power: extending beyond analysis into computational mediation, where **AI could both diagnose and potentially reconfigure the power dynamics of communication in teams**.

Our findings also show that women are penalized no matter they conform to or resist gendered expectations. Their polite, collaborative communication risks their contributions being dismissed or requests delayed, whereas being assertive or direct risks being judged as "aggressive". Similarly, behaviors admired in male leaders were criticized in women. Feminist organizational theorists (e.g., [46]) refer to such a no-win dilemma as "double bind". Envisions of AI code-switcher reflect an attempt to navigate this no-win dilemma by letting women communicate in ways that feel authentic while translating into forms that gain authority in male-dominated contexts. However, ambivalent sexism theory [39] points out the danger here: if workplaces require women to sound "masculine" to be heard, AI risks reinforcing the very bias that it is supposed to address, rewarding dominance while punishing warmth. This underscores that **the design challenge is not to "fix" women's behavior but to reshape the evaluative norms that produce inequity**.

7.3 Transparency as Organizational Communication Rather Than Technical Explainability

Prior HCI research emphasizes that transparency shapes trust in AI systems, particularly when power and accountability are involved [33]. Our findings suggest that for AI designed to promote team equity, transparency concerns arise primarily at the *organizational* *governance level.* Participants sought clarity about why the system exists, who controls it, what data it monitors, how outputs will be used, and what the boundaries of system authority are. These questions align with value-sensitive and governance-oriented perspectives in HCI, which emphasize communicating the purpose, data practices, and constraints of AI systems [21, 32, 34].

Across interviews, participants worried that equity-focused AI might be interpreted as a managerial oversight tool unless its organizational role was made explicit. They wanted to know whether the AI was intended to support learning, reflection, and facilitation, or whether it could be repurposed for evaluation or discipline. Transparency in this context therefore requires articulating the organizational commitments about the system, not just explaining its technical behavior. Making these governance structures visible helps establish psychological safety [30, 31, 69] and reduces fears that analytics will be used to target individuals.

Our findings extend transparency discussions in HCI by showing that, in collaborative and inequity-sensitive contexts, transparency must clarify not only what the system does but also its mandate and limits, and how its insights flow within the organization (e.g., to the team, the facilitator, HR, or no one beyond the user). This reframes transparency as a collective and institutional communication process rather than a purely cognitive feature. Such purpose-driven governance is essential for ensuring that equity-oriented AI is experienced as legitimate and supportive.

7.4 Designing Future AI Interventions to Empower Women in Teamwork

Unlike Sections 7.1 to 7.3, where we interpret the findings through feminist and sociotechnical theories. In this section, we distill the practical design tensions that arise when translating these insights into equitable AI systems. These tensions reflect contradictions in how participants imagined AI supporting collaboration and inclusion. Rather than prescribing solutions, we outline four dilemmas that HCI practitioners must navigate when developing AI for gender-equitable teamwork: **whether** it should be gender-based, **what form** it should take, **how** it should support inclusion without sliding into surveillance, and **when** it should be deployed to balance effectiveness with social appropriateness.

7.4.1 Balance 1: Empower women without patronizing. Regarding whether AI interventions should be framed as **gender-based or generic**, our findings highlight a key tension: the need to explicitly recognize gendered dynamics without framing it as a gender fix, which risks reproducing stigma or adding more labor to the very people already disadvantaged. As feminist HCI reminds us [72, 75], interventions that require women to compensate for inequitable norms can inadvertently reinforce them. Gender-aware analytics can help surface inequities that generic tools miss, but participants also cautioned that interventions targeted only at women may feel patronizing or burdensome.To reconcile these concerns, we argue for gender-aware but team-framed interventions: tools that surface gendered participation patterns and credit origins of ideas, while presenting these insights as supporting inclusion and balanced collaboration for all. This balance emphasizes marginalized perspectives without isolating them, and positions AI as a collective equity tool rather than an individual corrective [86]. Additionally, effective design should **shift expectations for dominant group members**. Rather than asking women to further refine communication strategies, equitable tools should help men adjust their behaviors, mirroring lessons from cross-lingual collaboration systems [27, 28, 38] where majority speakers were prompted to accommodate minorities. This redistribution of responsibility helps ensure that AI interventions support inclusion without reinforcing the gendered workload that already falls disproportionately on women.

7.4.2 Balance 2: Anthropomorphism: utility vs. social impact. Regarding **what form** AI interventions should take, our study highlights a tension between the perceived utility and social consequences of anthropomorphizing AI. Participants described how explicitly gendered or anthropomorphic AI could feel more comfortable and supportive, create an ostensible sense of gender balance, fill mentorship and leadership gaps, and serve as a role model that many women lack in their real workplaces. These possibilities sit uneasily within feminist critiques of gendered labor especially with "double-bind" [46]. A gender-coded AI that adopts either communication style may therefore reproduce the very bind it seeks to mitigate. A nurturing or collaborative female-coded agent may unintentionally reinforce stereotypes that women "belong" in supportive roles; conversely, a more assertive female-coded agent could trigger the same discomfort or resistance that assertive women face, thereby reproducing rather than disrupting gendered expectations.

Our findings therefore point to the need for context-sensitive design strategies rather than universal prescriptions. Gendered AI could provide stereotype-conforming support in private, individual contexts. For example, acting as a nurturing mentor, a collaborative leader, or an ally that validates women's experiences and vouches for their competence [48]. However, care is needed when placing such agents in collective team settings, where they may unintentionally reinforce bias. Conversely, gendered AI can also display counter-stereotypical behaviors. A female-coded agent that communicates assertively can serve as a role model for women to practice and perhaps mimic more authoritative styles through social learning [6], while also helping men normalize women's authority by regularly exposing them to such assertive female-coded agents. Yet from a double-bind perspective, such design choices require caution, as they may replicate backlash dynamics if team members interpret assertiveness as incongruent with a "female" persona. Rather than treating anthropomorphism as a binary design choice, our findings suggest it is a nuanced sociotechnical space. Designers must consider not only whether an AI agent is gender-coded, but how its "gendered" appearance and behaviors are interpreted in specific contexts (e.g., private vs. public, individual vs. collective). Gender-coded AI can, under the right conditions, expand the range of acceptable communication norms in technical teams, but it can also reinforce the very gender biases that feminist theory warns against. Recognizing these contradictions reframes gendered AI not as a panacea, but as a design tension that requires careful HCI attention.

7.4.3 Balance 3: Supporting inclusion without creating surveillance. A central design tension that emerged from the interviews is how AI can support inclusion without slipping into forms of monitoring [55, 64] that feel punitive. Participants valued AI that surfaces inequities, but warned that real-time flags or highly granular tracking could make team members feel "watched". Therefore, equity-supportive AI must not only detect biased patterns but also manage the social risks introduced by its own visibility. Practically, this suggests designing interventions that prioritize collective performance over individual evaluation. The default outputs should aggregate to the collective (e.g., team-level patterns of turn-taking or interruption rates) while person-specific diagnostics should remain private or only be visible to the facilitator. Additionally, group feedback should attribute patterns to roles rather than named individuals (e.g., "men are dominating 70% of the conversation" or "the discussion just concluded skewed senior voices"). Another design tension concerns actionability. Detection must come with recommended behaviors (e.g., inviting others, rotating turns) so that feedback can drive equitable and feasible actions. These tensions point to the need for AI interventions that balance transparency with psychological safety, offering insight without surveillance, and support without blame.

7.4.4 Balance 4: Real-time versus post-hoc interventions. Participants diverged on **timing**, with some preferring in-the-moment nudges that could prevent repeated interruptions and create space for women's contribution, and others fearing that real-time flags would embarrass people. Post-hoc summaries felt safer, but they risk allowing harms to accumulate without being addressed. This represents a classic groupware tension between immediate coordination aid and retrospective feedback [41]. Our findings suggest that timing of intervention should be **contingent on risk, certainty, and social appropriateness**. This calls for AI systems to be able to read context to tell when equity is *violated seriously* and poses *immediate harm*. In cases of light equity violations, post-hoc summaries can be used to raise awareness and propose recommended practices. When AI detection is highly confident that inequity and harms are immediate and/or severe (e.g., repeated interruptions directed at the same person/gender), the system can escalate progressively, starting with private nudges to the violator or the facilitator, then if needed, moving to ambient group cues that are unintrusive. Teams can encode these escalation principles collectively and in advance, so that interventions and mechanisms are agreed-upon. Additionally, AI interventions can be **staged across the phases of a meeting**: setting ground rules and norms before meetings, offering face-saving, phased nudges during meetings, and providing reflective summaries with actionable recommendations after meetings.

7.5 Limitations and Future Work

Our study has several limitations that should be acknowledged. First, the sample reflected an imbalance across gender and sector, with 16/22 women working in academic AI research settings and 7/7 men in industry, leaving the perspectives of men in academia underrepresented. This imbalance likely shaped the patterns we observed. Academic AI teams often center around informal attribution of intellectual labor and hierarchies, whereas industry teams are faster-paced and structured around formal authority and profit-driven goals. Accordingly, women in academia more frequently described subtle intellectual marginalization and self-development barriers, whereas participants in industry focused on leadership visibility and communication efficiency, which shaped the types of AI interventions they considered effective and appropriate. To capture how sector-specific gender dynamics shape visions for AI interventions, future work should intentionally sample men in academia and women in industry. Second, our sample is predominantly based in the Global North, which limits the generalizability of our findings to other cultural and organizational contexts. Gendered dynamics in AI and technical teams are deeply shaped by local norms, labor structures, and cultural expectations. Future work is needed to examine how AI interventions might operate in the Global South or non-WEIRD environments. We also had only one participant who identified as non-binary, preventing us from drawing meaningful conclusions about the experiences of gender-diverse professionals in AI. Future work should recruit more diverse participants across sectors, regions, and gender identities to broaden the scope of equity-centered AI design. Additionally, while our study focuses primarily on gender, we recognize that gender does not operate in isolation. Participants' accounts reflected that exclusion can also arise from power differentials, expertise hierarchies, seniority gaps, and cultural background. As such, an intersectional lens [22] is needed to understand how other types of marginalization shape women's experiences in AI teams. Our findings therefore speak to one dimension of inequity and should be expanded in future research that examines how AI might support inclusion across multiple, overlapping forms of disadvantage. Finally, our participants were AI professionals reflecting on their own domain. While their perspectives are highly relevant, gendered inequities may manifest differently in other domains where AI is developed or deployed, such as medicine, education, or government. Future studies could extend this inquiry to additional sectors to test whether the visions and concerns articulated here are generalizable or domain-specific.

8 Conclusion

This study explored how women in male-dominated AI teams experience barriers to influence and subtle exclusion, and how AI is envisioned as a potential to address these inequities. We showed that while participants saw opportunities for AI to regulate meeting dynamics, amplify contributions, mentor and prepare women to be skillful, confident, and assertive, they also raised concerns about stereotyping, backlash, social appropriateness, and surveillance. We conclude that AI interventions should be gender-aware but team-framed, and that AI is not a neutral teammate but a gendered and power-laden social actor, capable of shaping team dynamics for better or worse. Our contributions are threefold: an empirical understanding of women's challenges and envisioned AI solutions, a theoretical integration of feminist HCI and human–AI teaming, and a design space of strategies, risks, and safeguards. Together, these advance HCI and CSCW scholarship on computer-supported collaboration and equity by identifying new roles AI can play in fostering inclusive collaboration and empowering women. Looking forward, we encourage researchers and designers to treat equity not as an afterthought but as a preemptive design goal for AI-mediated teamwork. This calls for reflexivity, feminist principles, and careful attention to unintended consequences. In doing so, we can create collaborative technologies that not only support team productivity but also challenge and reshape entrenched gender inequities in technical workplaces.

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Table 2: Participant Demographics

PID	Gender	Age	Race/ethnicity	Native language	Education	Major	Profession or research focus in relation to AI	Gender composition of primary team	Sector
1	Woman	28	East Asian	Chinese Mandarin	Master	Human Centered Computing	PhD student studying human-AI teaming	7M3F	Academia
2	Non-binary	32	Caucasian/White	English	PhD	Computer Science	PhD candidate; research area is causal AI/ML	5M1N	Academia
3	Woman	31	East Asian	Chinese Mandarin	PhD	Human Centered Computing	Works on human perceptions of AI agents and human–AI interaction	10+M5F	Academia
4	Woman	32	Caucasian/White	English	PhD	Human Centered Computing	Faculty, research focuses on cybersecurity, adaptive autonomy	4M1F	academia
5	Woman	29	East Asian	Chinese Mandarin	PhD	Information science	Research engineer working on LLM agent.	14M6F	industry
6	Woman	29	East Asian	Korean	Master	Cultural Technology	HCI researcher studying AI in healthcare	3M1F	academia
7	Woman	32	Caucasian/White	English	PhD	Complex Systems and Data Science	PhD student studying LLM, NLP, predictive analytics	16M7F	academia
8	Woman	29	African American/Black	English	Bachelor	Computer science	Machine learning engineer	12M5F	industry
9	Man	26	East Asian	English	Bachelor	Computer Engineering	AI Software Engineer; I develop and optimize machine learning algorithms used in our products.	7M1F	industry
10	Man	40	South Asian	English	Bachelor	Information Systems	AI Operations Specialist.	8M2F	industry
11	Man	31	Caucasian/White	English	Master	Information Technology Management	Project Manager overseeing AI implementation in healthcare systems.	12M5F	industry
12	Man	35	African American/Black	English	PhD	Mechanical Engineering	Senior systems engineer in an autonomous vehicle startup.	12M2F	industry
13	Man	31	African American/Black	English	Bachelor	Computer Science	Software engineer for a fintech company specializing in anti-fraud solutions	7M1F	industry
14	Man	30	Caucasian/White	English	Bachelor	Robotics	Controls engineer	9M2F	industry
15	Man	33	African American/Black	English	Bachelor	Electrical Engineering	IoT solutions architect focusing on energy prediction and optimization	14M6F	industry
16	Woman	32	Southeast Asian	English	PhD	Human Centered Computing	PhD student working on integrating AI into VR	4M2F	academia
17	Woman	28	Hispanic	English	Bachelor	Computer science	Software engineer specializing in model monitoring systems for drift and data quality	7M3F	industry
18	Woman	23	South Asian	Urdu	Bachelor	Computer science	UX researcher working on AI-assisted object detection and accessibility	4M2F	industry
19	Woman	25	South Asian	Bengali	Master	AI policy and Governance	AI policy researcher.	5M1F	academia
20	Woman	29	Caucasian/White	English	Master	Human Centered Computing	PhD candidate in HCC working on human-AI collaboration and teaming.	10M2F	academia
21	Woman	25	Southeast Asian	Vietnamese	PhD	Human Centered Computing	PhD student in HCC working on human-AI collaboration and teaming.	7M4F	academia
22	Woman	36	East Asian	Chinese Mandarin	PhD	Information Science	UX researcher working on customer-facing agents	5M3F	industry
23	Woman	29	Caucasian/White	English	PhD	Computer Science	PhD candidate, human-robot teaming	4M2F	academia
24	Woman	32	South Asian	Bengali	PhD	Electrical Engineering	Faculty conducting research on smart grids	5M1F	academia
25	Woman	29	Caucasian/White	English	PhD	Human-Computer Interaction	UX researcher working on algorithmic fairness	8M3F	industry
26	Woman	26	Caucasian/White	English	PhD	Information Science	Postdoc researcher studying human-AI collaboration.	5M2F	academia
27	Woman	37	East Asian	Korean	PhD	Informatics	Faculty doing machine translation and NLP research	5M2F	academia
28	Woman	31	Southeast Asian	English	PhD	Human-Computer Interaction	Postdoc working on human-AI interaction	10M2F	academia
29	Woman	30	East Asian	Chinese Mandarin	PhD	Mechanical Engineering	PhD student research focuses on autonomous vehicles	8M3F	academia
30	Woman	33	East Asian	Korean	PhD	Computer Science	PhD student doing NLP research	4M1F	Academia