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INVISIBLE FILTERS: HOW DIGITAL AND HUMAN BIAS SHAPE WOMEN'S JOB SEARCH IN HIGH-TECH. EXPLORING ORGANIZATIONAL GATEKEEPING, AI TOOLS, AND THE GENDERED HIRING EXPERIENCE IN THE DIGITAL AGE

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Abstract
Despite the growing emphasis on diversity and inclusion, women continue to face disproportionate challenges in securing leadership and technical roles within the high-tech sector. This study explores the job-seeking phase through an organizational lens, revealing how both human and algorithmic biases perpetuate gender disparities. Drawing on qualitative interviews with women professionals in high-tech – including VPs, HR leaders, and mid-career candidates – this research surfaces patterns of exclusion masked by seemingly neutral recruitment practices. Participants reported being asked inappropriate questions about motherhood and travel commitments, while others described feeling "out of the loop" despite holding senior roles in global firms. The study also examines the unintended consequences of digital hiring platforms and AI-driven applicant tracking systems, which may reinforce rather than reduce bias. By combining empirical insights with contemporary literature on digital governance, algorithmic decision-making, and gender inequality in hiring, the paper calls for more transparent and inclusive recruitment systems. It proposes actionable organizational strategies to ensure equitable access to high-tech careers in the digital age.
Keywords: *digital age; gender bias; high-tech industry; AI recruitment tools; digital discrimination; women in leadership.*
JEL Classification: J16; M5; O33; M14; D83.

1. INTRODUCTION

As artificial intelligence (AI) becomes more common in recruitment, it promises to make hiring faster and more objective. Many companies now use digital tools like applicant tracking systems (ATS), algorithmic shortlisting, and online profile filters to handle large volumes of applications. These systems are promoted as neutral and efficient, but recent research shows they can reproduce old biases in new ways. For women seeking leadership jobs in high-tech – an industry already known for gender inequality – these tools can quietly reinforce barriers rather than remove them.

This study explores how both human judgment and algorithmic filters shape women's job-seeking experiences in high-tech. While much attention has been paid to diversity goals and inclusive hiring, there is still little understanding of how bias works in the early stages of recruitment, where many decisions are made invisibly. Digital systems often rely on past hiring data, which reflect male-dominated work histories. As a result, algorithms may prefer linear, jargon-heavy résumés or penalize career breaks and modest self-presentation – patterns that can disadvantage women. At the same time, human recruiters continue to rely on informal networks, "cultural fit," and sponsorship, creating a complex mix of digital and social exclusion.

The study draws on qualitative interviews with women and senior professionals in Israel's tech sector, combined with existing research on algorithmic bias, gender stereotypes, and workplace networks. Using theories from organizational sociology, psychology, and digital ethics, the paper shows how bias moves between people and machines. It also offers practical solutions: making hiring systems auditable, removing gendered language in job ads, using structured interviews, and tracking where women drop out of the hiring pipeline.

By understanding where and how bias operates – often silently – this study contributes to building more inclusive and fair recruitment systems in the high-tech industry. Recent studies also note that gender, age, and technological literacy shape how professionals engage with AI systems themselves (Draxler *et al.*, 2023), underscoring that digital adoption is never entirely neutral.

2. THEORETICAL FRAMEWORK

This study combines three well-established lenses to explain why women still face hidden barriers when they look for leadership jobs in high-tech and how those barriers now mix with AI tools.

First, ***Gendered Organization Theory*** argues that firms are built on an "ideal-worker" image that suits a man with no family breaks and a 24/7 schedule (Acker, 1990). Job descriptions, performance metrics and historic hiring data all encode that model. When a résumé-scoring algorithm is trained on such data, it simply learns yesterday's male-centred pattern and reproduces it. Human managers do the same when they favour candidates who "fit the culture," which often means fitting that embedded masculine norm. Thus, structural bias is baked into both digital and human gatekeeping long before a woman reaches an interview.

Second, ***Role Congruity and Lack-of-Fit Theory*** explain how individual evaluations add another layer of bias. Leadership in tech is stereotyped as agentic – assertive, decisive and always available – whereas women are stereotyped as communal and family-focused (Heilman, 2001; Eagly and Karau, 2002). When a woman displays the required agentic traits, she may be judged as unlikeable; when she does not, she is seen as under-qualified. This double bind depresses ratings of competence, salary offers and promotion chances, a pattern shown in laboratory experiments and field audits alike. AI systems trained on past promotion data inherit the same distorted signals: fewer historic female promotions teach the model that female applicants are a “riskier” bet, even if gender is not an explicit variable.

Third, ***Social Capital Theory*** highlights how careers depend on networks and sponsorship. Senior posts in tech still circulate through male-dominant referral chains and informal ties; women gain fewer influential contacts and are less likely to have a sponsor who will push their candidacy (Mickey, 2022; Contreras *et al.*, 2024). Platform algorithms that rank profiles or deliver job ads mirror these network gaps, giving men wider reach and reinforcing what Burt (2005) calls the advantage of “brokers” embedded in rich networks.

Taken together, these theories show a multi-level system of exclusion. Gendered structures feed biased data into algorithms, stereotype mismatch skews human and machine judgments, and unequal networks starve women of critical sponsorship. Understanding this interplay guides our analysis of interview evidence and points to integrated solutions: rewrite role criteria, audit and retrain hiring AI, and build formal sponsorship programmes that widen women’s social capital and break the cycle of invisible filters.

3. LITERATURE REVIEW

This review funnels from the broad strategic role of digital HR to the specific, intersecting biases that impede women’s advancement in high-tech hiring. It integrates seventeen core studies (see References) and is organised around six themes.

3.1. Digital Strategy & Competitive Advantage

AI-enabled recruitment systems are now marketed as engines of speed, scale and “talent intelligence”, aligning HR with digital-transformation agendas (Bogen and Rieke, 2018). Upturn’s audit found that 98 per cent of Fortune 500 firms use an Applicant-Tracking System (ATS), and almost half embed machine-learning models to rank or short-list applicants (Bogen and Rieke, 2018). From a resource-based view, such tools should enhance competitive advantage by securing scarce skills faster.

Yet evidence shows that algorithmic filters can also erode innovation capacity if they replicate historic homogeneity (Raghavan *et al.*, 2020). Amazon’s résumé-scoring pilot learned to demote candidates from women’s colleges because its training data were overwhelmingly male (Dastin, 2022). With the draft EU AI Act classifying recruitment algorithms as “high risk” and imposing mandatory bias audits (Lütz, 2024), bias-resilient hiring is no longer optional; it is a strategic compliance and reputational imperative.

3.2. Diversity as Strategic Human Capital

A rich stream links gender diversity to market performance and creativity. Firms in the top quartile for female leadership are 25 per cent more likely to exceed industry profitability medians (Ibarra, Carter and Silva, 2010). Conversely, homogenous teams may suffer "diversity debt" that surfaces later as lost innovation (Moss-Racusin *et al.*, 2012). Moss-Racusin's study showed that science faculty – male and female – rated identical CVs higher when labelled "John", offered him USD 4,000 more, and promised greater mentoring (Moss-Racusin *et al.*, 2012). When such micro-inequities accumulate, organisations forego the very creativity they seek from digital talent initiatives.

3.3. Leadership Pipelines & Sponsorship

The "leaky pipeline" in tech is widest at the sponsorship stage: women report similar levels of mentoring but are 54 per cent less likely to have a sponsor who actively advocates for them (Ibarra *et al.,* 2010). Hewlett (2013) found that sponsored employees are 30 per cent more likely to obtain stretch assignments – crucial for senior roles – yet only 18 per cent of high-performing women surveyed could name a sponsor. Digital platforms magnify the gap: a large-scale LinkedIn scrape revealed that male executives enjoy denser, higher-status networks, boosting algorithmic visibility in recruiter searches (Contreras *et al.,* 2024). Mickey's (2022) ethnography in Silicon Valley shows that informal social events (hackathons, gaming nights) serve as gateways to sponsorship, but women are often peripheral to these circles.

3.4. Recruitment & Selection Bias (Human)

Before algorithms, gendered organisations already advantaged men (Acker, 1990). Heilman's (2001) lack-of-fit model posits that evaluators expect leadership to be agentic and see women as communal; women who display assertiveness face social penalties, while those who do not are deemed weak. Correll *et al.* (2007) quantified the motherhood penalty: mothers were 80 per cent less likely to be recommended for hire and offered 7 per cent lower salaries than identical non-mothers. Rivera (2012) adds that "cultural matching" leads interviewers to choose candidates who share leisure pursuits and class markers, indirectly reinforcing male dominance in elite tech hiring.

3.5. Algorithmic Hiring Systems

Commercial AI tools promise objectivity but often entrench historical patterns (Bogen and Rieke, 2018). In Upturn's review, eight of ten résumé-parsing vendors filtered out CVs with employment gaps – a proxy that disproportionately penalises women returning from maternity leave (Bogen and Rieke, 2018). Raghavan *et al.* (2020) identify five common myths (e.g., "removing gender solves bias") and show that proxy features continually re-emerge. Field experiments paint an ambivalent picture: Avery *et al.* (2024) found that gender-blinding and skills-based scoring raised female short-listing by 12 percentage points, while un-audited tools in the same trials favoured men. Langenkamp *et al.* (2020) outline "fair-by-design" principles – counterfactual testing, balanced data, explainability – that reduce disparate impact but remain exceptions, not the norm.

Table 1. Layers of Gatekeeping in Tech Hiring

Layer	Description	Reference
Stage 1 – Algorithmic Filter	AI résumé-screening tools, trained on male-dominated hiring data, rate women lower or penalize "female" signals (e.g., women's colleges, career breaks).	Dastin (2022)
Stage 2 – Human Filter	Recruiters apply informal criteria like "cultural fit," often choosing candidates similar to the current male-dominated team.	Rivera (2012)
Stage 3 – Network Filter	Access to final roles depends on informal sponsorship networks, where women are underrepresented.	Hewlett (2013)

Source: developed by the author

3.6. Synthesis & Leadership Implications

The literature reveals a circular pattern of exclusion: past male-heavy hiring produces biased data; that data trains algorithms to prefer male profiles; human interviewers then validate these "objective" rankings through notions of cultural fit; and the resulting all-male sponsorship networks feed the next hiring round. To disrupt this loop, organisations must combine three levers. First, they should subject all recruiting algorithms to regular bias audits and bring them in line with the EU AI Act's fairness requirements (Lütz, 2024). Second, hiring decisions should rely on structured interviews and mixed-gender panels, an approach shown to dampen role-incongruity effects (Heilman, 2001). Third, leadership scorecards need explicit metrics for sponsorship and advancement of women, making senior managers accountable for building diverse pipelines (Hewlett, 2013). Firms that integrate these steps transform diversity from a compliance chore into a strategic resource, boosting innovation while satisfying growing regulatory and ESG demands.

4. METHODOLOGY

This study uses a qualitative approach to explore how digital and human biases affect women's job search in high-tech. Data was collected through 19 semi-structured interviews with professionals from the Israeli tech sector. The sample includes 17 women and 2 men, aged 28 to 55, with roles such as development managers, product managers, team leads, founders, VPs of R&D, DEI and HR managers, and a CEO. Interviews were conducted remotely, lasted 45 to 75 minutes, and all participants gave consent for recording and anonymous use of their input.

The conversations focused on personal career experiences, hiring dynamics, and perceived barriers in recruitment. Open-ended questions allowed participants to bring up themes like algorithmic screening, informal networks, motherhood bias, and visibility gaps. Transcripts were analyzed using thematic content analysis, with emerging patterns grouped into categories such as digital gatekeeping, confidence and visibility, and organizational culture.

The findings were then interpreted in light of existing literature on gender and bias in hiring. This helped connect individual stories with broader structural patterns and offered a deeper understanding of how digital tools and workplace culture interact to shape outcomes. The combined use of interviews, content analysis, and literature review supports a multi-layered view of gender inequality during the job-seeking phase in high-tech.

5. FINDINGS AND DISCUSSION: WHERE BIAS HIDES – FROM HUMAN FILTERS TO ALGORITHMS

5.1. Human Filters: A Familiar but Persistent Barrier

While the emphasis of this study is digital bias, interviews reveal that traditional human biases persist. These biases include overt experiences, such as inappropriate questions about family life, and subtler dynamics like confidence gaps and networking exclusions.

"Some women hesitate, thinking, 'What if I get pregnant quickly and have to announce it a few months into the job? How will it be perceived?'" – Participant 5

Such hesitation reinforces what is commonly referred to as the motherhood penalty (Correll *et al.,* 2007), which penalizes women for their potential caregiving responsibilities.

"I often receive applications from men who don't meet the requirements at all. But women rarely apply unless they meet all the listed criteria." – Participant 5

This finding aligns with Hewlett *et al.* (2010), who found that women often underestimate their readiness for leadership roles, contributing to underrepresentation at higher levels.

Professional networks also serve as exclusionary filters:

"Many promotions happen through informal connections – alumni networks, military units, or even things like playing soccer with colleagues after work." – Participant 5

These informal spaces reproduce gendered access to leadership, echoing Acker's (1990) theory of gendered organizations and Ibarra *et al.* (2010)'s work on network-based advancement.

5.2. Digital Filters: The Rise of Algorithmic Gatekeeping

As hiring processes digitize, participants described new layers of exclusion that feel more neutral but are equally, if not more, discriminatory.

A central concern raised by participants is the role of algorithmic screening tools, particularly applicant tracking systems (ATS), in perpetuating gender bias. These systems often reward linear, jargon-heavy resumes - formats historically aligned with male-dominated career trajectories (Bogen and Rieke, 2018). As one participant noted, "If your CV doesn't scream 'developer' in the first three lines, the system might never surface it." This structure disproportionately penalizes women whose resumes reflect career breaks due to caregiving or who use more modest language in self-presentation. Both Heilman (2001) and Gaucher *et al.* (2011) highlight the influence of gendered language in shaping perceptions of competence, which can significantly affect algorithmic parsing and ranking of applicants.

Beyond ATS, visibility bias also emerges from the sourcing practices used by platforms such as GitHub and LinkedIn. Recruiters frequently rely on "top contributor" filters or public activity metrics to identify promising candidates. However, this approach tends to favor those who are constantly visible online, a category that often excludes women with greater caregiving responsibilities or less inclination toward public self-promotion. "We use filters like 'top contributors' – but that already filters out many women," remarked one participant. Another observed, "If you're not always online or visibly 'out there,' you just don't get found." This aligns with Mengel's (2020) findings, which demonstrate that women engage less frequently in visible self-promotion on professional platforms, leading to lower algorithmic discoverability.

Finally, the use of AI-driven referral algorithms introduces a feedback loop that reinforces demographic homogeneity. These tools often suggest candidates who resemble prior successful hires, thus replicating existing biases under the guise of data-driven neutrality. As one participant reflected, "Our tools suggest candidates based on who succeeded before. It's self-fulfilling." This phenomenon echoes Cowgill and Tucker (2020) research, which showed that algorithmic recommendation systems tend to mirror entrenched organizational preferences, rather than challenge them. Together, these digital filters – while ostensibly neutral – form an opaque gatekeeping system that systematically disadvantages women at multiple stages of the hiring funnel.

5.3. The Human–Machine Loop: Bias Reinforced by Design

Rather than eliminating bias, technology often conceals it. Blind screening efforts, while well-intentioned, are frequently bypassed:

"We removed names on CVs, but the hiring manager Googled them anyway." – Participant 5

This illustrates the limitations of technical fixes in the absence of cultural change. As Eubanks (2018) and Citron and Pasquale (2014) warn, algorithmic tools can create a false sense of objectivity, making bias harder to detect and address.

5.4. From Black Boxes to Clear Pathways: Rethinking Digital Recruitment

To counteract these layered forms of discrimination, this study recommends the following:

To begin addressing digital hiring bias, one crucial intervention is the implementation of auditable applicant tracking systems (ATS). Rather than treating algorithmic processes as black boxes, these systems should log decisions and provide transparency around when and why candidates are excluded. As Raji *et al.* (2020) argue, such auditability enables organizations to identify where biased outcomes emerge and take corrective action, transforming ATS from passive filters into tools for accountability.

Another vital area for intervention is the language used in job descriptions. Participants noted that overly specific or jargon-heavy listings can unintentionally signal a preference for traditionally male-coded career paths. This aligns with Gaucher *et al.* (2011) findings that gendered language can significantly deter women from applying to roles. By stripping listings down to essential criteria and using neutral, inclusive language, companies can broaden their applicant pool and reduce self-selection out of the process.

Blind screening was also highlighted as a practice with the potential to reduce early-stage bias. By removing identifiers such as names, gender, or alma mater during initial evaluations, organizations can minimize the influence of unconscious stereotypes. However, participants stressed that blind screening should not stand alone. It should be followed by structured interviews that apply the same evaluation criteria to all candidates. Bohnet (2016) found that structured processes greatly improve objectivity and fairness compared to informal, impression-based interviews.

Finally, the systematic collection and analysis of gender-disaggregated data across hiring stages emerged as a key recommendation. By tracking gender ratios at each step – application, shortlisting, interviews, and offers – organizations can detect where attrition or exclusion occurs. This "leakage mapping" allows for targeted intervention and continuous improvement in equitable hiring practices, rather than relying on broad or symbolic diversity goals.

"If you don't track who gets to the interview stage, you'll never know where the leak happens." – Participant 5

This approach encourages ethical AI governance and inclusive hiring practices, aligning technology and human values toward greater equity.

6. CONCLUSION

This study set out to explore how invisible filters – both human and digital – shape women's job-seeking experiences in high-tech. Through interviews with professionals across development, HR, DEI, and executive roles, a clear pattern emerged: even as hiring becomes more automated, bias has not disappeared – it has only changed form. The findings reveal that applicant tracking systems, visibility algorithms, and referral tools often replicate past inequalities under a neutral interface, while human decision-makers still fall back on informal networks and cultural assumptions.

Three theoretical lenses helped unpack this dynamic. Gendered Organization Theory explained how legacy structures define the "ideal candidate" in ways that exclude those who don't match a male-centered norm. Role Congruity Theory showed how women face a double bind: seen as either underqualified or unlikeable depending on how they present leadership traits. Social Capital Theory illuminated the network gap – how access to referrals, sponsors, and visibility continues to favor men in subtle, cumulative ways.

Together, the data and theory point to a system that excludes by default, unless deliberately challenged. Bias is not only a matter of bad actors or outdated mindsets – it is embedded in the tools, metrics, and models organizations use every day. But bias is not immutable. This study highlights concrete interventions: audit your ATS, redesign job criteria, blind early screenings, structure interviews, and track leakage points. These actions help shift recruitment from a black box to a transparent system, aligning digital innovation with fairness.

As hiring enters a new algorithmic era, inclusion must not be left behind. If tech companies truly aim to lead in both innovation and equity, they must treat bias not just as a social issue but as a design flaw – one that can and must be fixed.

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