



# Values in Emotion Artificial Intelligence Hiring Services: Technosolutions to Organizational Problems

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Despite debates about emotion artificial intelligence's (EAI) validity, legality, and social consequences, EAI is increasingly present in the high stakes context of hiring, with potential to shape the future of work and the workforce. The values laden in technology play a significant role in its societal impact. We conducted qualitative content analysis on the public-facing websites ( $N=229$ ) of EAI hiring services. We identify the organizational problems that EAI hiring services claim to solve and reveal the values emerging in desired EAI uses as promoted by EAI hiring services to solve organizational problems. Our findings show that EAI hiring services market their technologies as technosolutions to three purported organizational hiring problems: 1) hiring (in)accuracy, 2) hiring (mis)fit, and 3) hiring (in)authenticity. We unpack these problems to expose how these desired uses of EAI are legitimized by the corporate ideals of data-driven decision making, continuous improvement, precision, loyalty, and stability. We identify the unfair and deceptive mechanisms by which EAI hiring services claim to solve the purported organizational hiring problems, suggesting that they unfairly exclude and exploit job candidates through EAI's creation, extraction, and *affective commodification* of a candidate's *affective value* through pseudoscientific approaches. Lastly, we interrogate EAI hiring service claims to reveal the core values that underpin their stated desired use: techno-omnipresence, techno-omnipotence, and techno-omniscience. We show how EAI hiring services position desired use of their technology as a moral imperative for hiring organizations with supreme capabilities to solve organizational hiring problems, then discuss implications for fairness, ethics, and policy in EAI-enabled hiring within the US policy landscape.

CCS Concepts: • **Human-centered computing** → Empirical studies in HCI.

Additional Key Words and Phrases: AI, emotion AI, emotion recognition, affective computing, artificial emotional intelligence, algorithmic decision-making, employment assessments, talent acquisition, psychometrics, recruiting software, labor, talent, AI ethics, values, future of work

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Human emotion and affect are intimately linked to behavior and decision-making [26, 65, 121]. As a “fundamental basis by which we compare, evaluate, and select among alternatives in nearly all domains of social life,” [55] emotions play a critical role in modulating important life outcomes. On a higher level, people experience emotions as intimate, private, complex, and prone to manipulation [7]. Despite emotions’ sensitivity and their important roles, Emotion Artificial Intelligence (EAI) technologies are built to “use affective computing and artificial intelligence techniques to sense, learn about, and interact with human emotional life” [75]. EAI’s proposed and current uses span low (e.g., entertainment) to high stakes (e.g., hiring, healthcare, education) contexts [75]. Though

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concerns about EAI's validity and commercialization remain high [11, 78, 100, 114], the emerging EAI market is expected to grow to \$43.3 billion by 2024 [70] and remains unregulated in the United States with limited public input.

Increasingly, “artificially intelligent” hiring services claiming to infer a candidate's emotions and other affective phenomena are entering the commercial marketplace [16], promising organizations the ability to better predict and control employment outcomes. The emergence of EAI hiring services comes at a social and historical moment where the ethics of using EAI in high stakes contexts like hiring are contested [41, 107, 118], while EAI's promises to organizations are profoundly alluring [85]. While more broadly AI development and design continues to grapple with how to best approach its negative societal impacts [35], commercial adoption of EAI hiring services continually increases [17, 85]. Consequently, job candidates are unwittingly [74] assessed by EAI despite its potential legal, ethical, and privacy consequences [11, 100, 114], the lack of available guidance to mitigate those consequences in ethical, responsible ways [32], and the contested validity of the technology itself [11].

Emotions experienced in work and job seeking contexts mediate peoples' perceptions in ways that influence future decisions and the pursuit of labor [46, 81, 93], rendering the examination of EAI a question of social impact [94]. While examining the role and social implications of AI in hiring is a growing and important area of scholarship [3–6, 63, 106], the implications for *emotion* AI in hiring remain relatively unknown thus far. Recent requests by the United States Office of Science and Technology Policy (OSTP) for information about the social implications of technologies that infer “attributes including individual mental and emotional states” [1] further highlight the importance of examining EAI's implications.

What are the implications of EAI in hiring for our socio-technical futures? Technology's societal implications are deeply entangled with humans' moral and political values [119], and are operationalized to make normative claims of what *should be* rather than just what *is* [102]. By eliciting how human values are negotiated and materialized in technology, we can reveal how technology is used by and affects society [61, 103]. EAI hiring services are a key stakeholder in the development, design, and adoption of EAI applications. To identify the values that underpin the desired uses of EAI in hiring these key stakeholders promote, we applied a values lens [61, 103] to a content analysis of the promotional claims made by EAI hiring services ( $N = 229$ ) on their public-facing websites to ask: *For what organizational problems do EAI hiring services promote their technology as a solution? By what mechanisms do EAI hiring services claim to solve these problems? What core values underpin these desired uses of EAI promoted by EAI hiring services?*

Our analysis contributes several key insights, including two novel concepts: (1) We find that EAI hiring services promote EAI as a technosolution to the purported organizational hiring problems of hiring (in)accuracy, hiring (mis)fit, and hiring (in)authenticity. (2) We unpack each problem to surface how EAI hiring services legitimize their technosolutions under corporate ideals. (3) We identify the mechanisms by which EAI hiring services claim to solve those problems, specifically: (3.1) the creation and extraction of a candidate's *affective value*, which we define as the value assigned to an individual's emotional and affective desirability as determined by the EAI, in turn facilitating the algorithmic *affective commodification* of human labor – affective commodification describes how affective value is commodified through the process of hiring decisions that purchase the labor of those candidates who meet EAI's encoded expectations for affective value; and (3.2) informational and psycho-biological exclusion of candidates. (4) Lastly, we reveal the core values that underpin the desired uses of EAI promoted by EAI hiring services as techno-omnipresence, techno-omnipotence, and techno-omniscience, showing how EAI hiring services position use of their technology as a moral imperative by characterizing EAI as the one true entity capable of solving organizational problems in hiring.

We discuss EAI hiring service mechanisms and values identified in our analysis, highlighting important implications for *any* ethical and responsible use of EAI hiring services. Pointing to tensions between company claims and broader algorithmic fairness and equity scholarship, we argue that EAI service claims dangerously obscure the potential harms introduced by EAI and reinforce exclusionary hiring practices *despite* their concurrent claims of debiasing hiring processes and outcomes. Lastly, we discuss this work's implications for design and policy to address deception and unfairness in EAI hiring services.

## 1 BACKGROUND

We discuss emotions' relevance to hiring, followed by a review of literature on AI in organizations, workplace management technologies, and critiques of AI use in hiring.

### 1.1 Emotions in Hiring

Hiring is conventionally emotional and interpersonal [93]. To assess an applicant's candidacy, employers use signals to make estimates of a candidates' human capital, social capital, and demographic characteristics [42, 86], which in turn influence their perception of candidates' interior traits [34, 93]. Such perceptions "may stem from implicit or explicit stereotypes, perceptions of average group ability, or personal experience" [93]. Attending to the variance in scholarship studying effects of subjective hiring decisions, Rivera introduces the theoretical framework of "emotional energy development" to describe how the emotional energy [23] interviewers feel toward candidates modulates hiring outcomes. Research suggests that employers describe the interviewers' emotional experience as the most important factor when evaluating candidates [93]. That is, interviewers tend to seek new hires who are not only competent but also excite them, and with whom they anticipate developing intimate personal and professional relationships [93].

The interaction of emotions with the hiring process is dynamic and interpersonal, also affording candidates important information to determine employment outcomes [93]. Employers may penalize applicants, for example, when interactions with candidates during interviews elicit negative feelings (e.g., anger, boredom) in the interviewer or if candidates fail to elicit positive emotions (e.g., excitement). In turn, candidates process their own perceptions of the interviewers' emotional reactions to inform how they proceed with the interview process. For example, candidates might "cash in on [interviewers'] emotional responses for jobs" by leveraging that information to effectively negotiate higher salaries [93]. Thus, the emotional experience candidates and interviewers engage in to assess candidacy and negotiate employment outcomes is one that both parties can, to varying degrees, use to their advantage. The automatic, one-sided way in which EAI hiring services augment or replace conventional, human-based employment decisions potentially disrupts the roles emotions play in hiring processes and outcomes.

### 1.2 AI in Datafied Organizations

Organizations are increasingly implementing EAI systems as part of human capital and talent management strategies to automate or augment hiring decisions [85]. EAI-enabled enterprise systems claim to generate inferences about internal employees' and external applicants' emotions and other affective phenomena [18, 73, 88, 89], which can then be used to assess an individual's candidacy and drive personnel decisions with data [85, 115, 116]. Such systems can be used in all stages of the recruitment process, including algorithmic candidate sourcing and matching [33], automated candidate assessments and screening [5], and fully automated hiring platforms [6].

How data-driven hiring systems justify their "ideological grounds of datafication" has important implications for workplaces, by invoking normative expectations about which types of work and workers should be assessed and allocated "around a vision of the common good" [29]. Dencik et al.

argue that studying the implications of AI in hiring from the perspective of technology providers is a critical component to understanding the technology's broader societal implications, as it "compels us to consider how data-led processes spread and how data-informed knowledge is sought to be legitimated" [29]. Ajunwa et al. [6] reveal how automated hiring platforms provide affordances to managers that together generate a "managerial frame" that enables the "fungible" allocation of workers, whereby workers are "available on demand and easily ported between job tasks and organizations" [6]. These examples highlight how using algorithmic tools and their inferences about candidates (including of emotion and/or affect) to inform hiring decisions is closely tied to strategic efforts to manage organizational workforces in data-driven ways.

Digital surveillance and datafication in the workplace is disparately applied to and perceived by different demographic groups in ways that reproduce social inequality, often along racialized and gendered lines [37, 105, 109]. Extraction and capitalization of data has political and moral dimensions, whereby people are classified and categorized against standards of desirable behavior defined by powerful actors [37]. We build on past work articulating the implications of AI in datafied organizations to examine the the moral and political implications of EAI in hiring.

### 1.3 Workplace Talent Management

Using EAI to infer the emotions and other affective phenomena of employees and job candidates is part of a longer history of academic and organizational interest in collecting information about workers' interior states. The industrial and organizational (I/O) psychology of personnel selection grew largely out of the work of Scott and Münsterberg, deeply influenced by Darwin's concept of "survival of the fittest" [59].

In the 1920s, US organizations began partnering with industrial and organizational researchers to attain information about workers' interior states (i.e., thoughts, attitudes, emotions), seeking to "penetrate a person's conscious barriers" and bring out their "latent or unconscious sentiments" regarding employee loyalty, work conditions, and relations with other employees [53]. Such practices grew during and after the cognitive revolution of the 1950s [51, 77], with employers increasingly interested in the potential of psychological and personality tests to reveal the "otherwise invisible inner man" [44, 51] to inform employee-related decisions. One popular psychological test, the Minnesota Multiphasic Personality Inventory (MMPI), assessed a candidate's fit for a job or promotion by screening existing and potential employees for personality traits (e.g., neuroticism) as well as inferences of health status and conformity to sex-typed norms [44, 51].

I/O psychology of personnel selection has persisted over the decades, despite concerns of its fairness, validity, and potential for discrimination [82, 110]. Today, the application of EAI to these processes to collect information about workers' and job candidates' emotions, affect, and other interior states and traits to inform personnel and workplace decisions is part of a larger trend of workplace digital transformation, increasingly adopted by organizations [50, 101] – more comprehensively covered in Computer-Supported Cooperative Work (CSCW) and Human-Computer Interaction (HCI) scholarship [2, 9, 52, 54, 68, 69]. Indeed, a recent HR Policy Association memo cites digital transformation as a motivator for adopting EAI in hiring [8]. Against this history, our study aims to highlight the implications of applying EAI to the I/O psychology of personnel selection – two domains contested for validity, fairness, and discriminatory practices [11, 82, 108, 110].

### 1.4 Criticisms of AI in hiring

Scholars, activists, and industry practitioners have raised concerns around AI use in hiring regarding ethics, privacy, technical accuracy, bias, and legality. For example, a Harvard Business Review report warns that AI may be able to infer information about a candidate's physical or mental disability in discriminatory ways, questioning the accuracy and scientific validity of AI hiring systems and AI's

ability to effectively control for adverse impact on protected groups [28]. The authors emphasize the lack of “convincing hypotheses or defensible conclusions” regarding whether and how such tools that generate inferences about an applicant based upon their physiological attributes are ethical [28], and raise questions about the effectiveness of existing legislation in the US to stem the potential discriminatory effects of AI in hiring.

Public deliberation about AI in hiring has largely focused on demographic bias concerns. In 2018, Reuters reported that Amazon’s gender-biased AI/ML talent management systems favored male applicants over other genders [27]. The controversy reinvigorated debate about how AI/ML systems reflect and perpetuate bias in hiring. Consequently, there has been increased attention aimed at mitigating algorithmic bias in hiring. Particularly, the development and application of technical solutions to this problem is an active research area [38, 122], aiming to de-bias machine learning models generally either through increasing the diversity of training datasets or technical de-biasing methods [35, 60]. However, some scholars remain skeptical about the effectiveness of technical efforts alone to mitigate algorithmic bias, including in hiring [90, 120].

On bias, Lee contends that *explicit* racial biases in algorithms can be reduced through existing policy and regulations, but that *implicit* racial biases are more difficult to detect and mitigate. Consequently, candidates adversely affected by implicit biases in hiring algorithms may have limited access to redress until larger structural changes are instituted, such as increasing diversity in workplaces and public policy [62]. Nakamura posits that implicit AI biases may privilege able-bodied candidates and reinforce discrimination against disabled people, as implicit bias can only be detected when tested on external datasets [80] – unlikely for organizations using AI developed and trained on internal data. Organizations consider this “as a feature rather than a bug – there is absolute deniability of any hiring bias against protected categories” [80].

The general commercial response to algorithmic bias concerns has involved companies that offer AI-enabled applications, claiming that they mitigate bias and discrimination in their algorithms. Some companies have provided publicly available documentation about how they mitigate bias, which researchers have analyzed. Closest to our work is a study by Raghavan et al. investigating the technical and legal implications of what automated pre-employment assessments vendors disclose about how they detect and mitigate bias [90], finding that their generally vague claims are unclear about how their datasets are selected, whether and how their models are validated, and how inferences generated are used to recommend candidates [90]. Moreover, few vendors explicitly discuss issues of compliance and adverse impact. Those who offer more details about how they detect and de-bias their systems claim that they test their models for bias, and de-bias with technical approaches such as “removing features correlated with protected attributes when adverse impact is detected” [90]. Raghavan et. al discuss limitations of outcome-based debiasing, showing how the principles and guidelines that govern anti-discrimination law have methodological requirements (i.e., representative samples) that are not addressed by the vendors, leaving open the question of the sufficiency of self-regulatory approaches to detect and mitigate bias in hiring algorithms. They argue for policy-based approaches to better understand and address bias in algorithmic hiring practices [90]. Sanchez-Monedero et al. also analyzed publicly available content from AI hiring vendors that address bias and discrimination and situate them in the social and legal context of the UK [98]. They show how industry practices of AI hiring services, especially those developed in the US, may not meet the standards of EU law, and argue that the UK’s data protection laws and regulatory approaches to hiring anti-discrimination offer a model to countries like the US to address concerns about AI hiring vendors’ transparency and their effect of obscuring, rather than improving, “systemic discrimination in the workplace” [98].

While scholarship on the social and ethical implications of AI in hiring has increased in recent years, most have focused on either technical or legal “solutions” to address concerns of accuracy and



bias in AI. There has been limited attention aimed at exploring the social and ethical implications of *emotion* AI in hiring particularly. This is important as emotions are central to our social and private lives [95] and are deemed a unique and sensitive data type [7]. Additionally, scholars have linked EAI use to the practices of physiognomy and phrenology [97, 108, 113], such as in a law article where Stark and Hutson describe EAI as “Physiognomic” AI that reanimates “the pseudoscience of physiognomy and phrenology at scale” [108].

While this past work is insightful, there remains a need to *systematically* and *empirically* investigate what exactly EAI vendors (such as in hiring) claim and what values they embody regarding their desired uses in hiring – a gap we address by adopting methods similar to [29, 90, 98] and building on critical AI studies.

## 2 METHODS

Values in technology shape our socio-technical presents and futures: with great normative weight, the values laden in technology assert how things ought to be [102], shaping the values of those affected by technologies. We turned to the claims made by EAI hiring services on their websites to identify the values that emerge in the desired uses of EAI they promote. Recent work has shown that, despite the practical challenges associated with the study of AI in opaque organizational settings, researchers can learn a lot about industry practices from the public claims that AI service providers make about their technology [90, 97, 99]. Therefore, we conducted an in-depth content analysis of the claims made on the websites of 229 EAI hiring services to address our RQs.

Some methods are better suited to locating values and their position on the values dimension spectrum than others [104]. Content analysis, as Shilton notes, is an appropriate method for revealing core values [104]. Our analysis aims to describe and interrogate the values that emerge in the desired uses of EAI in hiring, informed particularly by Shilton’s emphasis on the importance of identifying the location of values [102]) while maintaining a broad, non-prescriptive framing [58, 103] to our identification and analysis of values in EAI hiring services.

### 2.1 Data Collection

Data collection involved three stages: 1) identify commercially available EAI hiring services and their websites; 2) review websites to determine eligibility for study inclusion, 3) collect website content for analysis.

**2.1.1 Identification of EAI hiring services.** We consulted four websites: Crunchbase (a directory of start-up vendors used to identify AI services [90]), and three crowd-sourced enterprise software review sites: G2, TrustRadius, and Capterra. We first searched Crunchbase using the following terms: *emotion recognition, affect recognition, emotion AI, emotional AI, EAI, emotional artificial intelligence, sentiment analysis, emotion detection, affect detection, and emotion analytics*. This returned a limited number of results, and did not successfully identify EAI hiring services we knew existed (e.g., through existing market reports, news articles). We then queried Crunchbase for a small number of randomly selected names of these already-identified EAI hiring services that were not included in Crunchbase search results, and found that their Crunchbase profile did not specify use of *emotion* AI or related terms. For example, we expected to see Retorio in our query, identified in a biometric technology policy publication as a recruitment service that generates inferences about an individual’s affective states [48]. Yet Retorio’s profile on Crunchbase was labeled with general tags such as “Artificial Intelligence” and “Machine Learning” rather than tags specifying its use of EAI.

The research team then conducted a superficial review of websites for already-identified EAI hiring services, and found that claims made on the service’s websites were especially ambiguous in their technical descriptions of their product’s underlying technology. Rather than explicitly

describing their services as enabled by EAI, our review suggested that EAI hiring services generally described themselves more broadly as “AI” applications, employing vague descriptors to make claims about their product’s generation of inferences about a candidate’s interior state. For example, our review of Retorio’s website found they referred to their technology as “behavioral analytics AI” that “revealed” candidates’ “soft skills” based on “psychological science,” rather than explicitly describing their tool as enabled by EAI (or other related terms). Review of the tags, classifications, and websites of the already-identified EAI hiring services that did not appear in EAI-related search results revealed that EAI hiring services generally employ a broad variety of non-standard and non-technical terms to refer to their technology, and do so in ways that obfuscate their identification as an EAI hiring service. As a result, identifying EAI hiring service vendors using EAI-related search terms posed a unique challenge to our data collection efforts.<sup>1</sup>

**2.1.2 Application of inclusion criteria.** Consequently, we pivoted our data collection to first identify all commercially available Human Resources software vendors and their associated websites, and then manually reviewed each website for the following inclusion criteria: 1) if claims on the website marketed its technology to hiring organizations to inform hiring decisions, and 2) if claims on the website referenced generating inferences about a candidate’s emotions or other affective phenomena. In addition to Crunchbase, we searched industry-oriented crowd-source software review websites G2, TrustRadius, and Capterra to identify EAI hiring service websites to ensure we identified services that are commercially available and likely to be in current use. For each website, we collected the names and website information for all organizational software tagged under Human Resources related terms (i.e., HR Analytics, Workforce Analytics, Employee Engagement, Employee Recognition, Performance Management, Recruiting Software, Talent Management, and Talent Intelligence). This effort resulted in an initial dataset of 3195 unique commercially available Human Resource vendors.

**2.1.3 Dataset compilation.** We then divided this dataset among four researchers. Each researcher manually reviewed a website to determine each vendor’s identification as an EAI hiring service according to the inclusion criteria defined above. We excluded non-English websites given our research team’s lack of fluency in other languages. Between May 2021 and July 2021, this effort resulted in a dataset of 229 EAI hiring services and their websites. We used a browser extension that captured these 229 websites as PDF files and imported those files into a qualitative coding tool.

## 2.2 Data Analysis

We divided the dataset among three team members to analyze the website content for each of the 229 EAI hiring services, attending especially to their claims.

Values in technology can emerge in the definition of a problem and the ways in which designers develop technological solutions to solve them, and may be influenced by the assumed values of the various stakeholders with whom the technology interacts and for whom the technology is built [36, 103]. Though values manifest in locations at all points in the technological development and design process [102], we can reveal technologies’ core values by identifying the *practical end* for which they are desired to be *used* [47, 117] as a means to achieve. Values cannot be directly observed, but they can be inferred from language and behavior [57]. Our analysis of EAI hiring service claims to elicit their promoted values thus necessarily focused on language choices. The

<sup>1</sup>The non-specific terminology employed by EAI hiring services may be attributed to the longer, pre-digital history of organizations inferring candidates’ interior states, and the introduction of EAI hiring services as a technology that promises to digitally transform these processes by augmenting them with the application of AI [8] (review section 1.3 for further detail), or to vendors’ potential attempts to not be known as EAI vendors, given high-profile critiques of EAI platforms like Hirevue.

interpretation of language is multi-dimensional, context-dependent, and individually-situated [72]; as such, we employed interpretivist [21] approaches in analysis. Given our interpretivist methods and their epistemological roots in attending to power and discourse [10, 72], we deemed quantitative approaches to qualitative data, such as quantitative measures of reliability like Inter-Rater Reliability (IRR), as inappropriate here. Our goal was not merely to report EAI hiring service claims as the final outcome, but to *interpret* claims as part of the methodological process. As McDonald et al. argue, when “codes are the process not the product,” *non-use* of IRR is methodologically best practice. Further, it is important to note that the EAI hiring service claims we analyzed reflect the discourses of powerful actors: technology companies that have effectively shaped the hiring process in questionable ways, whose claims are oriented toward (and presumably influenced by) the hiring organizations for whom they design their service [36]. As a result, coding EAI hiring service claims *without* interpretation would have risked this study reproducing the power imbalance and inequality entrenched in EAI hiring service claims [15, 72].

Nevertheless, our analysis approach preserved our findings’ reliability. First, the first author conducted close, open coding of a random subset of data to develop an initial codebook that organized codes into distinct units of analysis according to the type of claim made. The research team then collectively reviewed the initial codebook to develop a common understanding of how to organize open codes. Next, the remaining content was divided among three research team members. All coders used close, line by line coding by using *in vivo* codes that mirrored the language choice in EAI hiring service claims. This choice functioned to 1) preserve the meaning present in EAI hiring service claims, and 2) mitigate potential disagreement regarding coding interpretation [22]. The team met weekly to discuss and document themes that surfaced during open coding.

Once emergent themes took shape, the team collectively refined the codebook’s organization to include observed themes, enabling axial coding. The research team collaboratively developed thematic codes and grouped existing open codes by theme. Similarities and differences between researchers’ codes and code groupings were iteratively identified, discussed, and resolved. Once agreement was established, the research team continued coding the remaining data with a combined open coding and axial coding approach. They continued to meet weekly to collectively discuss and refine emergent, recurrent, and divergent themes. Once axial coding was complete, the team’s weekly meetings turned to collectively interpreting relationships between codes, enabling theory construction [20]. Finally, the first author employed selective coding to delimit codes [20] around the core notion of desired and promoted use of EAI hiring services.

### 2.3 Limitations

As detailed in 2.1.1, the disparate and vague ways in which EAI hiring services refer to their technology posed a challenge to identifying commercially available EAI hiring services. As our methods to identify EAI hiring services required subjective interpretation of their claims, we cannot say with certainty that all of the EAI hiring services included use EAI. It is possible that our interpretation of website claims resulted in the mis-classification of a service as using EAI. Still, only services that claimed to measure and/or infer emotion and related affective phenomena were included. Further, our methods of identifying EAI hiring services by narrowing down lists of pre-categorized vendors may have missed some commercially available EAI hiring services not listed on these sites.

We are hopeful that our comprehensive dataset ( $N = 229$ ) of commercially available EAI hiring service claims, and our systematic process to identify and analyze them, mitigates the impact of these possibilities on the reliability of our analysis. Further, it is important to emphasize that our analysis is not intended as merely an identification of commercially available EAI hiring services



and the claims they make, but to reveal the values and ideologies present in the larger, collective discourse of EAI hiring service claims.

Importantly, said claims made by EAI hiring services should be interpreted as desired uses of EAI promoted by EAI hiring services, rather than values that necessarily emerge from EAI use in practice. Certainly, the values that emerge in EAI hiring services' promotional content may be influenced by the assumed values of the groups for whom they design their technology [36], and as our findings show, these claims are legitimized by corporate ideals presumably held by hiring organizations. Nonetheless, our findings locate values that emerge in the *desired* use of EAI as promoted by EAI hiring services, revealing the core values that emerge in the proposed uses for EAI hiring services as a means to achieve technosolutions to organizational hiring problems [47, 117]. As such, our findings should not be conflated with values that necessarily emerge with EAI use in practice – an area for future work (e.g., through interviews with hiring organizations).

Lastly, future work could build on this study to examine how EAI vendors whose publicly available artifacts we analyzed in this study may react to these observations and the potential implications of these services, for example, through acknowledging their services' limits.

### 3 FINDINGS

Values in technology emerge in the practical ends the technologies are designed to achieve: the problems they purport to solve and the culmination of those means toward a greater end [47]. Our analysis shows how EAI hiring services promote desired uses of EAI as means to achieve technosolutions to three purported organizational problems. For each purported problem and its associated technosolution, we first unpack what the claimed hiring problem is, why it is a problem, and for whom. Then, we interrogate those claims to: 1) identify the corporate ideals that legitimize the purported EAI hiring service technosolutions as a means to achieve those ideals; 2) the mechanisms by which EAI hiring services claim EAI solves the purported organizational problem; and 3) the core values that emerge in the desired uses promoted by EAI hiring services to solve each problem as a means to achieve corporate ideals.

We find that EAI hiring services promote EAI as technosolutions to the purported problems of hiring (in)accuracy, hiring (mis)fit, and (in)authenticity through the creation and extraction of a candidate's *affective value*. In turn, this process enables the *affective commodification* of candidates along affective and emotional dimensions, and the exclusion of candidates on the basis of psychological information generated about them by EAI hiring services that is asymmetrically visible to and wielded by hiring organizations. The desired uses of EAI that EAI hiring services promote to solve these hiring problems are legitimized by their claims that EAI use is a means to achieve corporate ideals including data-driven decision making, continuous improvement, precision, loyalty, and stability. Taken together, we locate the core values emerging in the desired uses of EAI promoted by EAI hiring services: techno-omnipresence, techno-omnipotence, and techno-omniscience showing how EAI hiring services position EAI as the *one, true entity* capable of solving hiring problems and achieving corporate ideals, organized below by the three aforementioned hiring problems.

#### 3.1 Hiring (In)accuracy: Objective, Unbiased, and Intelligent Hiring Decisions

The most salient claim made by EAI hiring services is that the adoption of their technology will improve hiring organizations' *accuracy* in hiring. As ZappyHire claims, features like their "AI-enabled video interview" platform will "*Improve Your [Organization's] Hiring Accuracy by 72%*" by analyzing candidates' "personal traits," promising organizations the ability to "*make the right hiring decision with the right data points.*" In other words, EAI hiring services market their product as a technological solution to the problem of hiring inaccuracies.

What is inaccuracy in hiring, and why is it a problem? According to our analysis, EAI hiring services claim that accuracy in hiring is achieved when the hiring decision is made in an 1) objective, 2) unbiased, and 3) intelligent way.

*Objective Hiring.* EAI hiring services claim that their technology enables objective hiring by standardizing the candidate evaluation process. Notably, the operationalization of objectivity as an attribute of EAI in EAI hiring service claims is not a claim about the objectivity of EAI inferences, but rather, of the technology computationally applying an automatic, algorithmic process to assess all candidates with the same, purportedly objective, parameters.

Take for example HiredScore, a “human resource intelligence” provider that recently partnered with EAI hiring service pymetrics to infer candidates’ soft skills. HiredScore claims to “*enable a future where hiring is efficient and fair*” by ensuring “*all people are evaluated the same for the same jobs*” with their “*highly-accurate candidate scoring (A, B, C, or D)*.” By applying the same parameters to all candidates, EAI hiring services like HiredScore deem their technology an objective way to achieve hiring accuracy.

Moreover, EAI hiring services claim that the defined parameters by which their service assesses all candidates are themselves objective. FaceCode, an intelligent technical interview platform that automatically analyzes candidate responses to interview questions to infer their level of engagement and other unclear “AI-based behavioral insights” claims that it “*combines objective, standardized evaluation parameters with AI-based insights for the most accurate and effortless coding interview reports ever. All to help you make the right decisions.*” At the same time, these services undermine the service’s objectivity claims by promising employers the ability to subjectively customize parameters to suit the organization’s needs. For example, the “talent intelligent platform” Eightfold.ai claims that its service can “*optimize every configuration and product feature to meet customer requirements.*” Parameters for EAI-based candidate selection that are designed to best suit the organization – or allow the hiring organization to customize the parameters – are not objective, but subjective, with moral and political consequences [15]. We posit that applying subjective parameters to evaluate all candidates in the same way does not sufficiently enable objective hiring. In contrast, it enables subjective hiring at scale.

*Unbiased Hiring.* EAI hiring services claim that EAI enables unbiased, and therefore more accurate, hiring. These claims are not directly related to EAI’s underlying technical capabilities (i.e., through technical debiasing methods; see Raghavan et al. [90]) but rather, as a result of EAI hiring services displacing human laborers and their purported biases in the hiring process.

EAI hiring services reinforce their implication that conventional, human-based hiring decisions are a problem for organizations because they preclude organizations from achieving hiring accuracy by discrediting the role of people in the hiring process. EAI hiring services refer to human-based employment decisions as mere human guesses riddled with bias and subjectivity, suggesting that replacement of people in hiring decisions is necessary to achieve unbiased and accurate hiring.

For example, Elevatus, a service that analyzes video interviews, claims that “*by using our Advanced Analytics, A.I. and videos, [organizations] can start making decisions based on reliable data, rather than guesswork.*” Echoing this claim, employee engagement platform Bob, which analyzes and profiles employees according to their predicted risk of “burnout” and “taking off,” claims that their service enables hiring organizations to “*base management decisions on evidence, not assumptions.*” Similarly, iMocha, a pre-employment assessment provider that analyzes candidates’ face and voice to identify “suspicious activity” and infer their “emotional intelligence,” claims that their automated scoring “*eliminates human error in grading [applicants]...ensur[ing] that the skill evaluation process is free of human error, and it is more valid and reliable.*” Such claims demonstrate EAI hiring service

suggestions that human-based employment decisions are at the heart of the purported problem of hiring (in)accuracy – a problem that EAI claims to solve.

By discrediting the human labor that conventionally makes employment decisions as mere assumptions, hunches, and guesswork that are inherently biased, EAI hiring services simultaneously position human hiring processes as the obstacle preventing organizations from making accurate hiring decisions and their technology as the solution to overcome it.

*Intelligent Hiring.* EAI hiring services underscore their claims that EAI in hiring is objective and unbiased with assertions of EAI's superior intelligence. Reejig, a talent management software that generates inferences of candidates' soft skills to profile and shortlist candidates, claims that organizations can *"use the infinite intel from the Reejig mastermind to map out succession plans right across your business, without bias."* EAI hiring services like Reejig market EAI as a "mastermind" with superior "intel," and posit that organizations that harness EAI's intelligence will improve the accuracy of their workforce planning efforts without bias.

Intelligence, here, is the technology's algorithmic ability to computationally analyze and interpret large amounts of data from multiple data sources. For example, talent platform retrain.ai claims its "accurate matching algorithms" improve hiring accuracy by *"leverag[ing] the power of artificial intelligence."* retrain.ai claims that *"by connecting three robust datasets about people, jobs and training programs, we generate useful, validated, unbiased and actionable workforce intelligence,"* demonstrating how EAI hiring services claim that through computational ability to derive insights from disparate datasets, EAI offers organizations superior intelligence to solve the problem of hiring (in)accuracy.

Thus, to solve the business problem of hiring (in)accuracy, presumably a dilemma for organizations that make employment decisions that rely solely on human-based employment decisions, EAI hiring services offer their products as a technosolution that promises objective, unbiased, and intelligent hiring. Now that we have unpacked the purported problem of hiring (in)accuracy, the following sections interrogate EAI hiring service claims that reveal 1) the *corporate ideals* that legitimize EAI hiring services as a desirable technosolution to achieve hiring accuracy, 2) the *mechanism* by which EAI hiring services claim to do so, and 3) the *core values* that underpin the desired and promoted use of EAI hiring services to solve organizational hiring (in)accuracy.

**3.1.1 Corporate Ideals: Data-driven Decision Making and Continuous Improvement.** In promoting the desired use of EAI to achieve hiring accuracy, EAI hiring services appeal to corporate ideals of data-driven decision making and continuous improvement. By promising organizations these qualities, EAI hiring services not only legitimize their technosolution to the purported organizational problem of hiring (in)accuracy, but also position EAI as a moral imperative required to achieve the organization's greater ideals.

Jive, a people analytics and productivity management software that uses features such as continuous sentiment analysis to keep an *"ongoing, real-time read on employee morale and engagement,"* claims to empathize with organizations' experiences of hiring (in)accuracy: *"You've had to rely on hunches, vague statistics and hindsight. But...what if you had accurate, data-driven insight to guide your tactics, make timely corrections and better target your efforts for maximum impact?"* In positioning their technology as a solution to hiring (in)accuracy, EAI hiring services like Jive appeal to organizational ideals: organizations are promised the ability to continuously improve their workforce with data-driven decisions and insight. Achieving these ideals is not simply an added bonus, but a moral imperative. As demonstrated by iMocha, EAI hiring services claim that their technology *"should be arranged for objectivity of scoring, and the elimination of personal judgment concerning correct answers,"* underscoring how EAI hiring services normatively claim their services "should" be used to enable objective and accurate assessments of job candidates, rather than

subjective, inaccurate human-based assessments. These claims illustrate how EAI hiring services are positioned not only as a solution to a particular organizational problem, but as an *imperative* for organizations to adopt to achieve corporate ideals of data-driven employment decisions and continuous organizational improvement.

To make data-driven decisions about human capital, thus, organizations must first quantify and measure those features. Lattice, a people analytics provider that applies sentiment analysis to employee-generated enterprise data, claims that its software can motivate team members by offering organizations the ability to “*measure the health of [their] organization and take data-driven action to increase productivity, decrease employee turnover, and build a winning culture.*” To achieve organizational labor objectives that continuously improve human capital investments (e.g., increased employee productivity and retention, “winning” organizational cultures), these services suggest that features contributing to human capital can and should be measured. Such measurements purportedly enable organizations to make better, more data-driven decisions.

JourneyFront, the self-proclaimed “World’s Most Accurate Hiring Software,” infers candidates’ personality, values, satisfaction, and other internal states and traits from pre-employment assessments and job interviews. Offering an example of how data-driven decision-making imperatives are underlain by an ideal of continuous improvement, JourneyFront claims “*continuous improvement...if you can’t measure it, you can’t improve it.*” If quantified, usable data points to use as measures are necessary for improving accuracy in hiring, organizations must use that data to achieve ideals of continuously improving organizational processes. As Journeyfront claims, “*our process constantly tests, tracks, and makes changes that continuously improve your hiring process.*” Calling attention to the organizational imperative to achieve corporate ideals such as continuous improvement, Jive reiterates: “*After all, if what you’re doing isn’t improving your results, why do it?*”

Legitimized by corporate ideals of data-driven decision making and continuous improvement, EAI hiring services position their technology as an imperative to achieve these goals.

**3.1.2 Mechanism: Creating Affective Value and Affective Commodification.** In order for candidates to advance in hiring processes using EAI, candidates must have what we refer to as *affective value*: the emotional data generated about job candidates as a measure of the candidates’ value to the EAI hiring service and hiring organization.

Through automatically generating inferences about one’s candidacy by analyzing their affective expressions, and advancing those candidates through the hiring funnel who fall within parameters of the EAI hiring service’s desired *affective value* – and excluding those who don’t – candidates then are rewarded if they satisfy the encoded expectations of *affective value*.

For example, JourneyFront claims that its “auto-score” feature scores and ranks candidates after generating inferences of their emotional and affective traits, allowing organizations to “*automatically filter qualified candidates*” in order to “*save time and know where to focus [their hiring] efforts.*” Similarly, Jabri, a talent acquisition and video interview provider that measures candidates’ “emotional and social aptitudes like interpersonal skills, communication skills, and personality traits” claims that hiring organizations can use Jabri’s “game-changing analytics” to “uncover crucial insights” about candidates by using “*the power of Jabri’s digital video interview to discover their character,*” purportedly enabling organizations to “*review all critical personality skills important to [the] organization.*” Here, EAI hiring services like Journeyfront and Jabri suggest that by “*measur[ing] what matters*” – the candidate’s affective value – hiring organizations can automatically make accurate hires by excluding those candidates whose affective valuation is deemed unworthy of the hiring organizations’ time and efforts, while advancing and rewarding those that do.

The algorithms assess and rank candidates with encoded rules that assign value to candidates’ emotional and affective expression – their affective value. By creating a determination of the desired

affective value of a candidate, and making employment decisions in part based on whether EAI hiring services' valuation of that candidate meets encoded expectations of affective value, EAI hiring services introduce invisible "rules" to the hiring process to which candidates don't have access. Candidates' affective value is then commodified through the process of candidate selection and subsequent employment decisions that purchase the labor of those candidates who meet the EAI hiring service and hiring organizations' expectations of affective value.

**3.1.3 Core Value: Techno-omnipresence.** The technosolution of EAI hiring services as a means to solve the purported problem of hiring (in)accuracy rests on its ability to be present everywhere: to generate inferences that reach into all places, even the once private domain of an individual's inner emotions, through their purported ability to access and process large amounts of data about a candidate in an objective, intelligent, and unbiased way. By positioning EAI hiring services as the only means to achieve hiring accuracy, EAI hiring services supplant human labor that conventionally makes hiring decisions and their alleged subjective and biased limitations as inherently incapable of solving the problem of hiring (in)accuracy due to their limited capacity to *be* everywhere.

Legitimized and enabled by corporate ideals of data-driven decision making and continuous improvement, the moral imperative in EAI hiring service claims that EAI "should" be implemented to correct the subjective and biased features of human-based employment decisions, reflects a belief in what we term *techno-omnipresence*; that EAI can and should be everywhere – in places previously inaccessible (i.e., a candidate's internal state) and by replacing the presence of the human labor that conventionally makes hiring decisions. EAI hiring services' embodiment of techno-omnipresence as illustrated here thus appeals to beliefs in EAI's divine superiority over humans.

QPage, an "AI Mock Interview Machine," demonstrates these beliefs in techno-omnipresent values, predicated on beliefs of EAI's superiority over humans: "*Picking out the right talent by conducting an interview seems like a job for everyone, or at least, that's what we all tell ourselves. In reality, however, choosing the right talent is well beyond ordinary comprehension, and it should be left to professional software.*" The belief that EAI is superior to humans, with its omnipresent abilities to make employment decisions "beyond ordinary comprehension," thus underpins the technosolution of EAI hiring services to solve hiring (in)accuracy. By situating EAI hiring services as the sole means to achieve hiring accuracy, beliefs in EAI's techno-omnipresence justify the displacement of human labor required to solve hiring (in)accuracy and the mechanisms by which EAI hiring services claim to do so: creating affective value and commodifying affect accordingly.

## 3.2 Hiring (Mis)fit: Candidate Alignment with Organizational Desires

What is a hiring (mis)fit and why is it a problem? EAI hiring services claim that "fit" is an organizational imperative that occurs when there is alignment between the job candidate and the hiring organization along the axes of values, beliefs, character, and culture. Conversely, a "misfit" is a candidate who does not fit those attributes. Misfits are an alleged problem because hiring (mis)fits impair corporate efficiency.

As HRPuls, a pre-employment assessment provider of automated "psychometry" that claims to recognize candidates' "conscious and unconscious motives" puts it, by "*identifying motivation and values through cultural fit analysis*" organizations can make employment decisions where "*talent matches the company's values.*" To achieve hiring fit, organizations must first algorithmically measure candidates' values, beliefs, and character to assess whether they fit the organization's culture. EAI hiring services position their technology as the only means to do so, with its unique capability to generate inferences about candidates' internal states as proxies for these attributes. As an example, Equalture, a "neuroscientific gamification" vendor that measures and auto-scores interior traits of current employees and external job candidates "*to hire the best-fits without bias,*"



explains to hiring organizations that “AI can help hire for cultural fit” by first “validating” company culture. To do so, Equalture subjects hiring organizations’ current workforce to their EAI technology to “objectively...assess whether candidates are aligned to this culture,” claiming that self-assessments for fit by either the job applicant or the hiring organization “will never be objective.” Moreover, EAI hiring services frame hiring for “fit” in normative terms. For example, Equalture, claims that “the principle of hiring for cultural fit is the #1 rising star in recruitment,” demonstrating how EAI hiring services posit the achievement of hiring for fit as a hiring “principle.”

Services legitimize this principle by positioning hiring (mis)fits as a problem that impairs corporate efficiency. For example, Ducknowl, a service that measures candidates’ “soft skills” in video interviews, claims to improve hiring “efficiency” with their technology’s purported ability to “identify candidates with strong resumes but who won’t fit well in an organization... lead[ing] to quick and hassle-free hiring results.” Here, we see how services like Ducknowl characterize hiring (mis)fits as a “hassle.” Likewise, HireOnboard, a software that automatically infers candidates’ cognitive and personality traits to assess “culture fit,” claims that hiring organizations that select the “right” talent will preserve organizational resources by “eliminat[ing] applicant mischiefs.” Such claims suggest that hiring (mis)fits are a waste of organizational resources, and that this problem can be “eliminated” by hiring for fit aided by EAI.

EAI hiring services promise organizations that adopting their technology offers the ability to hire only “fits” and exclude hiring (mis)fits, efficiently and at scale. As illustrated by Humantic, an “AI with Emotional Intelligence” that claims its automated pre-employment assessments and analyses of bot-based candidate communication and interview records will “convert 30% more top candidates by using custom personalization assistance,” whose technology promises to preserve organizational efficiency through EAI’s alleged ability to “judge [candidate] culture fit without taking a test” and develop “data-driven candidate shortlists that take zero effort.” Similarly, services like Logi-Serve promise efficient hiring for “fit” with “interactive job simulations” that automatically infer an applicant’s personality and other interior traits to “identify top performers”, “determine a candidate’s job fit and aptitude to perform” and “instantly predict future performance.”

Altogether, EAI hiring services position their technology as the only means to solve the problem of hiring (mis)fits and achieve the organizational imperative to hire for “fit,” through EAI’s purported ability to efficiently measure job candidates’ and hiring organizations’ values, beliefs, characters, and cultures. The automatic nature of the service promises organizations the ability to automatically determine the “right” hiring fit and exclude hiring (mis)fits.

**3.2.1 Corporate Ideals: Precision and Loyalty.** EAI hiring services claim that organizations can solve hiring (mis)fit problems by adopting their technology’s alleged ability to *precisely* measure the emotions and related affective phenomena of job candidates and workers to produce precise hiring fits. For example, HireOnboard claims that its AI-enabled “culture fit” assessments that measure interior traits like cognitive ability and personality will “find the perfect fit for the job,” illustrating how EAI hiring services promise to identify “perfect” hiring fits with absolute precision. While the EAI hiring services’ determination of hiring fit – a candidate that precisely aligns with organizational values, beliefs, character, and culture – *prima facie* appears value-neutral and “objective,” claims that hiring fits promise organizational loyalty demonstrate how such assessments are subjectively oriented toward organizational desires.

As one example, HRPuls claims its “psychometric” and “cultural fit” assessments select “talents that really fit” by identifying candidates whose “motivation and values” match “the company’s values...[and] achieve higher productivity, satisfaction, and loyalty to the company.” Here, we see how EAI hiring service determination of hiring fits are those whose human values like loyalty are oriented toward organizational ideals. As illustrated by Journeyfront, “When a person is working on

*things they are interested in they are more engaged, work hard, and stay at jobs longer. Measuring a person's interests is a must, when considering accurate job fit.*" By precisely measuring for job "fit," EAI hiring services suggest that the traits they measure for alignment with organizational values, beliefs, character and culture are traits of *loyal* employees that will "work hard" and "stay at jobs longer," maximizing benefit to hiring organizations.

The subjective determination of hiring "fits" whose emotional and affective traits meet organizational desires is further illustrated by people analytics provider KQ analytics, claiming that hiring organizations that adopt their technology can stay "*focused on building a high-performance organization that lives and breathes [the organization's] values.*" The precise measurement of a hiring "fit" then, on the basis of a candidate's internal states and traits, promises precisely "perfect" hiring fits that loyally live and breathe their commitment to the organization.

**3.2.2 Mechanism: Information and Psycho-biological Exclusion.** For EAI hiring services to solve the problem of hiring (mis)fits, they not only identify "perfect" hiring fits but exclude hiring (mis)fits. As illustrated by RecruitPack, a "predictive hiring" software that claims to read candidates' psychometric attributes, then automatically ranks and scores them to "pick 'A-player' candidates," EAI hiring services hire for fit by promising organizations the ability to move "*forward only those with desired attitudes and culture fit,*" by "*identifying misfits in attitudes and values at the time of application.*" According to EAI hiring service claims, excluding hiring (mis)fits is not only necessary to hire job fits, but a desirable outcome that avoids wasting organizational resources. As RecruitPack promises: "*you can eliminate [misfits] early and focus on the best candidates.*" Thus, the mechanism by which EAI hiring services solve the problem of hiring (mis)fits is by *exclusion*: 1) by EAI generating inferences that hiring organizations can use to make employment decisions while not making visible such information and/or its existence to job candidates, EAI hiring services enhance information asymmetry between candidates and hiring organizations; and 2) by EAI hiring services generating inferences about a candidate's emotional and affective states they claim are psycho-biological, immutable attributes inherent to their personhood, they purport to solve the problem of hiring (mis)fits by excluding candidates whom the EAI deems to lack those attributes.

**Information Exclusion.** Conventional, human-based assessments of "fit" between hiring organizations and job candidates involve dynamic, human interactions that inform a mutual determination of "fit" by both parties (i.e. during live, onsite interviews). In these processes, hiring organizations and candidates provide each other information about their respective values, characters, beliefs, and culture that each can use to determine "fit" for the job. EAI hiring services replace the conventionally mutual, two-way evaluation of "fit" with an automated, one-sided process that *excludes* candidates from participating in a determination of hiring fit by design.

The automatic, one-sided process deprives candidates of the opportunity to gain information they need to assess mutual fit, while generating information for hiring organizations to use to their advantage: to assess "fit" on the basis of whether candidates' internal attributes align with organizations' desires by using inferences EAI generates about candidates but generally does not make visible to them.<sup>2</sup> The exclusion of candidates' participation in assessing job "fit" is thus a *feature* of EAI hiring services. As Zappyhire, a software that features "robotic video interviews," "AI assessments," and other "predictive hiring" tools depicts, EAI hiring services promise hiring organizations that their determination of hiring "fits" will enable hiring organizations to spend

<sup>2</sup>Notably, the validity and accuracy of EAI is highly contested [25], with biases that reflect and perpetuate discrimination against minority groups [43, 49, 56, 92, 118]. As such, the information EAI generates about candidates' emotional and affective states to assess hiring "fit" may be inaccurate, but candidates cannot correct this information if inferences are not visible to them.

their time and resources only on those candidates who “matter,” by assessing candidates “*even before [hiring organizations] speak to them.*”

Altogether, we see how EAI hiring services frame the automatic exclusion of job candidates as a benefit to hiring organizations, to avoid wasting resources on mis(fit) candidates by automatically generating inferences about candidates’ internal traits beyond what they explicitly choose to disclose. In this process, EAI hiring services generate an information asymmetry between jobseekers and employers that reinforces the power employers already wield over job candidates, and further disadvantages jobseekers by excluding candidates from the participation of determining hiring fit with information (and/or the existence of it) that is invisible to candidates.

*Psycho-biological Exclusion.* In addition to information exclusion, we identify a second mechanism by which EAI hiring services claim to solve the purported problem of hiring (mis)fits: through the exclusion of (mis)fits based upon presumed immutable, psycho-biological attributes.

EAI hiring service claims suggest their inferences of a candidates’ emotional and affective states identify psycho-biological attributes about a candidate’s personhood, and assume those attributes are immutable. As evident in their service’s name, HireMojo’s “Job Genome Project” assumes there is a biological, genomic component to an individual candidate’s fitness for a job. As HireMojo asserts, “*historical, analytic and prescriptive analytics combined with machine learning and big data is yielding not only answers to the problem that many have never considered, but new questions that redefine relationships.*” Here, we see how the “Job Genome Project” assumes there is a scientific basis to the determination of a person’s fit for a job, based on biological markers that can be quantified to determine fit. Similarly, Jive claims that its sentiment tracking will improve “*culture fit while employees thrive naturally,*” suggesting that there is a biological, “natural” component to EAI’s automatic determination of job “fit.” Exemplifying how EAI hiring services presume a biological and immutable basis to the attributes they claim to identify, HRPuls claims its “psychometric pre-employment assessments “select talents that really fit” by “*determin[ing] values and corporate cultural competence by means of complex algorithms, evolutionary processes and computer linguistics.*” These examples illustrate how EAI hiring services justify their inferences about a candidate’s interiority and assumptions that those characteristics are immutable by suggesting that, as an “evolutionary process,” candidate selection through psycho-biological exclusion is “natural.”

To further ground their assumptions and legitimize their claims, EAI hiring services invoke scientific validity. For example, Good&Co claims its software can determine “cultural fit” through its “Proprietary Psychometric Algorithm (PPA)” that “*Explore[s] Candidates Beyond Their Resume.*” Good&Co claims its “bespoke measurement tool” is “*steeped in decades of research into career and individual differences literature, [and] is based on psycho-biological frameworks of personality, rooted in neuroscience and behavioral genetics.*” Here, we see how EAI hiring services justify excluding hiring (mis)fits based on assumptions that hiring for fit involves the identification of psycho-biological characteristics assumed to be immutable. Services legitimize the selection (and exclusion) of candidates based upon those characteristics by invoking “scientific” authority that assumes a genetic, evolutionary component to hiring for fit. It is worth noting that this controversial field of psychometrics has been used to legitimize racist and misogynist beliefs and practices [66, 96].

**3.2.3 Core Value: Techno-omnipotence.** The value emerging in adopting EAI hiring services as a technosolution to the purported problem of hiring (mis)fit is a belief in *techno-omnipotence* – that EAI technology can and should have the power to determine hiring “fits” and exclude hiring (mis)fits. EAI hiring services remove the power candidates have to determine whether a job is a “fit” for themselves with automated assessments that, as Good&Co puts it, use “*intelligent, scientifically derived, and probability-driven algorithms [to] match jobseekers with the culture that’s right for them.*” In their exclusion of (mis)fit candidates predicated upon racist and misogynist scientific

assumptions, EAI hiring services exercise a *techno-omnipotent* power over both job candidates and hiring organizations to determine hiring (mis)fit “for them.”

Belief in EAI’s techno-omnipotence is reinforced by EAI hiring service claims reflecting a belief in EAI’s divine power. EAI hiring services commonly describe their technology as powerful (i.e. “AI-powered”) and appeal to beliefs in EAI’s superior capabilities to justify transfers of power to EAI hiring services. For example, Jabri invites organizations to “*use the power of Jabri’s digital video interview to discover their character.*” As illustrated here, Services like Jabri claim to solve the problem of hiring (mis)fit by relying upon an uncontested belief in EAI’s superior power to “discover” a candidate’s character and determine a candidate’s fitness for the job.

Belief in EAI’s techno-omnipotence reflects hiring organizations’ attraction to power and dominion, promising organizations these qualities by first transferring control to EAI hiring services to determine hiring fits, and then using that bestowed power to inform workforce strategies. For example, Eightfold, an “AI-powered talent intelligence” platform, promises adoptive hiring organizations to share in the power of their “*deep-learning AI to help each person understand their career potential, and each enterprise understand the potential of their workforce.*” Similarly, RecruitPack promises hiring organizations that adopt its “unique blend of psychometric tools” the ability to “*quickly identify those with the can-do skills, will-do attitudes, and the fit-to characteristics for your role and your organisation*” and “*consistently shortlist the best applicants and secure them before your competitors do,*” illustrating how EAI hiring services promise hiring organizations enhanced abilities to maintain control over employees by using the “power” of EAI to “secure” hires that best “fit-to” the organization. These examples demonstrate how EAI hiring services promise organizations benefits that strengthen organizational control and domination over the workforce, by surrendering to the purportedly superior power of EAI to assess a candidate’s potential and determine hiring fit.

### 3.3 Hiring (In)Authenticity: Verification of Candidates’ Complete, True Self

What is truth in hiring and why is it a problem for organizations?

According to EAI hiring service claims, hiring organizations achieve truth in hiring when they have insights into a candidate’s interiority to fully and deeply *authenticate* a candidate. QPage, an “Autonomous Hiring Software” that offers automated psychometric assessments, claims to “get a deeper insight” about candidates to “verify” the truth about them, enabling organizations to “*decide on the next action by having a full flow of information from candidates’ detailed analysis.*” QPage claims that its “scientifically based” assessments combine “*measurement of cognitive skills and personality traits that will result in the best candidates match[ed to] the right job.*” Similarly, Reejig claims its technology allows organizations to “*gain full skills visibility so that you can have informed and accurate data to power your talent ...planning.*” These examples illustrate how EAI hiring services claim to verify the “full” truth about who candidates are by extracting “deeper” insights, and combining those inferences with other information to enable hiring organizations to make hiring decisions with “full visibility” into who a candidate is. The assumption that underlies this claim is that by EAI hiring services generating inferences about an applicant’s interior states and traits, they extract “deep” knowledge about their interiority to reveal the “full” and complete truth about a person – their authentic self.

To establish hiring truth as a problem, EAI hiring services position candidates as untrustworthy and inauthentic, and rely upon an assumption that there is an objective truth that can be revealed about presumably distrustful candidates beyond what they choose to disclose. For example, Equalture, a provider of “neuro-scientific gamification” pre-employment assessments, asserts that “*of course intelligence isn’t something you can fake; personality, however, is one of the easiest things to fake.*” Offering an explanation as to why a candidate might “fake” their personality, Equalture says, “*No, it’s indeed not smart to do, but you just want that job.*” Here, we see how EAI hiring services like

Equature refer to candidates and how they present themselves to hiring organizations as “fake,” justifying the use of EAI hiring services to extract the truth about candidates’ personality and other inner states beyond the “fake” and inauthentic persona they are deemed to display.

By adopting EAI hiring services, hiring organizations are promised a way to avoid making employment decisions based upon untrustworthy and inauthentic candidates and their “fake” displays of personality, by truly – “fully” and “deeply” – knowing a candidate. EAI hiring services like Ducknowl claim that their technology allows organizations to “*find the genuine candidate*” and “*avoid bait-and-switch situations*.” And they promise to do so quickly, with EAI hiring services like Idwall’s “face match technology” that promises to automatically uncover the truth about candidates with “automated solutions” that claim to read candidate emotions to ensure candidates are “*really who they say they are*,” to allow organizations to hire “quicker.”

**3.3.1 Corporate Ideals: Stability.** EAI hiring services appeal to the corporate ideal of stability to legitimize use of EAI to solve the purported problem of hiring (in)authenticity. EAI hiring services frame their technology’s “insights” into a candidate’s interiority as a technosolution that mitigates uncertainty associated with “fake”, inauthentic, and untrustworthy candidates, enabling organizations to make stable hiring decisions with information that purports to reveal the “truth” about candidates.

FaceCode, the self-described “most intelligent coding interview platform,” measures candidates’ interior attributes like engagement and “high-level thinking” during video interviews. Demonstrating how EAI hiring services promise hiring organizations the ability to make “truly informed” hiring decisions by generating inferences about a candidates’ internal states and traits, FaceCode claims that adoptive hiring organizations can make “*truly informed hiring decisions thanks to automated interview summaries with AI-based behavioral insights*.” Likewise, Eightfold, a provider that aggregates data about candidates from multiple sources (i.e., HR data and public web data) to create “rich profiles with deep insights” that provide “contextual intelligence” about candidates, promises that its “*deep-learning AI not only delivers a comprehensive understanding of workforce capabilities, but also understands each individual’s capabilities, skills adjacencies, and demonstrated learnability to provide a concrete, future orientation to talent strategy*.” Services like FaceCode and Eightfold illustrate how EAI hiring services appeal to the organizational ideal of stability to legitimize EAI as the technosolution to the alleged problem of hiring (in)authenticity: by using EAI to truly “understand” candidates, EAI hiring services promise hiring organizations a more “stable” “future” with “truly informed” talent strategies.

Under the assumption that EAI’s inferences reveal the whole truth about a candidate, EAI hiring services like Ducknowl promise to “mitigate the risk” and associated instability from making uncertain, “bait-and-switch” hiring decisions with “predictive” hiring. Retorio, a video interview platform that claims that its AI technology will “reveal hidden soft skills and traits,” allegedly “*measures personality and predicts future potential*.” EAI hiring services like Retorio appeal to the corporate ideal of stability by offering their services as a way to “predict” talent outcomes by “revealing” “hidden” information about candidates. Further, QPage, an AI “Mock Interview Machine” provider, claims that conventional interviews are “*rarely predictive of success on the job*.” By positioning EAI hiring services like QPage’s “AI-led,” “automated interactive interviews” as a technosolution to hiring (in)authenticity that enables hiring organizations to better predict talent success, EAI hiring services promise less risk and more stability to the hiring organization.

These examples illustrate the promise that EAI use leads to certainty, predictability, and stability for organizations. By avoiding hiring decisions made without the whole truth about who a candidate is authentically – “*those ‘bad hires’ who look good at interviews but under-perform on the job*,” as



RecruitPack describes it – EAI hiring services promise a hiring solution that mitigates the “risk” associated with “those bad hires” and in turn, a more stable, predictable organizational “future.”

**3.3.2 Mechanism: Extraction of Affective Value.** The mechanism by which EAI hiring services purport to solve the hiring (in)authenticity problem is extraction: using EAI to extract information about candidates’ interiority beyond what they choose to share about themselves to apply an affective valuation that assesses whether candidates “really are” of value to the organization.

The information extracted about a candidate’s interiority carries a particular value to the organization: a candidate’s affective value. EAI hiring services like Reejig promise that by using EAI to “*extract meaning*” about a candidate, organizations can “*create their workforce of the future*,” illustrating how the affective value EAI hiring services obtain about candidates is a valuation oriented toward organizational goals. eLamp, a service that claims to assess candidates’ “critical” skills, including “soft skills” from “any document,” echoes this assertion. eLamp posits that “*getting to know one’s employees better enables [organizations] to make decisions that are anticipated and better adapted to operational demand*,” demonstrating how EAI hiring services presume that by extracting information to truly know a candidate and assess whether they have affective value to their company, hiring organizations can make better “anticipated” and stable hiring decisions that suit the organization’s needs.

HireVue is a known EAI hiring service that recently discontinued facial recognition-based EAI after high profile criticism [19]; however, according to its website at the time of data collection, continues to generate inferences about candidates’ internal states with speech and text inputs. HireVue echoes this promise with claims that their technology enables organizations to “*Go Beyond Resumes*” to reveal “*what really matters*” about candidates. EAI hiring services like HireVue promise that using their technology to extract information about a candidate’s interiority ensures that organizations “*engag[e] with the highest quality candidates first*.” Thus, the technosolution of EAI to solve the problem of hiring (in)authenticity by extracting “what really matters” – candidates with high affective value to the organization – purportedly enables hiring organizations to hire the “highest quality” candidates.

**3.3.3 Core Value: Techno-omniscience.** The core value that emerges in EAI hiring services’ technological solution to the purported problem of hiring (in)authenticity is a belief in *techno-omniscience*, the idea that EAI embodies all-knowing “intelligence,” and its supreme ability to completely know who a person truly is ought to be used to attain authenticity in hiring.

The assumption that information about one’s interior states and traits constitutes one’s authentic, complete, true self, and that hiring organizations have a legitimate interest in knowing a candidate’s authentic self to determine one’s candidacy, form the foundation to the purported problem of hiring (in)authenticity. EAI hiring services claim that by EAI transgressing “beyond” what a candidate willingly and intentionally shares, EAI has the sole, supreme power to truly know a candidate. As exemplified by Adoreboard, whose “Emotics” text analysis platform classifies “*over 24 emotions from any text*,” EAI hiring services claim to solve the purported problem of hiring (in)authenticity “*by revealing the ‘Unknown Unknowns’ of ...Employee Emotions*” to deliver “business answers” only made solvable with EAI’s purportedly superior knowledge about who a candidate truly is. Thus, EAI hiring services’ technosolution to this problem requires a belief in EAI’s techno-omniscience to solve it.

## 4 DISCUSSION

*“Ethics is not missing in technology. Our ethics and values are always present in the creation and use of technology. The technology society creates and chooses not to create is a window into the ethics and values of the powerful” [76].*

Birhane argues that one reason why AI/ML practitioners have limited their engagement with the ethical and social implications of their field is related to the dominance of a rationalist “God’s eye view” paradigm: the view that data science practices have a uniquely superior ability to construct objective and absolute knowledge with advanced computational methods that overcome historical challenges to attaining such knowledge performed by neutral machines that claim to isolate objective reason from human complexity, interdependency, and emotion [13].

Our findings show how EAI hiring services position EAI as a technology with a “God’s eye view” derived from its alleged divine attributes of omnipresence, omnipotence, omniscience. In framing humans’ internal states and traits as isolable and immutable, EAI practitioners perpetuate a rationalist view of epistemology [40] that, as we show, claims EAI’s construction of knowledge about humans is universal, static, and objective. We argue that the perceived superior rationality and rightness of EAI’s neutral God’s eye “view from nowhere” [13] perpetuated by these claims rationalizes its “harmful artificial intelligence outcomes” [76] that operate by exclusion and dehumanization as rational [76, 83] and even “productive” [12] effects.

Yet, in a divergence from the rationalist Cartesian tradition of eliminating the taint of human feeling and emotion in the search for an absolute and objective truth about humans [30], our findings show how EAI practitioners explicitly seek to uncover human emotion as an essential finding necessary to objectively and absolutely “know” humans authentically. EAI hiring services position human emotion and affect as the elusive missing knowledge to the puzzle of objective and absolute truth about humans (in hiring), alleging that the conditions that had so far precluded possibilities to uncover this knowledge are now possible with EAI’s divine capabilities. Whether this departure is simply an attempt to reduce the complexity of human emotion to fit into the rationalist paradigm, or marks a turn in rationalist assumptions that renegotiate human emotion as the key to attaining absolute and objective knowledge, is an area for further inquiry.

Extending Birhane’s observations that the “God’s eye view” paradigm that dominates computational fields serves to excuse its practitioners from meaningful engagement with the technology’s ethicality behind a shield of value-neutrality, our findings show how EAI vendors suggest this convenient effect transfers to the organizations that adopt the “God’s eye view” of EAI hiring services as technosolutions to the purported problems of hiring (in)accuracy, hiring (mis)fit, and hiring (in)authenticity. The privileged interests and concerns of EAI hiring services and the organizations for whom they build their product render these “knowers” [13] as ill-equipped to detect oppression and injustice associated with their technology under what D’Ignazio and Klein call the “privilege hazard” [31], in positions that stand to benefit from this ignorance.

Next, in interpreting our findings, we center jobseekers adversely affected by EAI to discuss the implications of our findings for design and policy.

#### 4.1 Design Implications: Visible and Contestable EAI Inferences

While we do not advocate for EAI use in hiring and fully support regulation to limit its development and use, we recognize that EAI is already pervasive and deeply hidden in hiring services (which our challenging data collection process affirms). At the very least, we advocate for more transparent information sharing in EAI use, such as aligning with the Organisation for Economic Co-operation and Development’s (invaluable, albeit inadequate) [45] Fair Information Practice Principles (FIPP). As our findings show, information asymmetry operates as a mechanism by which services purport to solve the problem of hiring (mis)fits. We argue that EAI hiring services should reduce EAI-induced information asymmetry by: 1) designing for candidates’ transparent access to information generated about them, and 2) offering candidates the opportunity to correct inferences they believe to be inaccurate, challenging EAI services’ desire to discover “the truth” about candidates. Such

approaches would facilitate candidates' more meaningful participation in the hiring decision-making process, allowing them to reflect upon how their candidacy is evaluated based upon their affective expression in the job interview, and assess for themselves whether the job is a fit *for them*.

This suggestion does not address important implications of EAI hiring services' use to shape social norms and exclude those that do not meet normative expectations of affective expression. However, introducing such a process would improve transparency and accountability of the entire ecosystem, offering visibility into the inferences generated about individuals, ways to assess its accuracy, and facilitate contestability [79] and reform.

## 4.2 Policy Implications: FTC Enforcement Against Unfair and Deceptive EAI Hiring Service Practices

More transparent processes may also be facilitated by existing regulatory frameworks, including Section 5(a) of the Federal Trade Commission Act (FTC Act) (15 USC §45) that "prohibits unfair or deceptive acts or practices in or affecting commerce" [91]. Indeed, the FTC recently released a memo of their new enforcement priorities, which commits to addressing concerns of deceptive practices by nascent technologies that reinforce power asymmetries and the marginalization of communities by instituting timely interventions before deceptive practices lead to widespread harm [67].

Extending Stark and Hutson's argument that "Physiognomic AI" is unfair and deceptive [108], our analysis shows how the claims EAI hiring services make in their technosolutions to the purported problems in hiring operate under unfair and deceptive methods that amplify power imbalances and perpetuate hiring harms, falling under the purview of the FTC's priority goals. Moreover, Consumer Reports, in responding to OSTP's Request for Information [1] on private and public sector use of biometric technologies (including those inferring emotional and cognitive states), recommends increased funding for the FTC to "go after and identify companies that are engaging with biometric-related pseudoscientific claims in the AI space" [97]. Our work provides much-needed empirical evidence for these policy suggestions which are clearly important to the OSTP. We advocate for enforcement action by the FTC as one possible avenue to stem the concerns of unfairness, power imbalance, and inequity that accompany the use of EAI hiring services in hiring. Below, we explicate the 1) unfair and 2) deceptive acts and practices identified in our analysis of EAI hiring service claims.

**4.2.1 Unfairness in the Mechanisms of EAI Hiring Services' Technosolutions.** As we have shown, EAI hiring services claim to solve hiring problems through the mechanisms of 1) informational and psycho-biological exclusion; and 2) creating, extracting, and commodifying affective value. These mechanisms perpetuate unfair organizational practices that may unethically enhance power asymmetries and promote exploitation.

**Exclusion.** Hiring has emotional dimensions [93], despite what employers may wish to convey. Past work examining emotions' roles in employment decisions in traditional settings shows that the candidates' elicitation of positive feelings (i.e., excitement) in the interviewer "is a form of emotional capital that has economic conversion value" [14, 93]. Indeed, extant social psychology and organizational behavior studies have established that candidates' emotions and emotional expressions not only shape their own behaviors during interviews, but also the interviewers' and their subsequent evaluation of the candidate's suitability for the job [112]. Positive tones and self-promotion tend to lead to favorable outcomes [111, 112] while candidates presenting as anxious or introverted do not tend to receive favorable outcomes [24]. It is not hard to imagine why these processes might be inequitable in traditional settings, especially for candidates who do not fit some normative expectation of affective presentation and expression.

We argue that through its mechanisms of informational and psycho-biological exclusion to purportedly make “accurate” and “true” hiring “fits,” the use of EAI hiring services unfairly impedes the candidates’ ability to negotiate “emotional capital” in the hiring process, exploiting workers with processes that simultaneously advantage organizations while disadvantaging workers. While this unfairness extends to all job candidates subject to EAI hiring services, it is disproportionately unfair to those whom EAI excludes for their perceived lack of “affective value.” For those candidates that are selected by EAI hiring services, we argue these methods perpetuate the exploitation of human labor through the psycho-biological exclusion of hiring (mis)fits and normativizing the production of *loyal* hiring fits that “live and breathe” company values.

*Affective Valuation.* Ahmed’s concept of “disciplinary technologies” describes how powerful institutions use digital technologies to enforce the moral imperative of human “usefulness” by positioning the people subject to them as “potential” bodies and re-orienting them toward “useful” ends. Building on this work, Lin and Lindtner explore how the dominant “Techniques of Use” value system in HCI masks its associated harms, showing how the uncontested ideal of “usefulness” silences critical approaches in ways that reinforce and perpetuate injustice, exploitation, and exhaustion [64] in computing systems.

Applying these insights, we argue that under the ideal of “usefulness,” EAI hiring services operate as a disciplinary technology through their creation, extraction and commodification of a candidate’s *affective value*. Affective value, defined in 3.1.2, ranks and scores candidates based upon extraction of their affective expressions, according to measures of affective value developed by EAI hiring services and hiring organizations. *Affective commodification* turns affective value into a commodity. Processes of creating, extracting, and commodifying affective value ascribe a candidate’s worth to EAI hiring services and hiring organizations, and reward those that meet the EAI hiring service and hiring organizations’ expectations of affect. However, candidates are often unaware of how<sup>3</sup> or whether they are subjected to EAI due to a lack of transparent application (as challenges in our data collection also illustrate).

Through opaque affective valuation processes that assess a candidate’s desirability and usefulness to hiring organizations along emotional and affective dimensions, we argue that EAI hiring services unfairly and unethically promote the exploitation of human emotion. As a disciplinary technology, EAI hiring services orient not just human bodies, but human affect and emotion toward usefulness to the hiring organization. Moreover, we suggest that the ideal of usefulness that underlies the desired and promoted uses of EAI hiring services may obscure the harms associated with an uncontested belief in EAI’s techno-supremacist capabilities to *usefully* solve organizational hiring problems by hiring only those deemed *useful* to the organization, and hope to encourage more critical scholarship in this area.

**4.2.2 Deception: Pseudoscientific Approaches Obscure and Perpetuate Hiring Harms, Not Mitigate.** EAI hiring services claim that their technologies 1) resolve bias in hiring, and 2) exclude hiring (mis)fits. We argue these claims deceptively obscure and perpetuate – rather than mitigate – hiring harms facilitated by pseudoscientific, physiognomic EAI.

*Bias.* EAI algorithms may be biased along racial, gender, and ability lines [84, 92]. For example, facial emotion recognition performs poorly on individuals with facial disfigurement, paralysis, or Down syndrome; blind or low vision individuals who may not make eye contact with the camera; and hard of hearing or deaf individuals who may struggle to hear questions [84]. As such, biased EAI algorithms may lead to discriminatory outcomes for minority groups.

<sup>3</sup>While candidates may be aware that their “soft skills” are measured by a hiring service, they may not be aware that inferences of their emotions, affect, and internal states are generated by the EAI hiring service to make such measurements.

As we have shown, EAI hiring services invoke larger discourses surrounding concerns of bias and discrimination in hiring [27, 35, 39, 60, 62, 80] to claim that EAI hiring services improve “accuracy” in hiring without bias. We note a surprising misalignment between established algorithmic bias concerns and scaled discrimination prevailing in EAI hiring services’ description of how their technology mitigates bias in hiring. EAI hiring services generally do not make claims of their technology’s technical capabilities to mitigate bias, but rather, claim that EAI inherently lacks bias by virtue of a machine, rather than a human laborer, assessing the candidate.

We argue that by EAI hiring services invoking these discourses with claims that their technology is unbiased, EAI hiring services deceptively suggest that their technology has resolved concerns associated with bias in AI-enabled hiring (i.e., through technical de-biasing methods [90]). The insufficient and shallow explanation that EAI hiring services provide as cover to claim that their technology is “unbiased” suggests that their EAI’s algorithmic bias remains unaddressed.

Moreover, we raise concerns about the reliance that hiring organizations may place in EAI hiring services as technical authorities, amplifying the deception in EAI hiring service claims that their technology is unbiased. Under the guise of adopting “unbiased” EAI hiring services, hiring organizations may divert their corporate attention away from bias in hiring by displacing corporate accountability over fair hiring practices to EAI hiring services [71] that in reality don’t solve for fairness in hiring, but instead obscure bias and perpetuate unfairness. In effect, this displacement of corporate responsibility for fair and unbiased hiring onto EAI hiring services may serve as an “excuse for why [hiring organizations] need not act” [87] or respond to harms associated with (and obscured by) EAI use in hiring.

*Pseudoscientific, Physiognomic AI.* EAI hiring services purport to solve problems in hiring with unfounded, pseudoscientific approaches [106]. Moreover, the ways in which EAI hiring services engage with discourses of discrimination is deeply concerning. As our findings reveal, EAI hiring services promise to solve the purported problem of hiring (mis)fits by adopting eugenic rhetoric and invoking racist, misogynist histories [66, 96] to *exclude* presumed hiring “(mis)fits” on the basis of their psycho-biological characteristics. By uncovering the problems EAI hiring services purport to solve and what values underpin their solutions, our findings provide much-needed *empirical, systematic* evidence for suggestions that the “practice of using computer software and related systems to infer or create hierarchies of an individual’s body composition, protected class status, perceived character, capabilities, and future social outcomes based on their physical or behavioral characteristic” such as that in EAI hiring services should be “declare[d] unfair and deceptive” [108].

## 5 CONCLUSION

This study reveals the ramifications of taking claims of privileged knowers at face value. By unpacking and interrogating the claims EAI hiring services ( $N=229$ ) make in promoting their technology, we reveal how 1) the desired uses of EAI promoted by EAI hiring services are legitimized by their alignment with corporate ideals; 2) the mechanisms by which EAI hiring services claim to solve those problems unfairly exclude and exploit job candidates through the creation, extraction, and *affective commodification* of a candidates’ *affective value*; and 3) EAI hiring services promote beliefs in technology’s ultimate displacement and control of human labor by appealing to core values that EAI’s alleged supreme omnipresent, omnipotent, and omniscient attributes can and should be leveraged to the benefit of corporations. This work, we hope, helps enable the creation of more equitable and just futures of work by encouraging and facilitating discussion regarding the use of EAI hiring services within and beyond CSCW, better equipping us to consider human values



in the continued deliberation about EAI's ethical and responsible role in hiring, and make choices about the human values we want for our socio-technical futures.

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