How Data Workers Shape Datasets: The Role of Positionality in Data Collection and Annotation for Computer Vision

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Data workers play a key role in the big data industry. Clients hire data workers to collect and annotate data with human identity concepts, like demographic categories or clothing items. Often, such workers are treated as computational—they are expected to quickly and objectively conduct their work, with the goal of having huge, unbiased datasets for training models. Computer vision is especially interested in fair and impartial data due to biases and unethical practices in the field. However, far from impartial, data workers imbue computer vision data with "biases" beyond correct versus incorrect answers. Data workers embed their own specific positional perspectives about identity concepts in both collection and annotation processes. Through interviews and ethnographic observations of data workers (freelance and business process outsourcing (BPO) employees), we show how worker positionality influences decisions during data work. We also show the unintended outcomes, like social biases, that occur when positionality is not explicitly attended to in client instructions. We discuss how employing a lens of positionality in data work reveals the gulfs between data worker perspectives and client expectations, which are colored by a web of positional actors beyond isolated data workers. We propose positional (il)legibility as an approach to data work that embraces the reality of positionality in classification practices and addresses the failures of positivist bias mitigation practices.

CCS Concepts: • **Human-centered computing** → **Empirical studies in collaborative and social computing**; • **Social and professional topics** → **User characteristics**; • **Computing methodologies** → *Computer vision*; • **Applied computing** → *Annotation*.

Additional Key Words and Phrases: Data work, gig work, positionality, computer vision, work studies

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CONTENT WARNING: This paper contains potentially triggering participant quotes about race and ethnicity.

1 Introduction

Computer vision is increasingly used to make predictions about human features. Facial recognition is used to determine individual human identities; facial analysis software is trained to classify race (e.g., [31]), gender (e.g., [83]), age (e.g., [98]), emotion (e.g., [57]), and even personality characteristics

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(e.g., [124]); gesture recognition is designed to recognize the movement of human hands (e.g., [2]). Even in cases where human bodies are not the primary target for computer vision modeling, the tasks are still often imbued with human meaning. Vehicle detection, clothing classifiers, AI-generated art—all of these tasks reflect specific human cultures, practices, and values.

It has become relatively common knowledge that computer vision technologies reflect human beliefs and values. Like all machine learning technologies, computer vision models rely on data to "learn" what to predict. While some models may be trained using unsupervised techniques (e.g., [15]), most modeling is done using human-curated datasets. Individuals collect, clean, and label visual data, like images and videos, to train and evaluate computer vision models. This 21st century model of work has grown into a global labor sector coined *data work*. Big tech and startup technology companies alike hire huge numbers of data workers to produce datasets for machine learning. These data workers are largely hired from countries in the Global South, lack the benefits and protections of traditional labor, and are often subject to incredibly low wages ([9, 87, 93]).

Yet, given pervasive issues with inequitable computer vision model performances (e.g., [7, 12, 48, 125]), industry practitioners and researchers alike have sought to address bias at the data level, adopting a "garbage in, garbage out" perspective ([34]). One salient approach to dealing with data bias is to attempt to control the potential biases introduced by data workers—through methods such as instruction manuals (as seen in [74]), consensus [113], inter-annotator reliability [23], and performance testing [36]. Despite being incredibly undervalued, data work is crucial to both enabling computer vision work and ensuring that work is fair and ethical. Beyond monetarily undervaluing data workers' contributions to computer vision, data workers' perspectives are seen as a liability that needs to be carefully controlled [100].

Beyond implicitly acknowledging that data work is imbued with a sense of human subjectivity by trying to control it, few attend directly to how the subjective nature of data work shapes computer vision. Data workers, like all workers, occupy a specific position in the world as they conduct their work. Positionality—how values, experiences, social identities, politics, time, and space shape how one understands the world—tangibly affects all work. While there have been increasing calls for attending to how positionality shapes machine learning (e.g., [13]), work to date has largely focused on the marginalization of data workers and the power imbalances between data workers and their employers [40, 74]. Little knowledge has been produced about how worker positionality operates in computer vision beyond recognizing it as an inconvenient and risky reality that should be carefully controlled.

The role of positionality in research has recently become more explicitly acknowledged in social computing, with researchers attempting to outline how their own positionality might have influenced their work [67]. Understanding the role of the positionalities of others has remained largely implicit in social computing, as we present findings from the perspectives of participants. Yet understanding the positional perspectives of data workers can illuminate how identity is shaped by human values, experiences, and beliefs. This paper is focused acutely on how the positions data workers occupy influence identity concepts in data work for computer vision. More specifically, we attend to the following research questions:

- How do data workers approach different types of data work for computer vision and what do these approaches communicate about their positionalities?
- How do data worker positionalities influence the outcomes of identity concepts in data work?
- What, if any, tensions arise between data worker positionalities and the data work they are assigned?

In this work, we employed ethnographic observations and interviews to unearth more explicit understandings of worker positionalities. We conducted a year-long ethnographic study with a small business process outsourcing (BPO) company in Europe, where we observed and interviewed data workers and analyzed documentation. We also conducted interviews with freelance data workers providing services on the platform Upwork. Interviews were designed to understand how data workers reason through computer vision data work that is salient to human life—including both human-centric (e.g., images of people) and human-adjacent (e.g., images of clothing) data. We asked participants to describe how they approach annotating and collecting data, what is challenging about their work, and their perceptions about diversity in data work. We thematically analyzed data around the concept of positionality, identifying often implicit explanations of data worker positionality and how those perspectives influence data outcomes.

Through our findings, we showcase the various ways that data worker positionalities influence their approach to data work, including the factors data workers felt shaped their perspectives on the world, like cultural familiarity and media. We show that data workers rely on tacit knowledge—an implicit knowledge gained through one's personal life experiences—when conducting data work for computer vision. We also describe some of the unintended negative outcomes that occur when data worker positionalities do not align with client expectations of data outcomes; such negative outcomes are unable to be captured by simple bias control mechanisms. While positionality operates as a form of tacit knowledge in data work, data workers are also not entirely unaware that their own perspectives may be limited. As such, they advocate for diverse workforces that can provide different subjective perspectives and experiences to make up for gaps in knowledge or understanding.

We discuss how these findings illuminate gaps in the positional knowledge of data workers and also their clients, who fail to realize data workers act on their tacit knowledge about identity when conducting data work. We highlight how positionality does not exist solely within the confines of an individual but is negotiated across a web of positional actors that influence data work—including clients, trainers, supervisors, other data workers, and data instances themselves. We then describe how current bias mitigation practices fail to account for positionality, implicitly adopting a positivist worldview that prioritizes "correct" versus "incorrect" classifications. Finally, we propose positional (il)legibility as an approach to data work that explicitly embraces positional perspectives. We argue that certain data is legible or illegible to positional actors based on their own positional worldviews. Positional (il)legibility offers promising opportunities for actively and explicitly accounting for positionality in data work.

2 Related Work

We situate this work within three areas of social computing. We begin by reviewing scholarship on data bias in computer vision, highlighting that data bias stems from human perspectives. We then review research on data work, particularly the undervaluing of data work as a crucial component of computer vision development. Instead, data workers are problematized as the major source of bias who should be controlled. We conclude by detailing the theory of positionality and its role in studies of machine learning datasets. We establish that this paper centers data workers as positional actors who are neither inherently biased or unbiased, but operating from specific positional standpoints.

2.1 Data Bias in Computer Vision

Like other machine learning fields, computer vision has a penchant for bias. Unfairness in machine learning is generally defined by a model showcasing bias towards specific classes of data, performing better on some classes than others or reinforcing stereotypes or undesirable values about those classes. Tasks which are salient to humans bear significant fairness concerns, given the wide variety of individual and societal harms they can cause [60]. Facial analysis tasks tend to be centered heavily on discussions of bias, as they commonly demonstrate performance biases favoring specific social groups (e.g., [3, 12, 26, 48, 103, 125]). Yet object-centric computer vision also regularly exhibits unfair or biased results. For example, scholars have uncovered biases against certain social groups in scene understanding and object classification (e.g., [26, 72, 123]) and problematic associations between tags and marginalized social groups (e.g., [7, 9]). Biases in dataset creation show how the human authors behind datasets exhibit narrow worldviews biased towards their own experiences [7, 27, 66, 106, 111].

Given data is often considered the source of model bias, a great deal of research has focused on creating better datasets and debiasing models that have already been trained (e.g., [6, 11, 17, 24, 114]). Centering data in bias mitigation practices insinuates that data and associated model outputs can be inherently objective and neutral, and that objectivity and neutrality are the goal of computer vision.

However, beyond focusing on whether models perform equally well on different classes, scholars are also increasingly examining the underlying values instilled into computer vision representations. In these cases, there is an implicit acknowledgment that "bias" is ever present, even in systems that seem to perform equally well on the present classes the model was trained on. This is because the present classes reflect a specific worldview, which inherently leaves out other possible worldviews. For example, a model working equally well on cisgender men and women is still inherently biased against transgender and non-binary genders, because those representations are simply not accounted for in the worldview instilled in the model [61, 103, 104].

That data can be biased towards specific worldviews reveals the underlying reality that human beings, with their own perspectives and values, are the ones shaping computer vision. In particular, the data workers, tasked with collecting and labeling the data computer vision is intrinsically reliant on, teach the model their subjective worldviews. This study centers the subjective worldviews instilled in data. Unlike prior work on data bias in computer vision, this work is not focused on how to solve the problem of bias, but rather how to understand and account for the reality that all data is subjective and biased. We thus augment prior work on how values are embedded into dataset design, offering insights into how human workers implicitly embed their own perspectives of human identity concepts into data. Far from promoting the notion of inherently unbiased and objective data, we showcase the impossibility of removing human positionality from data work.

2.2 The (Under)valuing of Data Work

Broadly speaking, data work describes a type of labor focused on the preparation of data, often for machine learning tasks [110]. The human laborers who perform data work are often called data workers. Data workers may be platform users (e.g., Google Crowdsource, where users label data for points), domain experts (e.g., dermatologists hired to label skin shades [12]), or contingent laborers (outsourced workers hired through freelance platforms like Upwork or business process outsourcing companies like Samasource). In the context of the study at hand, data workers are contingent laborers whose work is specific to the collection and annotation of visual data for computer vision.

Contingent data workers are hired by companies for short-term tasks, projects, or role-based jobs and do not receive the same benefits and labor protections as traditional workers. They are generally given instructions or guidelines for completing their work, such as how to label certain classes or what data to collect [32, 73]. Unlike other more conventional types of contract work, like construction or web development, contingent data work is known for being precarious and underpaid [88, 117, 118]. This contingent work often underlies the foundation of the AI industry, a type of "ghost work" that is unrecognized and invisible [40, 70, 78, 81]. Contingent data workers are often considered part of the "gig economy," on-demand work that is generally paid in extremely small increments for tasks—sometimes only a few cents per task [4, 39, 74]. Data workers might label hundreds of images for only a few dollars [43]. Platforms specific to digital gig work, such as Upwork, Amazon Mechanical Turk, and Samasource, allow clients to "crowdsource" data workers for tasks quickly and cheaply [14, 55, 89].

Given the desire to keep data processing costs low, companies largely outsource data workers from the Global South, in areas where they can legally pay far lower wages than in the Global North [35]. Numerous researchers have pointed out that the undervaluing of data work negatively affects the quality of datasets, and thus increases the likelihood of undesirable model outcomes (e.g., [53, 68, 86, 101]).

Since data workers tend to be located in the Global South and are often economically disadvantaged, scholars are increasingly examining the power differentials between data workers and their clients. For example, Posada argues that the disembodied, highly gendered nature of data work is unsustainable as it negatively affects worker livelihood and degrades local community development [91]. Data workers' clients usually enact mechanisms for controlling data worker perspectives through documentation and guidelines. Miceli et al. show how an annotator's work is influenced by the values and priorities of their clients; these values are imposed on data workers who then apply those values to data [75]. Miceli and Posada demonstrate how the documentation guiding data work reflects the worldviews of clients [73]. The precarity and poor working conditions of data workers create an atmosphere of obedience, where data workers adopt and implement client worldviews.

In this paper, we center data worker practices to better understand how their positionalities influence data practices in computer vision, and thus the implementation of identity concepts in computer vision systems. Rather than examining data workers as an inherent source of bias who must be controlled through documentation and surveillance practices, we value data workers as experts who operate from a specific positional perspective. Therefore, their work is reflective of their own experiences, beliefs, values, and social identities, as well as their relationships with other actors in the development process—clients, trainers, data subjects, and the data itself.

2.3 Positionally-Aware Data Work

Not all aspects of identity in computer vision are tied up in notions of bias. Rather, all computer vision models are tied up in notions of *identity*. Central to how identity concepts are implemented in computer vision is the concept of positionality. Positionality refers to how an individual's "position" in the world shapes their outlook—how the complex web of identities like race, gender, nationality, location, sexuality, class, and more influence their experiences and thus beliefs, values, and relationships [21]. Such positions are not static or necessarily chosen, but mutually constituted through one's relationship with others and also themselves [19, 20, 49]. As described by Iris Marion Young, "one *finds oneself* as a member of a group, which one experiences as always already having been" [120, p. 46, emphasis in original].

From positionality comes a specific epistemic vantage point, a socially-situated way of viewing the world [19, 44, 45, 97, 107]. Such epistemic vantage points are theorized through feminist standpoint theories, the theory that all views come from somewhere and no view stems from nowhere [21, 95]. Standpoint theorists argue that those occupying some positions may be more knowledgeable on certain subjects than those occupying different positions. As Wylie writes, some individuals "may know different things, or know some things better than those who are comparatively privileged (socially, politically), by virtue of what they typically experience and how they understand their experience" [119]. Women understand misogyny in ways that men cannot; Black women understand misogynoir in ways that white women and Black men cannot [20]. In contrast, a view from nowhere would posit some objective and observable truth about the world—and human identity—that can be captured in an unbiased manner.

Linda McDowell argues that "we must recognize and take account of our own position, as well as that of our research participants, and write this into our research practice" [71, p. 409]. Feminist scholars posit a "reflexivity that aims, even if only ideally, at a full understanding of the researcher, the researched and the research context" [97]. Rose highlights the uncertainties in this goal—to fully account for the positionalities of all actors in a research project—are not deficits, but rather opportunities for more transparently understanding the limitations of research and why they might occur [97].

Many scholars have examined the role of human subjectivity in shaping data (e.g., [18, 29, 42, 70]). For example, Vertesi and Dourish propose a data economy framework for CSCW aimed at exposing how the context of dataset production instills datasets with specific values and meaning [112]. Scheuerman et al. describe how computer vision dataset authors in research contexts sacrifice data work in the name of model work, prioritizing efficiency over care and erasing contextuality and positionality in data practices [101]. Denton et al. propose a genealogical methodology for researching machine learning datasets, "for investigating how and why these datasets have been created, what and whose values influence the choices of data to collect, the contextual and contingent conditions of their creation" [25]. Promoting reflexivity among machine learning researchers and practitioners, a core tenet of this genealogical methodology is focusing on the role of human values in the creation of datasets.

Some scholars have focused on understanding the impact of data worker subjectivity on datasets specifically. For example, Patton et al. examined the differences between domain experts and graduate students who annotated Twitter data from African American and Latino youth and young adults; they argue that disagreements between the two annotator groups emphasize the importance of annotator background, particularly "nuances in culture, language, and local concepts" [85]. Sen et al. conducted a survey study to see whether Amazon Mechanical Turk workers from different cultural communities produced different ratings on the same data [105]. Beyond finding that different communities produce different rating labels, they also found that algorithms trained on datasets sourced from different communities perform dramatically differently. Litman et al. found that lower compensation rates for platform tasks led to lower quality data work, particularly in India [68], showcasing that the locational context and economic conditions of data workers are highly influential on their data production. These studies engage with how the worldviews of dataset authors and annotators shape dataset outcomes, even if they don't explicitly label these worldviews as positional. Data, no matter how simple it appears, does not simply exist—it is designed.

Positional perspectives are generally bound up in tacit knowledge. In contrast to explicit knowledge, tacit knowledge makes up the skills and ideas we gain from our experiences yet have difficulty articulating or formalizing [90]. Despite the importance of tacit knowledge in work practices, it is often difficult to capture. Understanding the role of tacit knowledge in work practice has thus been a major focus of CSCW (e.g., [80, 90, 94, 108]). In this work, we attend to the explicit and tacit knowledge that data workers had of their own positionalities and the role they played in conducting their work. We align with Rolin's perspective on positional standpoints [96], rejecting that knowledge is neither biased or unbiased, correct or incorrect, but instead operates from a specific social position that influences how one views the world in the data they are working with.

3 Methods

We conducted both ethnographic observations and interviews with data workers as part of a larger project on understanding how tech workers shape identity concepts in industry-scale computer vision projects. In this paper, we sought specifically to understand how a data worker's subjective positionality influences data collection and annotation processes in computer vision. Analysis was grounded in the ethnographic context of a specific BPO data provider, EnVision Data. As EnVision

Data at times relied on freelance data workers via the platform Upwork, further interviews were conducted with Upworkers to gain insights into their experiences as well. Data collection broadly occurred over the course of a year. The analysis presented here was conducted on a slice of the data collected in a larger project focused on industry-scale computer vision.

We direct readers to the Appendix for more robust details about our methods, including: participant tables and figures, limitations in recruitment, our specific language choices when discussing participants and geographic locales, and descriptions and examples of projects.

3.1 Field Sites

3.1.1 EnVision Data The findings presented in this paper come from an ongoing relationship with EnVision Data and are based on data collected between October 2021 and October 2022. Based in Southern Europe, EnVision Data has a globally distributed workforce of 480 active annotation workers and additional contractors on a per project basis. EnVision provides data collection and annotation services for computer vision, as well as output validation (e.g., verifying model performance) and edge case handling (e.g., 24/7 human annotation coverage to detect failures). Projects range from object classification, such as assigning labels to clothing styles, to facial recognition aimed at identity verification. The projects relevant to this study can be found in Table 1.

EnVision Data is unique in comparison to more traditional data BPOs in that it is also a social enterprise focused on providing remote work to at-risk populations. Specifically, their workforce is comprised of individuals displaced by human conflict: refugees, asylum seekers, and those located in conflict-affected zones. They have public labor standards focused on fair pay given the country the worker is based in, intentionally attempting to mitigate unfair labor standards commonly experienced by data workers. Further, EnVision Data supports ethical AI initiatives and desires to contribute to more ethical AI systems; discussions with the CEO of EnVision Data revealed acknowledgment of past projects that she no longer considered ethical, and which will appear in the findings of this study. Unlike traditional data solution companies, instead of relying on APIs to connect data requesters with workers [40], EnVision Data partners with non-governmental organizations (NGOs) to recruit, train, and manage workers and payments. Further, in opposition to micro-task platforms like Amazon Mechanical Turk and UHRS [40], which attempt to make invisible the humans behind annotation tasks, EnVision Data makes visible and centers their human workforce. They offer trainings in various areas, spotlight workers on their website, and release yearly reports on the status of their workforce. Given EnVision Data is unique in its mission as an ethical AI company with ethical work practices, they are not representative of data BPOs as a whole. Work with more traditional BPOs (e.g., Appen, Sama) might uncover different insights than work with EnVision Data.

EnVision Data also employs Upworkers in cases where their main internally employed workforce cannot meet project requirements. Generally, hiring Upworkers occurs in cases of data collection, rather than annotation. Given data collection requirements are often focused on broadening geolocational diversity, EnVision Data hires Upworkers from specific locales dependent on client needs. We spoke with four freelance data workers that EnVision Data hired on Upwork for data collection projects (shown as EnVision Data Freelance workers in Table 2).

3.1.2 Upwork Freelance participants did not undergo training in the same manner as EnVision Data participants; they were often simply given the instructions for the project, and able to ask clarifying questions from a point of contact or other team members (if given access to the team via platforms like Slack or Discord). Unlike EnVision Data workers, who largely had no experience doing data work prior to joining EnVision Data, the majority of freelance workers had a variety of different data work experiences. Some data workers had worked for more traditional BPOs like Samasource; others had worked for smaller data startups.

Also unlike participants from EnVision Data, who worked in groups on specific projects with specific companies, freelance workers often worked individually for a number of clients across the globe. Much like Table 1 showing the locations of clients served by EnVision Data, we present a visualization of which countries each freelance participant had clients in (see Table 3 and Figure 6 in the Appendix). The geographic context of both worker and client is crucial to understanding how workers negotiate their positionalities in data work. The table and figure also showcase which freelance workers are particularly experienced and have worked for a variety of clients across the globe. We discuss the limitations of our geographic sample in Appendix A.

To recruit Upwork participants, we posted job ads for an interview about data annotation and collection experience. The job ad requested applicants who had primarily worked on human-centric computer vision and had been hired by companies rather than researchers. The study's IRB approval documentation and consent form were attached to the ad. We posted two job ads: first, we posted a general job ad; later, we posted a job ad aimed at participants in Northern America, Western Europe, and Eastern Asia (as defined on Upwork's platform). On both job postings, we used Upwork's "invite" feature to search for relevant workers and invite them to apply to the job ad. We invited 16 people; 5 invites were ignored. Beyond the invite feature, any freelancer can also apply to a job by submitting a "proposal" outlining their qualifications. We received a total of 48 proposals. We selected proposals based on the relevance of the workers' projects, the number of relevant projects, and their country of origin, in an attempt to get diverse perspectives from both a geographic and work experience perspective.

3.2 Projects

Much like the data workers interviewed by Milaceli and Posada in [74], the participants in this study worked on a variety of data tasks, including data generation, data annotation, algorithmic verification, and AI impersonation (i.e., real-time human-in-the-loop labeling and verification) [110]. We discuss different projects in the following categories: data collection (i.e., generation) and data annotation. Many projects require data workers to address identity characteristics (like race and gender) and identity-adjacent concepts (like clothing styles and emotions). Before delving into descriptions of participants' positional approaches to their data work, we first describe the different types of projects and their requirements that participants worked on. Given in-depth year-long work with EnVision Data, we describe projects by name and provide deeper documentation (see Table 1). We give shorter descriptions of projects on Upwork, as freelance participants described numerous projects in briefer detail. In this work, we primarily examined how workers engaged with specific tasks (e.g., classifying emotion), but we also acknowledge that the software and physical environment they were in while annotating likely had an influence on their interpretations as well—for example, participants mentioned difficulties with collection software and the physical toll annotation took on their bodies.

Clients, whether they hire data workers directly through Upwork or went through an intermediary BPO like EnVision Data, generally provided documentation on the requirements and expectations of a project. Yet, project guidelines rarely attend to the identity aspects of this data work, and provide no explicit instructions or examples for determining ground truth or for attending to potential biases. Without identity-specific instructions, data workers are left to fill in the gaps on their own.

3.2.1 Collection Data collection involves the collection of images from either the "real world" (physical settings) or the web. In the case of human-centric computer vision projects, the data collected was largely images of people or images of concepts that held some form of cultural significance. For example, EnVision Data's client SensEyes requested a dataset of diverse faces for their face authentication application to be used in mobile banking applications (see Appendix for further project details). Despite being asked to collect data based on specific demographic classifications of ethnicity and gender, no instructions were given to data workers on how to determine data subjects' gender or ethnicity. Participants on Upwork similarly described that, in the case of data collection projects, they were not given instructions on determining demographic or identity-based information. Some workers were asked to collect non-human images which held cultural or identity-based significance, as well, such as clothing types, food, or even infrastructure. Such non-human image requests often also provided insights into positional perspectives of data workers.

EnVision Data Projects			
Company Location	***Project Alias***	***Project Purpose***	***Workers Involved***
United Kingdom	ChAI	Video interviewing with personality insights	Yasmin, Ghaliyah, Aakrama, Dinorah
France	SensEyes	Face authentication	Jaako, Rebecca, Thanh, Manjola
Switzerland	Emovos	Emotion classification for advertising	Wares, Sumbul, Shokouh
United States	CaringHearts	Real-time patient monitoring	Yasmin, Aakrama, Abyar
Bulgaria	Codeguard	Labeling of images as adult or non-adult for automatic moderation	Ghaliyah

Table 1. A table describing all of the EnVision Data projects we observed during our study. The remainder of EnVision Data participants (Sadham, Raiha, Makaarim, Hijrat, Baksish, Azyan) were interviewed regarding EnVision Data's ethical annotation training.

As can be seen in the instructions for collecting data for SenseEyes (see Section 7), labeling was also largely built into these products. For example, collecting images of "Caucasians" meant data collectors found images they believed were representative of the label "Caucasian." However, often data might also be labeled, or further labeled, after being collected.

3.2.2 Annotation Annotation, or the labeling of images with concepts, categories, keypoints, or bounding boxes, was done in the following areas in the context of this study: annotating demographics, annotating emotion, annotating cultural concepts (e.g., clothing types), and annotating the explicitness of an image. Table 1 shows each of the projects we observed and/or discussed at EnVision Data. Freelancers also described a number of annotation projects, including: labeling identity categories like gender and race; labeling emotions; conducting keypoint annotations of facial features; and classifying objects which held differential meanings across cultures, like clothing and infrastructure.

3.3 Interview and Observation Methods

3.3.1 Observations with EnVision Data We conducted observations of EnVision Data over the course of about a year. Due to the COVID pandemic, borders were still shut during the time of data collection and thus we conducted observations digitally. Digital observations were appropriate given almost all work at the company, with the exception of an in-person training in Portugal, was conducted remotely from 2021 to 2022. Some data workers described going into a physical office in areas where they suffered power outages, such as those located in Afghanistan. However, workers largely worked from home when power was not an issue.

As part of our observations, the first author was added to the company's Slack workspace. This allowed us to observe general communications between workers and to communicate directly with different people in the organization. The first author also observed project meetings, specifically the negotiations for the project Xavient, a diverse data collection project that EnVision Data decided to turn down due to its large scale. The first author was given virtual walkthroughs of the systems the company uses for project management and annotation, and demos of annotations by data workers during one-on-one interviews with them. Beyond gathering and reviewing all of the company's public documentation, the first author was also given access to private documentation, such as contracts, client pitch decks, and annotation guidelines. The first author completed all of the private training modules that EnVision annotators are required to take to better understand how data workers are trained to do their jobs. The first author kept a diary of field notes with recorded observations and thoughts on meetings, demos, documentation, email exchanges, and any other relevant data that arose during time with EnVision Data. In the context of this study, observations provided contextual understanding of work conditions and expectations, client and project backgrounds, and the specific cultural situations of conflict-affected workers. We were thus able to compare the formal work environment and trainings of EnVision Data workers with the more informal and contingent work environments of freelance workers on Upwork.

3.3.2 Interviews with Data Workers Beyond observations, we conducted semi-structured interviews with EnVision Data workers and freelancers on Upwork (see Table 2). Semi-structured interviews provided the opportunity to gather rich insights from workers on how they conduct data work. Interviews lasted an approximate average of 57 (27-121) minutes across all participants, and were of similar length for both EnVision Data and freelance workers.

The first author conducted all interviews using video conferencing software. We both audio and video recorded all interviews, allowing us to capture both the audio interviews and annotation demonstrations. In some cases, the first author used text chat to communicate questions to participants who wanted to use translation services to better understand questions. Participants would then communicate answers back in English. Translation issues and language barriers were present realities during interviews. Chat logs were also saved in these cases, and cases where participants shared links to websites or images. All recording was done with participant consent. Participants' internet connections were occasionally slow or unstable; in these cases, interviews were generally suspended until internet connectivity was restored.

3.4 Data Analysis

We adopted a constructivist approach to conducting and thus analyzing this work [79]. We conducted a series of theoretical memoing practices informed by grounded theory [16]. As data was collected across numerous months and with different participant populations, we took notes and conducted open coding as we continued to collect data. We conducted open coding to understand the range of themes present in all interviews. Documents were not formally coded. Instead, notes were initially taken on documents, focused on piecing together a larger contextual picture of EnVision Data as an organization. Documents were then returned to in analyzing interviews and to bolster and support the construction of thematic memos.

As we became increasingly familiar with the data, we began writing theoretical memos focused more acutely on how participants' expressed their positionalities—the subjective experiences they described and how those seemed to inform their work. Participants rarely discussed concepts like

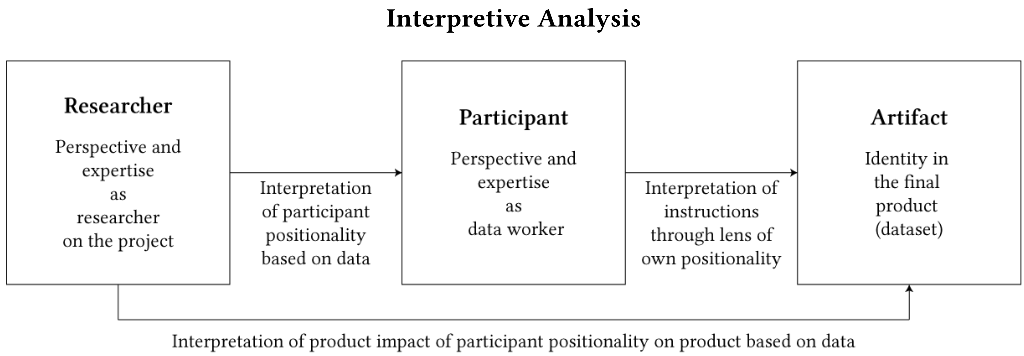

Fig. 1. A visual representation of how researcher positionality shaped the analysis of the data. The arrows represent the direction interpretation flows in the case of this research project.

"positionality," "perspective," or "subjectivity" explicitly. Rather, they described experiences, opinions, and culturally contextual characteristics relevant to how they interpreted project requirements. As themes coalesced, they were informed by observations, interview data, and our own positionalities. Figure 1 visualizes how our positionalities act as a lens through which we attempt to clarify participant positionality and its implications for identity in computer vision artifacts.

3.5 Researcher Positionality

Feminist practices of reflexivity posit that research is mutually shaped by researcher and researched. In the study at hand, that is especially pertinent. The perspective of both the researcher and the researched intersect to produce findings about the role of positionality in data work. From our own sociocultural and epistemic perspective [37], we interpret how participants express their identities, both implicitly and explicitly. Participants' expressions of their perspectives is shaped by the context of research—for example, by the language of interviews (English), the remote format and their location at the time of the interview (where family may have been present in the home), their perspective of the interviews as part of their work, and their perception of the interviewer as a person.

In trying to understand how the positionalities of data workers influence the outcomes of computer vision artifacts, it is crucial that we also actively engage with which aspects of our own positionalities we believed shaped our engagement with participants and the interpretations we made about the role of their positionalities. As researchers born and based in the United States, we have a Western-centric perspective based on the culture, context, and communities we were raised in and continue to be part of. Given all three authors are also white, we have had a very particular experience in the U.S. and as researchers—one which has granted us great power and privilege.

While the first author comes from a lower class economic background, his position as a U.S. researcher and experience with traditional white collar tech work awarded economic privilege when recruiting participants from the Global South who held lower paying jobs. Most of our participants were both non-US and non-Western citizens; they were also primarily non-white. These dichotomies undoubtedly shaped our interactions with participants, often in ways invisible to us. However, some interactions were visible to us. For example, because we are English speaking, all interviews were conducted in English, shifting power to the researchers and necessitating many participants to communicate in a second language. This likely resulted in some miscommunications and loss of nuance and context that we might have been able to account for could we communicate with participants in their first languages.

We also acknowledge that two authors' identities as queer not only motivated us to pursue this line of research on identity in AI, but shaped how we interpreted and engaged with gender and sexuality characteristics in this study. We are all three also committed to continuous (trans)feminist and anti-racist learning, and thus intentionally challenged how our own positionalities might shape our assumptions. Even while trying to consistently consider our own power and privilege, we undoubtedly have gaps in our ability to understand certain perspectives due to the positionalities listed above. Engagement with the results and implications of this work should keep in mind the reflections above.

4 Findings: Positional Perspectives in Data Work

Throughout the variety of data work participants conducted, they regularly relied on tacit knowledge about identity, a knowledge they implicitly gained through their personal life and experiences. Participants' descriptions of their work provided insight into how the various positionalities they inhabit influence their approach to their work. Given the nature of tacit knowledge as innate, informal, and intuitive, participants had difficulty formally and explicitly identifying how they made decisions about identity.

In this section, we argue that data workers inscribe tacit knowledge about identity into their data work and that this tacit knowledge reflects certain positionalities. Findings show that data workers embed their own positional perspectives in both annotation and collection tasks. Generally, referring to one's own tacit knowledge is an implicit act; data workers were not explicitly aware how they were using their own positional perspectives to attend to their work. How they relied on positional knowledge was generally contextual to the specific task and specific categories they were attending to.

4.1 How Worker Positionality Influences Data Work

Data workers, whether conducting data annotation or data collection projects, regularly relied on the tacit knowledge developed by their own positionalities—a synthesis of experiences, values, beliefs, affinities, and sociocultural context. Participants regularly relied on contextual familiarity they personally built through life experiences, localized values and norms, personal affinities with identity categories and values, and other characteristics that make up one's positionality. Such knowledge was approached as "common sense," an approach also reflected in the lack of explicit instructions or engagement with positional perspectives on behalf of clients. In particular, we saw tacit knowledge influenced by both media and individuals' own sociocultural contexts and identity affinities.

4.1.1 Media Influence on Identity Interpretations When the workers found their subjects to be familiar to them in some way, they had a much easier time with annotation. In the case of tagging faces with emotion concepts for the Emovos project, participants seemed to have an easier time with actors or content that they recognized. For example, Shokouh described how familiarity with actors and media made understanding their expressions easier for her: *"Some people, like the movie stars, it was more easier cuz we have seen that exact movie or series or show so we knew how was he or she [feeling at] that time, it made it easier."* Based on our analysis, those who have seen the media in the dataset may tag emotions differently than those who have not, simply because they are already familiar with the emotional context of the scenes they are tagging. It is possible that, for example, an emotion like "disgust" is perceived as "sadness" if one does not know the narrative informing a facial expression.

Sadham similarly discussed how he knew the differences between different races because of what he saw online and on television. In this case, familiarity and access to certain media, informed by larger market trends and international media exchange, made certain faces more or less accessible to data workers. For those public figures or actors they were unfamiliar with, they could not refer to a prior contextual knowledge informed by a specific media context. Those who do not have access to media may be less familiar with the emotional context of the faces being annotated or the way racial categories are described. Neither familiarity nor unfamiliarity with the original media context of the dataset indicates more correct or incorrect answers. Instead, familiarity can be viewed as a positional lens that colors how data workers view the data in front of them.

4.1.2 Sociocultural Familiarity with Identity Concepts Beyond familiarity with media contexts, data workers showcased certain culturally contextual perspectives of identity categories. Ghaliyah worked as an annotation supervisor on the ChAI project for interview video interpretation. Annotators on the project were asked to tag each person with a gender: "male," "female," or "undefined." When asked how she made decisions about determining each person's gender, she largely relied on cultural cues she was familiar with as a Muslim woman: *"Most of the people in the videos, they were from Islamic countries. For example, for the women, most of them were wearing hijab. ... in those countries, the cultural uniforms are divided between men and women."* While data workers were not given any guidelines for determining gender, she had tacit knowledge of how religious garb is typically divided between binary gender categories. Ghaliyah viewed something like classifying gender as something so obvious within her own culture that she never questioned labeling gender in her work practices.

On the other hand, sociocultural knowledge made categories that were "obvious" to some workers difficult for other workers. Gemma expressed that trying to annotate gender was difficult for her, because she was aware that some people are transgender or do not fit into clear boxes of male or female:

> *Actually for gender I find it a bit tricky because some people are transgender and they don't perceive they are transgender as another type of face, so ... they just put it as female, male, so that's what they consider most of the time in such projects.*

In this case, Gemma expressed a personal knowledge of transgender identities that was not expressed by other data workers. Such personal knowledge reflects an exposure and awareness unique to her own life experience, that other data workers may not have experienced. Because she felt she could not make a decision about gender in these cases, she would relay all edge cases to her supervisor to make the decision instead. In such cases, she did not have to make a labeling decision; her supervisor applied the label, and the data never came back to her to verify it.

4.1.3 Singular Dataset, Multiple Worldviews Different positional perspectives would also clash within projects, resulting in data within a singular dataset reflecting multiple worldviews. For example, the ChAI project involved multiple annotators labeling the same data. In these projects, disagreements between annotator worldviews began to surface, showcasing how not all workers interpret the data the same way. For example, Ghaliyah labeled a data instance as "South Asian," while Yasmin labeled that same instance as "Black African." For these projects, workers relied on locally contextual and experiential knowledge about racial categories to make determinations about identity concepts. However, their determinations did not align.

Data workers relied on their positionality to make decisions about both data annotation and data collection, both human-centric and object-centric data. The tacit knowledge informing data work varied by each data worker's positionality. As showcased by the examples above, some data workers had differential positionalities that lent them unique perspectives, such as the difference between Ghaliyah's and Gemma's ideas about gender categories. Even when explicit instructions do provide examples, like with the ChAI project and emotions, data workers must rely on their own tacit knowledge to make sense of the data in front of them. Further, group projects highlighted that each data worker had different positional perspectives, yielding different decisions for the same data.

4.2 Unintended Outcomes When Positionality is Unattended To

Clients rarely provided explicit expectations about identity concepts; such expectations were often implicit in client-provided labels (e.g., "male" or "female," "South Asian" or "Black African") that evoked tacit knowledge about those identities. Given that clients provided little information on identity-based and culturally contextual expectations for their projects, data workers relying on their own experiences and intuitions did not always perform as expected. As participants relied on their own positionally-situated tacit knowledge to make decisions about data, they also often ran up against misunderstandings, introduced implicit biases, and engaged in unexpected practices to complete their work. This section highlights the types of unintended consequences shaping computer vision data when clients do not consider how data worker positionalities might differ from their own.

4.2.1 Mistakes and Misunderstandings Sometimes, the positionally-informed interpretations data workers made seemed to clash with the expectations of Western-centric clients. Many data workers submitted work that clients deemed incorrect, but data workers explained was simply different in their own cultural context. For example, workers had a difficult time when certain objects, like garments, differed greatly in their own sociocultural context from the expected context of clients. Sadhil, an annotator who worked for two and half years at a computer vision company before switching to freelancing on Upwork, described an instance of cultural confusion between himself and his client. Sadhil is based in India, and his client, who was based in Japan, requested annotated data for a clothing classifier. He says that in India, a blouse is a type of women's clothing that goes underneath a sari, and so when he was asked to collect images of blouses, he *"collected the images according to blouse that [I know] in India."* However, the client said this was not a blouse, and so he had to research what a blouse looked like in the context of Japan and found that it was completely different and was a much longer shirt-like garment. He had to shift his own view and build an understanding of what a blouse looked like in Japan, so that he could annotate in a way that his client deemed correct.

Annotation guidelines did not explain how objects and environments could differ depending on locale. Therefore, clients regularly approached data workers to explain their own cultural expectations in cases where they received labeled data that did not match their expectations. Such moments represent an unintentional and implicit exchange of cultural ideas, where data workers then adopt and change their own perspectives on the world to accommodate client expectations.

Misunderstandings and confusions also occurred when data workers had differential perceptions about identity categories than clients. For example, Gemma, who as already mentioned, was attentive to queer identities, described being unsure how to annotate gender in cases where she felt gender was ambiguous. Similarly, Gemma found certain racial categories she was asked to annotate difficult to differentiate, possibly because they held no meaning in her own context: *"You cannot differentiate between a Caucasian person and Hispanic person, so it was sometimes a bit challenging."* Challenging data meant that datasets might end up with worldviews more reflective of the context in which they are annotated, rather than the context for which the model is intended to be deployed.

Many data workers referred to these instances of misunderstanding or differential interpretation as "mistakes," even in cases where they might be technically correct in their own local context or there may be no way to ascertain a correct answer, like with gender and race. Misunderstandings—framed as mistakes—highlight the shortcomings of guidelines and trainings that are presented as neutral or technical. Misunderstandings become cultural boundary objects from which clients begin to attend to data worker positionalities in the form of corrections. Mistakes may also highlight for clients the limitations of their own positionalities, revealing realities they had never thought to include in the instructions. However, misunderstandings often surface during client review processes when clients notice large swaths of data do not match their expectations. In other cases, misunderstandings are so implicit that they become invisible.

4.2.2 Implicit Social Biases Beyond instances where data workers described being uncertain about the cultural or identity-based labels they were applying, some data workers showcased implicit social biases when trying to describe annotation difficulties. They did not describe their perspectives as biases explicitly, but instead demonstrated having more difficulty interpreting certain gender, race, and age groups. In some cases, their explanations of these difficulties reflected common social biases that cut across cultural contexts (e.g., misogyny, anti-Blackness, anti-Asianness) and are commonly reflected in AI.

Instances of **gender bias** did not always show up when explicitly labeling gender; instead, they showed up when labeling faces for other concepts. For example, Sumbul described having more difficulty understanding the emotions of women in comparison to men when annotating the Emovos project. She said:

> *Woman are mostly difficult to know in which mood they are than men. For example, we saw the disgust and fear expressions mostly in woman, not in men. In women, it was a bit difficult to know in which mood they are.* (Sumbul)

It was interesting that Sumbul had a harder time identifying the emotions of people of the same gender identity; while she could not describe what made it more difficult in concrete terms, it is likely that internalized perspectives of women influenced her perspective that women's emotions are more difficult to read. Such gender biases might lead to differential performance or subtle misclassifications for women versus men.

Sumbul, who is relatively young, also had more difficulty understanding the emotions of younger people. *"Because we know that younger people are more excited and they show other expressions as well, but the younger was a bit more difficult than the olders."* In this case, she ascribes a wider range of diversity of emotions to younger people, which means she both has a harder time annotating them and is viewing older people as portraying more simplistic expressions. **Age biases** may impact outcomes for both young and old faces.

The majority of implicit biases that data workers exhibited were **racial biases**. In particular, data workers living and working in homogenous cultural contexts expressed having difficulty annotating certain features on certain ethnic groups of people. Bernardita, Raiha, Sadham, Lyonis, Pelumi, Shokouh, and Wares all described having difficulty annotating certain racial groups, across multiple different project types. In particular, participants across multiple countries described having difficulties with Black and East Asian individuals specifically.

Bernardita described accidentally annotating different people as the same in a facial recognition project. She attributed her mistakes to an implicit racial bias, which made her unable to distinguish the difference between different Black individuals. Wares and Shokouh, Afghan-based workers hired by EnVision Data for the Emovos project, both expressed having a difficult time interpreting the emotions of certain groups. Shokouh felt "Africans" were particularly difficult for her, saying that she often interpreted their facial expressions as "angry."

Lyonis, Pelumi, and Raiha all had difficulty annotating East Asian faces, particularly emotion and keypoint annotations around the eyes. Though her intent was not malicious, Raiha described this difficulty in ways that reflected common racist descriptors about East Asian eyes, saying she had a hard time because they are not *"completely open."* She felt that guidelines specific to East Asian faces would help her improve her annotations.

Many instances of social bias are particularly hard to ascertain, because the task (e.g., emotion tagging) and the bias (e.g., racial bias) are not necessarily the same. It is difficult to tease apart the intersections of both social bias and misunderstanding. Thus, clients may be unable to discern when data workers have applied less accurate keypoint annotations for East Asian faces or attributed more negative emotions to Black individuals. This difficulty could arise because those annotation differences are not glaringly "incorrect" in the way that labeling a "bus" as a "train" is. Difficulty might also arise if both client and annotator share similar implicit biases, especially considering Sadham's observation that identity beliefs may be learned from Western or global media. Also, while the biases data workers held themselves were implicit, they explicitly named the groups of people they had difficulty with. It is likely that other biases remain entirely invisible, simply because workers do not find annotating them difficult.

Positionality represents how a person fits into a metaphorical space; how one's position enables them to more closely relate to or understand those like them, while disabling their ability to relate to or understand those unlike them. The implicit biases held by annotators against certain populations might result in poor model outcomes for these groups. While popular media was seen as a resource for data workers to ground their interpretation in specific contexts, it was also seen as a potential source of biases. Sadham expressed concern that social media and television could *"give wrong ideas"* about specific groups of people. He said that media he has encountered has promoted racist ideologies. He was concerned that such ideas might be insidiously shaping data work practices. In the absence of explicit guidelines, data workers fell back on resources like media to act as training guidelines. Clients seem unlikely to consider the ideas that data workers are exposed to about identity in media, or in other aspects of life. Insidious and unintentional racial biases were not accounted for in how clients approached or assessed the projects.

4.2.3 Unrepresentative and Unethical Data Collection Thus far, the majority of the unintended outcomes in this section have focused on how data workers imbue data with unexpected or biased positional perspectives. However, the positionalities data workers inhabit also impacted how data is collected. When data is collected, workers act as the connective tissue between client expectations and the cultural worlds that data subjects inhabit. Data collectors become aware of the context of collection, the culture data subjects are situated in, and how they might navigate data collection to meet client demands. To meet project goals, data collectors attempt to hone their tacit knowledge about culture to ensure collection is successful. However, the cultural gulfs between clients and collectors could often result in unintended consequences, such as difficulty collecting certain demographic data and unethical data collection practices.

Gender was a salient factor influencing data collection practices, making some data collectors more or less able to collect human data. Manjola described being wary of approaching strangers as a woman and allowed her older woman neighbor to accompany her, possibly resulting in a dataset of images of mostly women as she was "more comfortable with women." Lyonis, on the other hand, said that women were much more reluctant to talk to him, given that he was a strange man.

Gemma and Jaako, both based in Kenya, described similar culturally contingent barriers to collecting face data. Both spoke of common religious concerns with face photographs being used by data collectors for *"black magic"* (Gemma) and *"devil worship"* (Jaako). Gemma explained that there were times asking participants for their face data that they became violent with her, because they did not trust her intentions. *"Some become violent when you're taking their pictures ... especially [when] there are some projects like you have to take pictures of children,"* Gemma explained. Her tactic for trying to make collection easier and to avoid potentially dangerous situations was to offer a portion of her payments to participants.

These examples indicate that not all data collectors are able to easily access all populations, solely because they are in a certain location or are of a certain gender. That could mean that the data collected is biased towards others they are more comfortable or able to approach. It also makes certain populations, such as children in Kenya, far less amenable to data collection.

Beyond barriers to data collection limiting who is represented in a dataset, it also led to datasets being collected unethically, without the knowledge of clients. Jaako said he would lie to participants about what the images he was collecting would be used for, saying that they were for a personal project:

> *I told them that is my project, that I'm coming up with, that I'm creating an identity management system that could be used in future for the bank, and I needed their support for the videos. That's how I made them believe me, because if I told them it is something international, they wouldn't believe and they would have thought it was a ... some kind of, devil worshiping thing, because in Africa, people are very primitive still ... Most of them are not finished primary school, and I think that's the reason. They are primitive.* (Jaako)

Jaako, who expressed a positive perspective of technology and AI, in particular, described the culture in Kenya as *"primitive"* multiple times. He felt that people's reluctance was uneducated and unreasonable, which is possibly why he did not feel lying about what the images would be used for was problematic. Clients were likely unable to predict or understand the cultural context of their data workers and how it might implicate the collection of their datasets. The selfies Jaako collected for EnVision Data were collected in a way that could be deemed unethical, despite the BPO's mission to provide ethical data to its clients.

4.3 Awareness of the Limitations of Personal Positionality

While thus far, the Findings of this work suggest that positionality is typically implicit to data workers, there were also instances where data workers were aware that they held differential positionalities. Participants acknowledged that some concepts were unfamiliar to them and thus presented more difficulty to their work. As already demonstrated by Gemma in Section 4.1, participants acknowledged several different positional characteristics that might contribute to poorer data work outcomes, including language barriers, inexperience with certain groups of people, and the desire to avoid causing harm due to a lack of knowledge or familiarity.

4.3.1 Gaps Between Client and Data Worker Positionalities Given that the majority of participants serviced clients in the Global North, commonly seen as "Western" countries, most clients relayed instructions to data workers in English. Maakarim noted that this might cause gaps in fully understanding or interpreting instructions. In discussing the required ethical AI training module in particular, he said that the majority of his colleagues have an *"under intermediate level of English"* and that *"the command of English for the course is higher than they have."* He stated that even when subtitles were available, many workers would push themselves to understand English because it is *"the language of the environment"* (data work).

It became apparent in discussing the course with data workers that many of the concepts were being interpreted differently than intended. The course was aimed at teaching workers how to collect and annotate data *"without bias,"* but the majority of workers viewed the term "bias" as directly related to the examples given in the course. For example, Azyan, Hijrat, Baksish, and Sadham all believed that the term "bias" was specifically about ensuring equal representation between men and women, as that was the example given in the course. It is likely that the term "bias" and how it is explained through examples in English did not translate conceptually for those workers whose strengths were in their first language, and not English. Beyond training, many concepts in implementing data collection and annotation tasks might be misinterpreted or confusing for annotators, because they are either underexplained, narrowly scoped, or conceptually untenable between languages.

4.3.2 Concern about Introducing Negative Biases due to Positional Gaps However, despite ambiguity around the term "bias," some data workers were aware of the potential for different biases to impact data work. They were concerned about annotators accidentally embedding their biases in the data. For example, Aakrama discussed his fear that bias would permeate how Arab people were assessed in the ChAI project:

> *I think the culture is important, because ... in Arabic culture, people speak loud, and most of this video is about Arabic culture. When you don't know, thinking this man is angry, but some people in Arabic country speak very loud ... and when you don't know this, maybe you make a mistake about this man, [like he] is angry ... In this project, because this project is in English language, sometimes people, because they don't have knowledge about language, cannot speak it. But if speaking native language, [they] don't have a problem. We can't decide ... is it about language or about nervous[ness] or stress? ... because the person is trying to find some word to say but you might be thinking it is about nervous[ness] or stress.* (Aakrama)

Aakrama highlights concerns about potential implicit cultural biases leading to Arab speaking candidates in the ChAI project being rated more poorly in desirable categories, like "Would you invite this person for a job interview?" It is possible that those annotators who do not understand speaking patterns or facial expressions commonly presented in Arabic cultures view individuals negatively. Further, Aakrama feels that crucial context for properly rating videos is lost when the annotator is unable to understand the language in the videos, or when the candidate is asked to speak in their non-dominant language. Similarly, Gemma spoke to how collecting data was much more accessible to her due to shared language: *"So, I mostly collect data for Africans, because language is something different, when you speak to someone in your language they can understand you [more] easily than going to speak to someone who doesn't understand your language."* Concerns about annotator biases also highlight the interaction between annotator worldviews and data subjects. Certain characteristics may only be legible to annotators who identify a shared positionality with how they perceive the data subjects. Aakrama might find confidence in the speaking patterns of Arabic data subjects, while other non-Arabic annotators might find this confidence illegible to them.

4.3.3 Acknowledgment of Local Access Limitations in Collection Some workers also explicitly take on the role of shaping what data subjects look like in their work, opting out of collecting subjects unfamiliar to them. Gemma stated that she only collects images of Africans, because she doesn't have *"access [to] a lot of Caucasian people ... other people can do [that collection]."* Gemma actively limits her role as a data collector to subjects who are accessible and familiar to her. Gemma provides an example of how a data worker might attempt acknowledge and attend to their own limitations in their work. Yet, such personal responsibility fundamentally requires that a data worker is aware of their own positional limitations—and that clients are pliant to such decisions.

4.3.4 Empathetic Data Practices to Fill Positional Knowledge Gaps In order to improve outcomes, some workers might explicitly attempt to close positional gaps through practices of empathy. Maakarim described engaging in empathetic practices by *"putting [himself] in another's shoes"* and trying to do more research on certain identities:

> *I do know the LGBT, there are multiple genders ... I'm not quite knowledgeable in this area, so maybe I have to make my research before I speak about it. I do because maybe sometimes I do not have enough context or knowledge knowing which label will make this person anxious or feel bad.* (Maakarim)

In this example, Maakarim starts with a base knowledge of LGBT and gender expansive identities but is aware that his knowledge is minimal. He describes feeling *"concerned"* because he might accidentally label data in a way which is offensive or causes harm to LGBT populations. Research in this case is an attempt to close the gaps caused by his own lack of experience with LGBT populations, while also realizing he still might not feel comfortable annotating such data. Further, tensions arise between Maakarim's concerns about what a potential data subject might feel about his interpretation of their appearance and his work to provide data to an organization that may not share his concern with the data subject's feelings. Maakarim has chosen to prioritize, at least on an emotional level, the potential harm his individual interpretations could cause to a data subject, even if his work—and income—are predicated on a client's desires and beliefs.

In the end, all forms of annotation are subjective, filtered through the worldviews each worker brings to the table. Wares summarized how annotation is not an objective process and that "ground truth" is imbued with specific values. He described an instance on the Emovos project where he had disagreed with his supervisor on what was the *"correct"* label, specifically because he believed that there was no *"correct"* answer:

> *It's about recognition from every person differently. When we look to someone, we select the things that we get from their face ... but maybe, another person gets something else.* (Wares)

4.4 The Benefits of Diverse Positionalities in Data Work

Despite some of the concerns in Section 4.3, many participants expressed a belief that diverse perspectives and experiences can improve the outcomes of data work. Data workers believed that the diverse positionalities of their peers helped to educate them and expand their own worldviews, and also helped to close knowledge gaps in the annotation process. As Abyar commented, *"The more we work, the more we know."* Work experience, especially with diverse colleagues, can make data workers more effective and thoughtful in their approach to their work. As workers are exposed to different perspectives and ways of viewing the world, they develop new tacit knowledge that influences their approach to their work.

Raiha expressed that having a diverse team made datasets not only more accurate, but also helped to avoid biases: *"When we collect the dataset we need people from different nationalities, different races, ... maybe gender also... in order to collect a good and accurate dataset."* Raiha saw the diversity of worldviews from the types of diverse positions a data worker might occupy as a boon. Despite the different opinions workers might bring to the table, Raiha felt the more diverse a workforce is, the more accurate the annotation would be. She also felt that the more voices there were in the room, the more likely it was that a dataset would avoid undesirable outcomes, like racist views.

None of the participants in this study expressed negative views of diversity. Instead, participants' commentary insinuates that having diverse teams working on the same project might provide a richer and fuller vision of the world. At least, having diverse data work teams can highlight the different perspectives which are currently overlooked or made invisible by current processes. Much like standpoint theorists, participant viewpoints on diversity recognize that people approach problems from different positional perspectives. Most importantly, these different perspectives may fill gaps which may otherwise be missed—and eventually introduce negative and harmful outcomes once a model is deployed.

5 Discussion

We have built on the prior work of Miceli and Posada [73, 74] to center data workers and their practices, specifically in the development of computer vision datasets. We have documented how data worker positionalities influence their work, as well as unintended outcomes when positionality is not attended to. Moveover, our findings highlight an important tension: while workers believe diversity is a boon for computer vision, there are limitations on what aspects of their positionality they are aware of.

In our discussion, we further contextualize the role of positionality in data work demonstrating the benefit of adopting positionality as a lens. We begin by highlighting insights relevant for computer vision, specifically how positionality highlights gaps and un(der)considered actors. We then discuss ways that bias mitigation in dataset curation fails—specifically in its inability to account for positionality. Finally, we conclude by proposing an approach to data work we call *positional (il)legibility*, an approach which actively centers and attends to how positionality shapes datasets.

5.1 The Centrality of Positionality to Computer Vision Data

The positionality of data workers is salient to data work in both data collection and data annotation and across human-centric and object-centric data types. Concretely defining the way data workers referenced and exercised their subjective positions is difficult, if not impossible, given workers referred to a tacit knowledge influenced by a number of interlocking identities and relationships in conducting their work. Much like Rose argues in [97], we found that fully accounting for positionality in research contexts is an ideal; despite reflexive practice, much of positionality is inaccessible and uncertain, especially when analyzing the practices of research subjects through one's own positional lens. Rather than attempt to define a taxonomy of data worker positionality, we instead revealed the multitudes of positionalities participants expressed in discussing their approach to work. Understanding how data workers express their positionality through their work allows us to do two things.

First, it paints a more contextual and rich image of how identity concepts are applied to data concepts for computer vision. It reveals how workers refer to culturally situated notions about identity, rather than idealized universal ones—like religious garb and what it communicates about gender. Identity is designed through a positional lens. Given that identity is interpreted through the positionality of data workers, they hold knowledge about some identities, but not others, which in turn impacts their understandings and beliefs (e.g., understanding of trans people, exposure to certain media portrayals). Such knowledge is deeply implicit, based on experiences, values, local context, and economic conditions. Thus, beliefs about identities are largely tacit to workers and difficult to unearth. It is because positional understandings might seem so obvious that it is important for scholars to piece together how it manifests in data projects. Doing so can reveal gaps in current practices.

Second, it reveals a web of positionalities present in the process of data work. Figure 2 showcases the web of relationships revealed through examining only data workers as the central point, but one could imagine centering clients or supervisors would expand this map of positionalities into further networks. Data workers not only interpret data instances, like individual images, through a positional perspective. They also negotiate positionality with other human actors during the process of their work. For example, Jaako relied on his own positional familiarity with cultural beliefs in Kenya to navigate asking data subjects for their face data. Gemma decided to offload the responsibility of making a decision about gender classifications to her supervisor when she was unsure.While data workers are central to this specific study, others who data workers interact with also have their own positionalities which influence the practices of data work. While not documented in the scope of this study, Gemma's supervisor then had to make their own decisions about gender, as influenced by their particular standpoint. Even data instances themselves demonstrate a specific worldview, documenting a place, time, and perspective as they are captured. Positionality has a different impact depending on what the data options are (e.g., data workers having trouble when data has people of certain races).

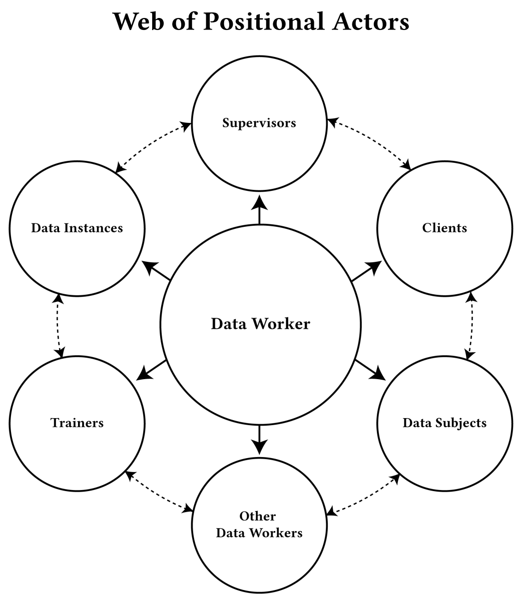

Fig. 2. A diagram illustrating the other positional actors that data workers interact with. Data workers interact with data instances, but also data subjects, trainers, supervisors, clients, and other data workers. Further, all of these positional actors may interact with each other outside of the context of centering data workers (e.g., data subjects may also interact with data instances, and supervisors interact with trainers.) Each actor in this network may influence and negotiate with one another.

As argued by Miceli and Posada [74], instructions begin to offer glimpses into the worldviews of clients, which data workers must attempt to adopt. When Sadhil interpreted the definition of a "blouse" as something different than the clients' expectations, it revealed that the client also had their own worldview which was otherwise left implicit in the term "blouse." While such definitional worldviews are often easily reconciled with communication and examples, many other worldviews are much more difficult to address. For example, trying to attend to differential perspectives on keypoint annotations for certain racial categories is more difficult, because "accuracy" is dependent on pixel-level annotations. Further, many worldviews are so deeply embedded that workers likely couldn't describe them; trying to build shared understanding about such deeply implicit perspectives is extremely difficult. Jaako's perspective on his own country's culture as "primitive" also begs questions about the relational exchange of positional perspectives between data workers and their clients in the Global North. Did Jaako have this perspective due to his regular interactions with more technocratic clients, or was it something else? Attending to questions raised by the web of positional actors involved in the process of data work, and how data workers relate to this web, reveals a reality that data workers are not the sole source of "bias" in computer vision. There is ample opportunity to further understand how relational positionalities shape data work—and thus intervene at these points of interaction.

5.2 The Failures of Bias Mitigation Approaches

Positionality is complex. Many of the positional standpoints that data workers are operating from are invisible. To make matters more difficult, workers also have a difficult time articulating the role of positionality in their decisions. Further, positionality is not confined to the individual. Positionality is relational. Data worker perspectives are shaped through interactions with trainers, supervisors, clients, data subjects, other data workers, and the data itself. As Bowker and Star suggest in their advocacy for exposing the underlying political work of structuring and deploying data infrastructures [10], we argue that attending to the underlying sociocultural context of data work can highlight new possibilities for data production. Exploring positionality reveals the limitations of viewing data in computer vision from a positivist episteme—as something objective, neutral, and containing an inherent ground truth.

Current approaches in bias mitigation (e.g., [38, 46]) attempt to debias and align data with some universal truth. Bias discussions often imply that bias can be easily identified, measured, and mitigated. Bias mitigation frames bias as discrete categories to be attended to and measured, presenting group parity or performance parity as fair [62]. From the perspective that data is not biased but instead laden with positional worldviews, bias mitigation approaches can be seen as a failure to attend to positionality. Rather than attending to bias as the implementation of a specific worldview on identity, bias mitigation largely assumes one reality is correct. For example, "debiasing" gender classification technologies might showcase parity between the categories of female and male (e.g., [22]). However, this parity might mask the reality of different perspectives and realities of gender. First, it fails to account for other lived experiences like trans experiences, other gender identities outside this binary worldview like non-binary genders, or other intersecting identity categories like race or skin color. But further, it fails to acknowledge what gender means in context. Data workers embed cultural perspectives about race, gender, age, emotion, clothing, etc. For what culture, time, or politic does gender parity operate?

Further, bias mitigation approaches fail to account for the context of data generation and annotation. In data work, the tools that data workers have are: instructions (which they do not always get), their positionality, and their exposure to the categories they are expected to collect or annotate. Clients imbue guidelines with their own worldviews, yet fail to acknowledge, document, or explain these worldviews. They also fail to account for data workers as people with their own positional perspectives. Clients in the Global North regularly fail to realize that data workers might be unfamiliar with certain Western-centric categories, like Hispanic vs. Caucasian (e.g., Gemma). They do not account for how exposure to certain categories might occur for data workers. Often, this is through daily life, or exposure to media, which may or may not reflect the expectations of a Western context. Clients instead present barebones guidelines that do not engage with differing perspectives or provide examples that clearly articulate an expected worldview. Implicit in this failure to account for data worker positionalities is the expectation that workers automatically adopt a Western worldview.

In reality, bias mitigation can make "bias" invisible. Invisible are the ways that data workers, operating from specific positionalities, interpret the instructions given to them by clients, whose own positionalities influence these instructions. In reality, positionality very subtly shapes data and thus model outcomes. Model outcomes can differ between contexts based on data [105], showcasing there is no universally unbiased gold standard for computer vision. The types of subtle "biases" that arise when exploring the nuances of positionality reveal major limitations to a positivist, universalist approach to machine learning and fairness.

5.3 Positional (Il)legibility

Even in cases where a model does perform well in its intended context, applying the lens of positionality to data work can reveal how practices influence data work, in desired or undesired ways. Given that positionality gives workers certain perspectives—and some workers might be epistemologically "closer" to certain subjects than others—we propose an approach that attends explicitly to epistemic standpoints. Rather than focusing on whether data is biased or unbiased, we propose attending to certain perspectives in data work as either legible or illegible to workers. We use positional legibility to refer to the perspectives on data that are familiar, clear, and understandable to workers. On the other hand, we use positional illegibility to describe data that workers are unfamiliar with or do not understand.

Prior scholars have also proposed that worker identity influences the accuracy of their work. Those with identities shared by their data subjects are more accurate at annotation, for example [85]. However, in a positional-first approach to annotation, accuracy is not the primary goal, as accuracy purports a universal ground truth. Unlike traditional debiasing approaches, the notion of positional (il)legibility would mean adopting an interpretivist epistemology that posits there is no objective reality, only subjective and situated interpretations.

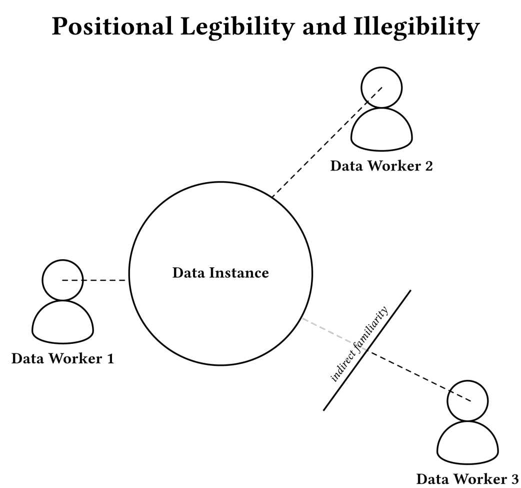

Fig. 3. A visual representation of different levels of positional (il)legibility. Data Worker 1's positionality (e.g., gender, race, culture) aligns most with the data instance, making the data positionally legible to them (Highly Legible). Some of the data instance is legible to Data Worker 2 (e.g., gender), but not all of it—they are viewing it from a much different angle than Data Worker 1 (Partially Legible). The data instance is illegible to Data Worker 3, who has no experience with any aspects of the data instance; they instead view the data instance through the lens of others—like client instructions or media—but have no personal experience with the characteristics themselves (Illegible).

Currently, context in the process of data work is lost to debiasing approaches. Workers tacitly refer to positionality as an interpretive resource—making sense of a Western mindset as best as they can. They must translate the positionality implicit in guidelines through their own lens, then conduct the work based off of their interpretations. Misunderstandings reveal gulfs between positionalities of clients largely based in the Global North and data workers based in the Global South. For example, clients looking to collect data ethically might not realize when data workers have breached their own personal view on ethics. In such cases, data workers likely do not realize when they are engaging in “problematic” practices from the perspective of Western ethics. They are not being purposefully unethical but are relying on tacit knowledge about the context of collection to get their jobs done. Similarly, clients assume that data workers in different contexts, where racial and gender categories might differ greatly from client countries, will innately understand these categories without examples. They not only fail to consider these categories may have different meanings (or no meaning) to data workers, but that any knowledge of these categories that workers have might come from portrayals in the media, rather than from exposure to people in their daily lives. Such exposure might result in annotations such as those Wares was concerned about, that all Arabic men in hiring videos are “angry.” Clients need to make their own positions on data work legible to workers explicitly, outlining their own worldviews, their expectations based on those worldviews, and why it matters. Clients also need more open channels of communication, so that workers are not solely relaying confusions or mistakes, but also negotiating their own perspectives. Some data might be more legible to data workers than they are to clients. Gemma might have more knowledge about gender identities beyond cisgender male or cisgender female than her clients. However, current practices prioritize the worldviews of clients, regardless of whether the data is actually legible to them.

Adopting positional (il)legibility as an approach to classification, rather than assuming that objective classifications are possible regardless of data worker positionality, grabs positionality by the horns. Positional (il)legibility assumes positionality is always present in data work, given the range of positional actors involved in the process. Given that positionality is always present in data work, and thus data work is never neutral, objective, or “unbiased,” we might design guidelines, select data workers, question assumptions, and attend to open questions surrounding issues of positionality by mapping out our relationships with data instances (as seen in Figure 3). Wares’ point about contacting one another when confusions arise points to areas to begin closing these different gulfs: better training, better guidelines, and better communication. While there are already many resources available for hiring and training data workers (e.g., [65], creating guidelines (e.g., [63, 84]), and documenting decisions (e.g., [33, 76, 77]), there is still ample opportunity to appropriate such resources for a positional approach to classification, rather than a positivist one.

6 Considerations for Positional (Il)legibility

Despite datasets being regularly portrayed as neutral and unbiased [101], they are laden with the values and perspectives of the humans who work to create them. While many scholars have focused on correcting biased datasets, we have shown that “bias” extends beyond the binary values of “correct” and “incorrect” classifications. All datasets are steeped in “bias”—values, perspectives, *lived experiences*—in the form of positionality. Each data worker involved in the construction of a computer vision dataset has their own relationship with the data instances they are asked to collect and label. Some workers may be closer to the data instance than others, through personal experience, identity affinities, cultural knowledge, exposure to concepts, and so on. In other words, as we described in Section 5.3, the data instances of datasets are legible and illegible dependent on each worker’s positional vantage point.

In this section, we present some initial steps for adopting positional (il)legibility into data work practices. We outline four initial possibilities for actively acknowledging and engaging with positionality as a core feature of dataset construction.

6.1 Assess and document the positional perspectives of data workers.

Given both the qualitative insights from the study at hand and the quantitative insights from prior work which showcase the effect of annotator demographics on data outcomes (e.g., [85, 105]), the role of positionality should be more acutely engaged with in dataset construction. Both research on the role of positionality in defining data and documenting the positions of data workers are currently underdeveloped in current machine learning practices. We advocate expanding both research and documentation practices on positionality in dataset construction.

There are still vast opportunities to understand how data worker positionality shapes datasets, in both broader academic research contexts and more product-specific industry contexts. For example, given it was difficult for data workers to describe otherwise tacit knowledge about how they made data instance-level decisions about identity, we see opportunities for digging deeper into understanding how data workers label concepts like race, gender, or emotion—through both qualitative and quantitative approaches.

Improved research on positionality in data work should also go hand-in-hand with adopting documentation practices for positionality. To improve the transparency of machine learning datasets, numerous scholars and practitioners have already put forth frameworks for documentation (e.g., [1, 33, 50]). We advocate for expanding documentation practices to explicitly include data worker positionalities. Beyond solely listing out data worker demographics or locations, we promote including deeper insights about how data worker positionalities shaped the dataset and its implications for dataset usage.

6.2 Train models for specific positional vantage points.

Numerous scholars have critiqued the notion of generalizable AI as it would ignore meaningful differences between populations (e.g., [28, 92, 101]) and promote Westernized perspectives and identity-based marginalizations globally (e.g., [52, 58, 64, 102, 106]). Rather than attempting to build massive datasets aimed at building generalizable models that claim a "view from nowhere" [107], practitioners and companies should consider positionality as a method for building positional models. Given data workers offer different levels of legibility to specific identity experiences when collecting and annotating data, leveraging data worker positionality could be useful for building models aimed at more specific experiences, cultures, or locales.

Models aimed at a United States audience could be built using the expertise of data workers located in the United States, rather than relying on data workers in Kenya or Afghanistan who are expected to learn and apply United States values. Similarly, models aimed at consumers in Kenya could be built using the expertise of Kenyan data workers. Beyond building models specific to consumer locales, positional models also offer researchers opportunities to assess how cultural or identity-based differences might manifest in machine learning data. Technical researchers and engineers might consider exploring techniques for handling subjective and shifting concepts, such as through dynamic fuzzy machine learning [69].

Adopting the perspective that data workers should be hired to conduct data work for the goal of positional legibility would also necessitate a rethinking of the value of data work. Currently, like the data workers featured in this study, data workers are largely hired from the Global South due to practices of labor arbitrage—practices adopted not only by Silicon Valley tech companies, but also by academics in the Global North. As described in Section 3.1.2, locating any data workers employed in the Global North was difficult, given the low compensation rates offered on platforms like Upwork. Thus, we also point to the vast literature on improving labor conditions and regulations for outsourced data workers (e.g., [51, 56, 109]) and encourage researchers and practitioners to adopt fair working conditions and labor policies when employing data workers.

6.3 Involve data workers in scoping dataset requirements.

Beyond being a core feature of dataset construction, we posit data worker positionality as an *asset* to dataset construction. As demonstrated through numerous examples—such as Jaako's ingrained understanding about cultural beliefs and practices and Gemma's knowledge of trans identities—data workers bring a situated expertise to the data they work with. Yet data workers are not involved in determining the requirements for dataset construction. Rather, they are often employed through the lens of human machines, encouraged to make quick and otherwise "neutral" decisions, setting aside the intrinsic natures of their positionalities.

Instead of viewing data workers as cheap outsourced labor for applying client visions to data categories, data workers can instead be involved as co-creators at the outset of dataset construction. Much like the consideration just presented in Section 6.2, the positional legibility of data workers can be leveraged in scoping data needs and categorical definitions—and their illegibility can highlight gaps in collective knowledge and data needs. As we saw with confusions over defining a "blouse" in different cultural contexts, involving data workers in scoping stages could help teams avoid miscommunications and improve data quality.

Here, we foresee two potential avenues for involving data workers in scoping dataset requirements. First, we foresee the potential for co-design on individual dataset projects. Social computing researchers have long turned to co-design, action research, and participatory design methodologies for involving stakeholders who are otherwise disempowered to participate in design processes. Thus, we recommend turning to the rich history in social computing of involving stakeholders in design processes, including with contingent workers (e.g., [122]).

Second, in cases where data curation is a core component of a team or business, we promote hiring data workers as full-time employees embedded into product and research teams, rather than hiring them as contingent workers for low-level data tasks. Datasets are crucial to machine learning models and thus earn the companies which collect them vast amounts of money [30, 54]. Yet, datasets continue to be treated as a lesser concern than model work [99, 101]. Hiring data workers into traditional employment roles would mean embracing and valuing their expertise in different methods, benefits, and challenges for curating data.

7 Conclusion and Future Work

Computer vision is premised on its training data, the data used to teach a model what the world looks like. The necessity of training data has resulted in a whole new industry of tech work, called data work. Data workers collect and label the images needed to train computer vision. Emerging research on data work for machine learning has revealed issues of economic precarity [4, 5, 39] and a lack of power over work conditions and procedures [47, 74, 116]. Nonetheless, data workers are regularly expected to provide "unbiased" and objective data in the pursuit of fair computer vision.

This study rejects the notion of "unbiased" and objective data to specifically explore how human positionality—the standpoint through which an individual views the world—influences the processes and outcomes of computer vision data work. We conducted 27 interviews with data workers (employed as freelancers or at a data BPO) about how they interpret identity concepts when doing collection and annotation work. We found that worker positionality influences decisions during data work through implicit tacit knowledge, which data workers had a difficult time articulating. We also found unintended and unexpected approaches to data work, like social biases and unexpected collection procedures. Such unintended outcomes occur when positionality is not explicitly attended to by the clients hiring data workers.

We discussed how attending to positionality in data work reveals not only the gaps in worker perspectives, but also a range of positional actors that influence data work. We outline how current approaches to bias mitigation in computer vision actively fail to account for bias beyond a positivist view of "correct" versus "incorrect," instead of attending to the reality that positionality is not black or white. We propose positional (il)legibility as a framework for capturing positionality in the data work process and actively attending to both the pros and cons of positionality in data work.

Our work was not focused on unearthing the exact standpoints important to specific computer vision tasks, as it has so much to do with what a model will be used for, who is using it, and where it will be used [101]. Rather, we offer a taxonomy of actors and contexts which are relevant to attend to within specific development scenarios. Future work should consider attending to this taxonomy within specific, highly constrained scenarios to better understand the role of specific standpoints.

Finally, we feel the need to highlight that, given the unstable labor conditions and lack of formal labor regulations governing data work (and other gig work) [126], our recommendations are intrinsically tied to larger legal and economic incentives connected to machine learning. While we believe our recommendations would benefit the design and quality of all data-centric projects, we also hope that they might provide some insights into ways that future regulations might be implemented. Further, while we examined the role of data workers in defining identity concepts in datasets, we also acknowledge that clients (or requesters [74]) play in shaping datasets. Thus far, there has been no scholarship examining the role of client positionality in defining data categories or scoping datasets. Thus, in looking beyond data workers as a source of "bias," we hope to see future research assessing the positionalities of those scoping the requirements for machine learning datasets. Given positionality is inherently bound up in issues of power [49], we hope to conduct future work on *differences of positional power* between the numerous actors involved in shaping datasets for computer vision and machine learning.

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A Participant Appendix

A.1 Tables and Figures

All Participants					
Alias	***Source***	***Employer***	***Role***	***Country***	***Subregion***
Yasmin	EnVision Data	EnVision Data	Annotator, project supervisor	Bulgaria	Southern Europe
Ghaliyah	EnVision Data	EnVision Data	Annotator, trainer	Bulgaria	Southern Europe
Dinorah	EnVision Data	EnVision Data	Project supervisor	Bulgaria	Southern Europe
Aakrama	EnVision Data	EnVision Data	Annotator	Bulgaria	Southern Europe
Abyar	EnVision Data	EnVision Data	Annotator	Bulgaria	Southern Europe
Wares	EnVision Data	EnVision Data	Annotator	Afghanistan	Central Asia
Sumbul	EnVision Data	EnVision Data	Annotator	Afghanistan	Central Asia
Shokouh	EnVision Data	EnVision Data	Annotator	Afghanistan	Central Asia
Sadham	EnVision Data	EnVision Data	Annotator	Lebanon	Western Asia
Raiha	EnVision Data	EnVision Data	Annotator	Lebanon	Western Asia
Makaarim	EnVision Data	EnVision Data	Annotator	Lebanon	Western Asia
Hijrat	EnVision Data	EnVision Data	Annotator	Lebanon	Western Asia
Baksish	EnVision Data	EnVision Data	Annotator	Lebanon	Western Asia
Azyan	EnVision Data	EnVision Data	Annotator	Lebanon	Western Asia
Jaako	EnVision Data	Freelance	Collector	Kenya	East Africa
Rebecca	EnVision Data	Freelance	Collector	Phillipines	Southeast Asia
Thanh	EnVision Data	Freelance	Collector	Vietnam	Southeast Asia
Manjola	EnVision Data	Freelance	Collector	Albania	Southern Europe
Lyonis	Upwork	Freelance	Annotator, collector, trainer	Uganda	East Africa
Pelumi	Upwork	Freelance	Annotator, collector	Uganda	East Africa
Malik	Upwork	Freelance	Annotator, collector, supervisor	United States	Northern America
Sadhil	Upwork	Freelance	Annotator	India	South Asia
Nedeljko	Upwork	Freelance	Annotator	Serbia	Eastern Europe
Gemma	Upwork	Freelance	Annotator, collector	Kenya	East Africa
Raines	Upwork	Freelance	Annotator	Russia	Eastern Europe
Bernardita	Upwork	Freelance	Annotator, trainer	El Salvador	Central America
Lucano	Upwork	Freelance	Annotator, collector	Venezuela	South America

Table 2. A table describing all participants in the study. The source column refers to where the participants were recruited from. The employer column refers to where the participant is employed. Freelance participants were recruited from Upwork but often worked as freelancers on a variety of platforms. Some freelance participants were recruited as part of field work with EnVision Data. The role column describes the various roles the worker described doing.

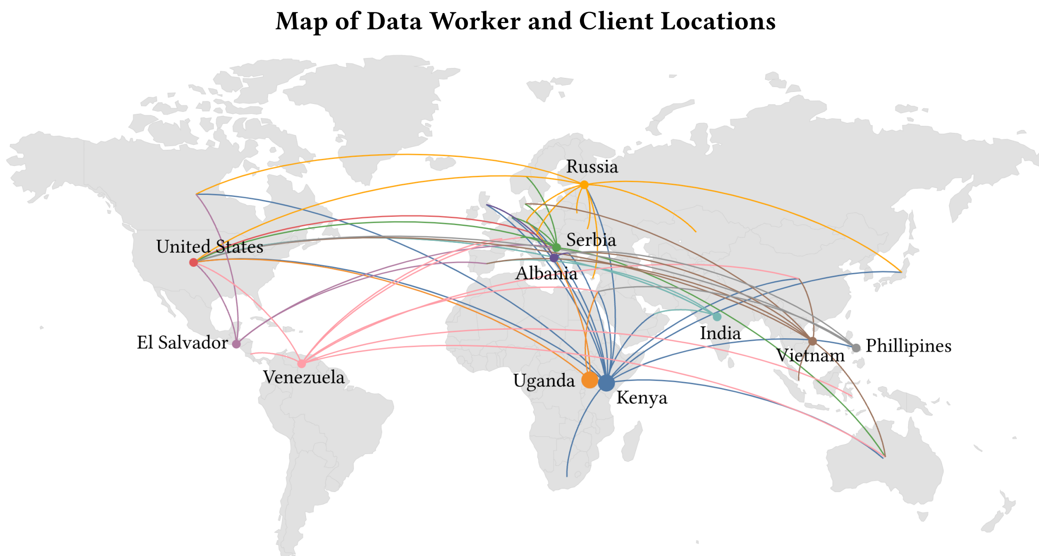


Fig. 4. Dots in this world map represent areas where freelance data worker participants were located. Dot size represents the number of participants in each country. Each line branches from a participant's country to where their past clients have been located. The dot on Kenya is slightly larger because 2 data workers are located there; similarly, the line from Kenya to the US and from Kenya to Russia is thicker because both data workers had clients there. The map showcases not only shows how worker/client relationships span globally in our study, but where the majority of participants' clients are located.

Client Location	***Data Worker Location & Names***	***# Locations***
United States	Kenya (Lyonis, Gemma); El Salvador (Bernardita); India (Sadhil); Phillipines (Rebecca); Russia (Raines); Serbia (Nedeljko); Uganda (Pelumi); United States (Malik); Venezuela (Lucano); Vietnam (Thanh)	10
Australia	Kenya (Lyonis); Serbia (Nedeljko); Venezuela (Lucano); Vietnam (Thanh)	4
Bulgaria	Albania (Manjola); Kenya (Jaako); Phillipines (Rebecca); Vietnam (Thanh)	4
Israel	Kenya (Lyonis); Phillipines (Rebecca); Uganda (Pelumi); Venezuela (Lucano)	4
Canada	El Salvador (Bernardita); Kenya (Gemma); Russia (Raines)	3
China	Kenya (Gemma); Venezuela (Lucano); Vietnam (Thanh)	3
Germany	Kenya (Lyonis); Russa (Raines); Uganda (Pelumi)	3
Spain	El Salvador (Bernardita); Vietnam (Thanh); India (Sadhil)	3
Austria	Russia (Raines); US (Malik)	2
Denmark	Serbia (Nedeljko); Vietnam (Thanh)	2
India	India (Sadhil); Kenya (Gemma)	2
Japan	Kenya (Gemma); Russia (Raines)	2
Netherlands	Kenya (Lyonis); Serbia (Nedeljko)	2
Philippines	Kenya (Gemma); Phillipines (Rebecca)	2
Russia	Kenya (Lyonis, Gemma); Russia (Raines)	2
Switzerland	Serbia (Nedeljko); Venezuela (Lucano)	2
United Kingdom	Albania (Manjola); Kenya (Lyonis)	2
The remaining client countries were served by only one freelance participant each: Albania (Albania, Manjola); Belarus (Russia, Raines); Costa Rica (Venezuela; Lucano); Cyprus (Russia, Raines); France (Venezuela, Lucano); Indonesia (Venezuela, Lucano); Kazakhstan (Russia, Raines); Norway (Serbia, Nedeljko); Serbia (El Salvador, Bernardita); Singapore (Vietnam, Thanh); South Africa (Kenya, Gemma); UAE (India, Sadhil); Ukraine (Russia, Raines).		

Table 3. A table describing where each freelance data worker's clients were located. Most data workers (11; see "United States" under "Client Location") had clients based in the United States.

A.2 Language for Geographic Locales

In describing the geographic locales of specific employees, we have chosen to use the United Nations geoscheme subregions. Subregions are more specific than broad regions such as "Europe" or "Asia." We chose to use geoscheme subregions as an attempt to avoid Eurocentric and colonialist terminologies [41] and shifting geopolitical conditions present in colloquial terms like "Middle East." To respect the origins of each participant's true name, participant pseudonyms were intentionally chosen using the culture of origin of each participant's real name.

A.3 Data Worker Roles

Participants took on a variety of data work roles, in both EnVision Data and as freelancers. Annotators conducted various types of annotations: categorical labeling, semantic segmentation, bounding box annotation, keypoint selection, polygonal annotation, real-time validation, and more. Data collectors collected image or video data. Trainers oversaw the training of other data workers for annotation or collection projects, often writing up the guidelines for the projects. Finally, project supervisors oversaw the overall project, interfaced with management about project confusions or goals, acted as resources for other data workers, and conducted quality checks.

A.4 Recruitment Limitations

As can be seen in Table 2, we were successful in recruiting participants from East Africa, South and Southeast Asia, Southern and Eastern Europe, and Central and South America. However, recruiting participants from some geoscheme subregions was challenging. We were unsuccessful in recruiting participants from Western Europe and Eastern Asia, and only got one participant from Northern America. The participant from Northern America was also an immigrant from Western Asia (Jordan), and thus held a specific positionality as an Arabic-speaking immigrant. We had hoped to include further perspectives from those based in Northern America and Western Europe because there has been little research on data workers from those regions; primarily, Northern Americans have featured in research on "gig work" broadly [59, 115] and content moderation more specifically [82]. We had also wanted to include Eastern Asian participants, particularly those located in China, because China has a massive AI industry and is a hub of data annotations [8, 121]. However, we could not locate workers who did data collection or annotation to invite from these subregions on Upwork. It is possible that workers from these regions are less likely to freelance data work and more likely to work for specific BPOs, like Appen China. While we explored options for including Chinese data workers by reaching out directly to Chinese data BPOs and joining Appen China forums, gatekeeping and language barriers were prohibitive. Inclusion of participants from these subregions remains prime for future work.

B Project Appendix

B.1 CaringHearts Project

CaringHearts is a human-in-the-loop project where data workers actively monitor patients in elderly care facilities in the United States. Data workers see a blurry live feed of a patient's room with automated skeleton tracking in place of the actual person. The data worker is asked to monitor this skeletal figure to determine the state the person is in. The worker is given a guide for different scenarios where they would alert an adminstrator of a potential safety issue.

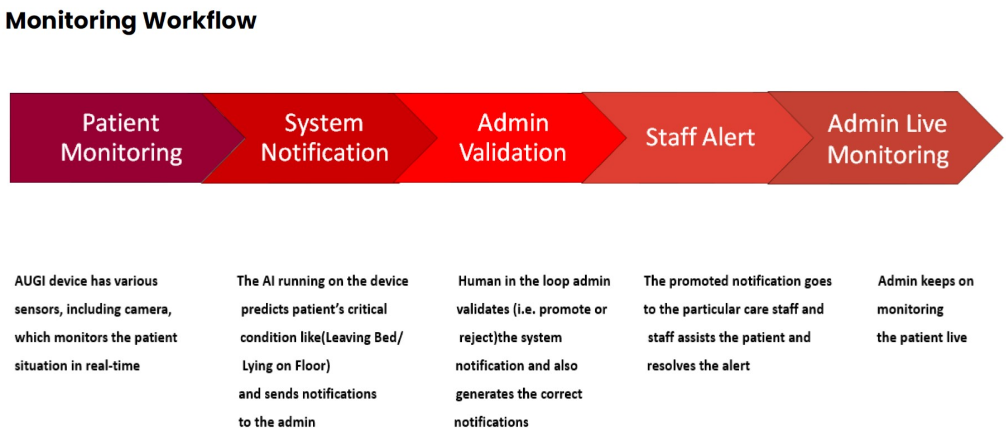
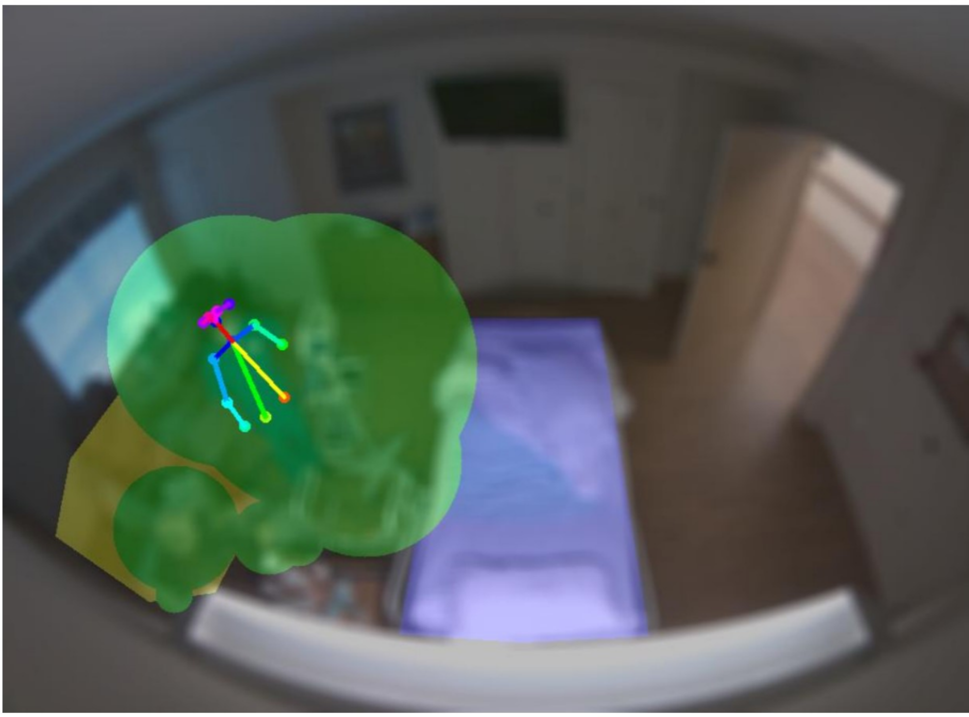


Fig. 5. The CaringHearts patient monitoring workflow.

An example of a CaringHearts annotation



Notification	Color	Definition	Admin App Process
Lying on Floor Level 0	Red	The patient has fallen on the floor or appears to be in a highly compromised position	If Positive: Promote, and notify manager If Negative: Reject

Fig. 6. The image shows an example of the screen a CaringHearts worker would see, with automated human skeleton detection showcasing the joints of a person. The text below describes this as a "Red" scenario, where a person has fallen from their bed.

B.2 CodeGuard Project

The CodeGuard project was a project where data workers were asked to both collect and label images of sensitive content, including images of weapons and human nudity. For example, data workers were asked to collect "350 to 500 representative images" of 11 different safe or unsafe categories during the second phase of this project. Irina described discontinuing projects about sensitive content because data workers felt uncomfortable doing such projects, particularly due to religious and cultural values.

B.2.1 An email from the client asking for new example images: Task "Extension of the NSFW classifier specificity" would require 350 to 500 representative images for each of the following 11 categories:

(1) very near close-ups of male and female genitalia and/or breasts/nipples
(2) otherwise clothed person but with fully or partially visible genitalia
(3) nude men/gay porn
(4) nude teen boy selfies (18+ y.o. so it's legal to store such files)
(5) nude teen girl selfies (18+ y.o. so it's legal to store such files)
(6) home pornographic content (for example such as the video stream preview images here https://chaturbate.com/)
(7) unsafe close ups of hands (for example involved into handjobs, male and female solo and/or mutual mastrubation)
(8) vulgar gestures with hands or face/mouth/tongue
(9) artistic but fully nude images
(10) tattooed bodies (sketchy, but not nude/pornographic)
(11) close ups of hands (safe images, no pornography)

B.3 SenseEyes Project

The SensEyes project focused on collecting a dataset of diverse faces for the client's face authentication application to be used in mobile banking applications. The client requested that data workers collect selfie videos from people using a web application that they built . The goal of this dataset was to ensure that their face authentication model worked on diverse groups of people. The client wanted the following identity-based distributions in the data: gender (men: 50% of images, women 50% of images) and "human group" (Caucasian: 20%, Asian 20%, African: 20%, Latin American: 20%, Middle East: 20%). EnVision Data worked with the client to determine how best to target the "human groups" in particular, and decided to target specific regions through Upwork's job posting affordances. No instructions were given to data workers on how to determine data subjects' gender or ethnicity.

B.3.1 An excerpt of the job posting showcases how requirements were communicated to potential data collectors: We are looking for people from African and South East Asian countries who can work as "video selfie collectors" for our project. The task of each collector would be to reach out to friends and family and to have 60 unique people record a 2-second video selfie on our app (Webcam or Mobile phones). When you complete 60 unique faces, you will be paid $30.

This project is for a startup that aims to detect identity fraud attempts, developing a software that detects fraudsters who would try to open bank accounts by showing somebody else's picture for verification. Please note that we, and none of our representatives would ask for personal information like name, email or contact details of people in the video selfies. We simply need as many and as diverse facial samples we could gather, in order to train our liveness detection solution which will be used to detect a spoof attempt (a fraudster trying to impersonate another person) by determining whether the source of a biometric sample is a live human being or a fake representation (photo, mask, etc.).

B.3.2 An excerpt from messages sent to each individual EnVision Data worked hired or invited to the job posting: We'd love to consider you for this project. For the first stage we simply need you to answer these 2 questions:

(1) Which country are you from and where are you currently living?
(2) Can you reach out to a minimum of 50 people to collect video selfies?
If YES, which of the following groups can you collect?
  (a) Caucasian
  (b) Asian
  (c) African
  (d) Latin American
  (e) Middle Eastern

Kindly note this information is only needed for the purpose of the project (e.g. regional/diversity).

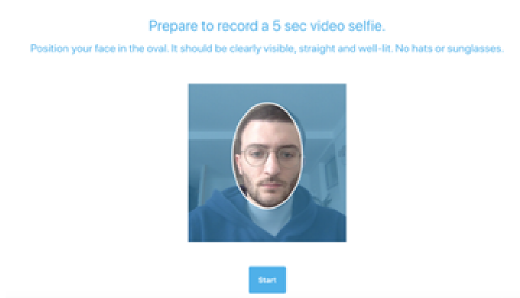


Fig. 7. Screenshot shows the interface for recording selfies each worker used.

B.3.3 SenseEyes Interface

B.4 ChAI Project

The ChAI project was focused on annotating "psychometrics" (emotion and personality characteristics) to train a digital interview platform. The client provided EnVision Data with a dataset of interviews to annotate and a pitch deck with project requirements, which Dinorah then used as the basis for creating an annotation spreadsheet for each annotator to fill out. Annotators were asked to choose from a set list of options in the following categories: gender (male/female/unknown), age range (below 20, 20-30, 30-40, 40-50, 50-60, 60 and above, unknown), ethnicity (Caucasian, Hispanic/Latino, East Asian, South Asian, Black/African, unknown). They were also asked to answer questions about candidate expressions, such as: "Did the person exhibit brow furrows? (yes or no)". Finally, they were asked to rate the candidates on a scale of 1-10. Each video had three annotators, and the final annotation was determined through majority rule (i.e., if 2 annotators chose "yes" and 1 chose "no," the final annotation was "yes").

While examples were given to annotators on categories like "Did the person exhibit brow furrows", they did not provide examples for gender, age, or ethnicity.

B.4.1 A sample of ChAI project annotation categories: **Gender**

(1) Female
(2) Male

(3) Undefined

Ethnicity

(1) Caucasian
(2) Hispanic / Latino
(3) East Asian (Japanese, Chinese, ...)
(4) South Asian (Indian, Pakistani, ...)
(5) Black African
(6) Undefined

Age Range (20 years age band):

(1) Under 20
(2) 20-60
(3) 40-60
(4) 60+
(5) Undefined

Education Level:

(1) No Degree
(2) High School
(3) Bachelors Degree
(4) Masters Degree
(5) PhD Degree
(6) Undefined

Did the person exhibit brow furrows while recording his/her response?:

(1) Yes
(2) No

Would you describe this person as being a direct/serious person?:

(1) Yes
(2) No

Where was the person in the video looking the majority of the time throughout the video?:

(1) In the middle - directly looking at the camera or at their screen
(2) Looking around - avoiding looking at the camera or at their screen

Did the person look enthusiastic through the video?:

(1) Yes
(2) No

What emotional state did the person appear in?:

(1) Anxious
(2) Relaxed

On a scale from 0 - 10, would you invite this person for a job interview?:

(1) 0
(2) 1
(3) 2
(4) 3
(5) 4
(6) 5

(7) 6
(8) 7
(9) 8
(10) 9
(11) 10

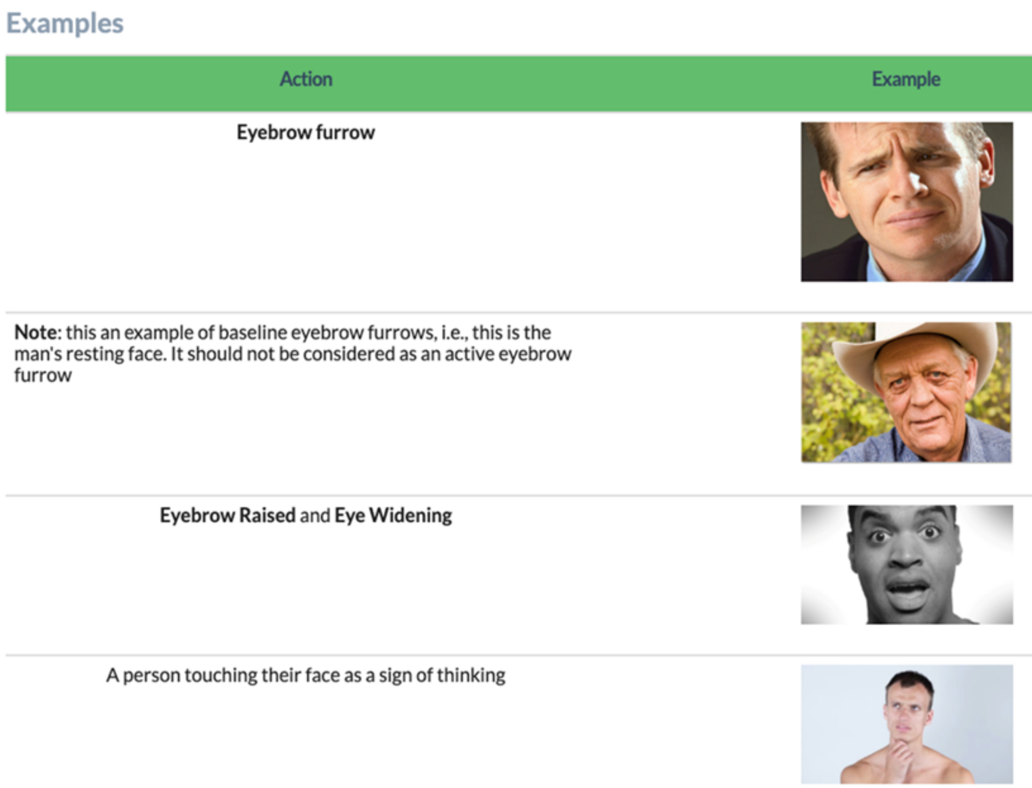


Fig. 8. ChAI project examples. Examples were given to annotators to refer to when labeling facial expressions.

B.5 Emovos Project

Emovos focused on emotion classification for a computer vision advertising application. The client requested data workers annotate the Flickr-Faces-HQ (FFHQ) dataset, a large-scale dataset of faces including public figures and celebrities, with seven pre-determined classes of emotion: sad, happy, angry, disgust, surprised, fear, and neutral.

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