The FATE Landscape of Sign Language AI Datasets: An Interdisciplinary Perspective

DANIELLE BRAGG, Microsoft Research, USA
NAOMI CASELLI, Boston University, USA
JULIE A. HOCHGESANG, Gallaudet University, USA
MATT HUENERFAUTH, Rochester Institute of Technology, USA
LEAH KATZ-HERNANDEZ, Microsoft, USA
OSCAR KOLLER, Microsoft, Germany
RAJA KUSHALNAGAR, Gallaudet University, USA
CHRISTIAN VOGLER, Gallaudet University, USA
RICHARD E. LADNER, University of Washington, USA

Sign language datasets are essential to developing many sign language technologies. In particular, datasets are required for training artificial intelligence (AI) and machine learning (ML) systems. Though the idea of using AI/ML for sign languages is not new, technology has now advanced to a point where developing such sign language technologies is becoming increasingly tractable. This critical juncture provides an opportunity to be thoughtful about an array of Fairness, Accountability, Transparency, and Ethics (FATE) considerations. Sign language datasets typically contain recordings of people signing, which is highly personal. The rights and responsibilities of the parties involved in data collection and storage are also complex, and involve individual data contributors, data collectors or owners, and data users who may interact through a variety of exchange and access mechanisms. Deaf community members (and signers more generally) are also central stakeholders in any end applications of sign language data, and the centrality of sign language to deaf culture identity, coupled with a history of oppression makes usage by technologists particularly sensitive. This piece presents many of these issues that characterize working with sign language AI datasets, based on the authors' experiences living, working, and studying in this space.

CCS Concepts: • **General and reference** → **General literature**; **Reference works**; • **Applied computing** → **Law, social and behavioral sciences**; *Enterprise computing*.

Additional Key Words and Phrases: sign language; dataset; artificial intelligence (AI); machine learning (ML); fairness, accountability, transparency, and ethics (FATE);

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1 INTRODUCTION

As the success of Artificial Intelligence (AI) and Machine Learning (ML) grows in speech recognition, language translation, and other areas that impact people's daily lives, concerns have also grown about Fairness, Accountability, Transparency, and Ethics (FATE). In particular, some major concerns about bias, privacy, accuracy, and over-promotion have arisen. Several authors have addressed these concerns with relationship to people with disabilities [121, 142, 144, 190–192]. Narrowing in, this paper explores FATE issues specifically related to large sign language datasets and their use in AI/ML research and applications.

FATE issues related to sign language AI datasets impact many people worldwide. According to the World Health Organization, there are about 466 million deaf[1] people in the world. Communication barriers can arise between deaf people who primarily use a sign language to communicate and people who do not know that sign language. Though sign language courses are popular in high schools and colleges, especially in the United States, there are few places in the world where a sign language is a majority language. In addition, as speech recognition and spoken/written language translation technologies become more widely used, deaf people may be increasingly left behind due to lack of access. Some AI researchers and practitioners have recognized this lack of language support as a fertile space for innovation in sign language modeling, recognition, and translation (e.g. [209]). However, when these efforts do not involve members of deaf communities and do not account for the social and linguistic complexities of sign languages, there is often a lack of trust and adoption from signers.

In this paper, we explore FATE issues inherent to sign language AI datasets, and examine the relationship between deaf communities and AI/ML researchers and practitioners. The purpose of this paper is not to answer questions about FATE issues in sign language datasets; rather, we aim to describe FATE questions that arise in the context of sign language datasets used in AI.

1.1 AI for Sign Languages

For training models, the fields of computer vision, natural language processing, speech recognition, and machine translation offer powerful methods, and recent advances in deep learning have produced promising preliminary results for modeling sign languages. Three categories of sign language applications that could make use of AI are: sign language recognition (computer identification of human generated signs or signed sentences), sign language generation (avatar production of signs or signed sentences), and sign language - spoken language translation (conversion of signed sentences to spoken/written sentences and vice versa). These technologies may be leveraged in ways that benefit and/or harm various stakeholders, in particular sign language communities.

The state of sign language AI is far behind the state of AI systems for spoken and written languages, primarily due to lack of adequate sign language data. Sign language data is essential to training AI models, and ultimately to building more powerful technologies in support of sign language users. However, far fewer sign language datasets exist than spoken/written ones, and the size of individual corpora is also orders of magnitude smaller (up to 100,000 signs in a typical sign recognition corpus [100] compared to up to 5 million/1 billion words in a typical spoken/written recognition corpus [26]). Small dataset size results in unreliable models. Beyond limited size, the quality of available datasets is limited in a variety of other ways. For example, all existing datasets contain a small number of signers, which results in models that do not generalize well. Such dataset limitations impact the functionality of models trained on

[1] For a time many authors capitalized the word 'Deaf' to refer to a cultural membership and used the lowercase 'deaf' to refer to the audiological status. We do not use this convention in order to avoid the impression that there is a singular deaf culture, and to acknowledge the many, often complex cultural identities of deaf people globally.

them. Furthermore, given the lack of a conventionalized written system of signed languages, the structural differences between spoken/written languages and signed languages, and the fact that most existing language modeling methods were developed for spoken/written language, it is likely that sign language modeling requires the development of new models, rather than the application of existing ones built for spoken languages.

1.2 FATE issues for Sign Languages

There are a number of FATE issues surrounding sign language datasets used for AI, some that are relatively unique to sign languages and some that are common across domains. As we review in the following section, deaf people have faced systemic discrimination and oppression, often on the basis of language and communication [116]. New technologies have the possibility of mitigating or exacerbating these systemic barriers. Though the idea of using AI for sign languages is not new, technology has now advanced to a point where AI-enabled sign language technologies are no longer outside the realm of possibility. The burgeoninKLg of this field presents a critical opportunity to be thoughtful about how to maximize benefits while minimizing harms to deaf people and other stakeholders.

In this paper, we outline FATE-related issues that have emerged in our personal and professional lives in relation to sign language datasets used in AI. The authors are a group of computer scientists, accessibility researchers, cognitive scientists, and linguists. Four of the authors are deaf, and five are hearing. We are from the US, Germany, and India. One of us currently lives in Germany, and the rest reside in the US. Eight of us are fluent in ASL and one of us is also fluent in Kenyan Sign Language. We are not representative of all of stakeholders in this space, and so while we have attempted to be as inclusive as possible, the picture of the FATE issues is certainly incomplete. The questions and concerns raised are extremely large, and we do not attempt to answer them. Rather, we attempt to outline the landscape, and add nuance to major concerns that characterize work in this space. The primary FATE-related issues we will explore are as follows. Each concern is explored in further depth in its own section.

- **Content** - What type(s) of content might a sign language dataset contain? Does the dataset contain deaf fluent signers, and are the signers diverse? Does it contain continuous signing or isolated single signs, interpreted content or unmediated language? Is the signer's visual background static or dynamic? Which sign languages and sign language varieties are included? What are the implications associated with different types of content, for example privacy concerns associated with sign language videos?
- **Model Performance** - How do sign language datasets impact AI model performance? For example, who might be included or excluded from models as a result of dataset design?
- **Use Cases** - What use cases or end applications do sign language datasets enable? What impact do these applications have on people's lives? Who might be responsible for these effects?
- **Ownership** - Who owns the data? What does ownership even mean? Might deaf people claim ownership to sign language data? What about the universities, companies, and other organizations that collect and maintain sign language datasets? And how about the people who contribute data own that sign language data?
- **Access** - Who might desire access to the data, and for what purposes? Is the data publicly available, or held privately? If it is held privately, who is the private entity holding the data, and with whom might they share the data? Who gets to make these decisions? Who is able to copy the data or use the data in situ?
- **Collection Mechanism** - How might sign language data be collected? What implications does the design of the collection mechanism have on who can contribute and how they are compensated? What will the resulting datasets look like, and ultimately what will be the impact on people using end applications built on those datasets?

- **Transparency and Understanding** - What information might interest various stakeholders? How can this information be communicated clearly? And whose responsibility is it that people understand these nuances?

The main contributions of this work are to:

- describe the FATE landscape related to sign language dataset collection and usage in AI research and applications,
- provide orientation and insights on FATE issues for researchers and practitioners, especially AI researchers new to sign languages, and
- outline major FATE concerns and potential pitfalls of work in this space, to help enable people to maximize benefits while minimizing harm.

2 BACKGROUND

In order to understand FATE issues related to sign language AI datasets, it is necessary to have some understanding of sign languages, deaf communities, and the historical context of technology within deaf communities. This section outlines this social backdrop. Background on technical aspects (e.g., existing datasets, and relevant AI/ML models) is incorporated in subsequent sections.

2.1 Sign Languages

Although they are usually marginalized and neglected in education and research, there are hundreds of different sign languages in the world (e.g., American Sign Language (ASL), British Sign Language (BSL), and Kenyan Sign Language (KSL)), and each has a unique lexicon (vocabulary) and grammar. They are naturally-evolved, meaning that they were not the product of a one-time planned innovation; rather, they emerge from and adapt to the communities that use them over hundreds and thousands of years, just as spoken languages do [140, 168]. As scholars have demonstrated since the 1950's, sign languages are not manual versions of spoken languages (e.g., ASL and English are very different, despite being used in some of the same geographical regions). Not only are there many different sign languages; groups of people who use the same sign language can also be extremely heterogeneous. Just as there are different varieties of spoken languages (e.g., British English, Australian English, and African American Vernacular English), there are different varieties of sign languages (e.g., Black ASL [79, 80, 135, 189], and Philadelphia ASL [63]). Different varieties of languages may be named, as the examples above, but determining clear boundaries between varieties can be difficult or impossible. Although signed languages are natural and primary modes of communication, they are rarely included in research, e.g., it's common to equate speech with language.

Signed languages are in close contact with spoken languages, and so are often influenced by and mixed with the relevant spoken language(s). Most sign language users are bilingual (or multilingual), and know at least a signed language and a written and/or spoken language. Like other bilinguals, they switch between languages regularly depending on the context. Unlike spoken language bilinguals, it is physically possible to produce both a sign and a spoken word at the same time (though it is generally not possible to produce grammatically accurate sentences in both a sign language and spoken language at once). This means that bilingual bimodals not only code-*switch* between two languages, they can code-*blend* using bits and pieces of each language at once [52]. When communicating with people who are not fully fluent in a sign language, signers might modify their signing to mirror the structure of the spoken language (e.g., using ASL signs in English word order with mouthing or voicing English words). Written language could also influence signing: a signer reading from a script might use structures from the written text in their signing in a way that they would not otherwise.

Structural differences between signed and spoken languages make signed languages particularly rich. For example, the visuospatial modality is uniquely suited to describing visuospatial scenes (e.g., a car ride through the mountains). Sign languages often do this by making use of depiction or iconicity – where signs physically resemble their meanings [61, 182]. For example, in depicting signs (also known as classifier predicates — not to be confused with classifiers from the domain of machine learning), the handshape often represents a class of object (e.g., a vehicle) while the placement and actions of the hands and arms convey action and manner in relatively unconstrained ways. Additionally, locations and objects in the signer's physical space can be meaningfully used in discourse [155, 167]. For instance, ASL users can direct the sign "ask" from themselves to multiple locations away from them in an arc to indicate they asked multiple people, or they can direct the sign "ask" to the same place repeatedly to indicate they have asked the same person over and over. Another difference is that spoken languages are articulated with a single articulatory system (the vocal tract), while sign languages are articulated with multiple independent articulators (hands, arms, body, and face). Additionally, the hands, body and face are visible whether or not a person is actively signing, while the voice is only audible during word production.

After the ground-breaking observation that the sign (like the spoken word) is made up of meaningless parts (location, handshape, and movement) that can be combined in countless ways [176], various linguists have pursued sign language phonology (the study of how these parts are composed into meaningful language). Originally, linguists viewed the sign as a synchronous unit, as the "meaningless parts" (phonemes), largely occur at the same time. In the 1980s, linguists began to observe that the sign is actually sequentially organized; it has a beginning, middle, and end with unique, active features (hand configuration, placement, orientation, contact, path, nonmanual signals, etc.) that can change at each juncture [33, 125, 154]. With this shift, linguists have tried to better understand which features may persist through the sign and which are dynamic. While combinations of articulatory features in spoken languages can be parsed into sequential phonemes (albeit not without controversy), this approach cannot work for signed languages where at least some features are produced simultaneously and segmental boundaries between features often do not exist or are unclear.

2.2 Deaf Cultures

Languages and cultures are always deeply intertwined, and sign languages are no exception. Many deaf people identify as members of a deaf cultural and linguistic minority, united by common linguistic, social, and political experiences. Just as there is not one universal sign language, there is not one unified deaf community or deaf culture globally. Like any cultural group, members of a deaf cultural group often share a set of values, behaviors, traditions, and goals. At the same time, deaf people are diverse and no single deaf person is representative of all deaf people or even all deaf people in their culture. This *sociocultural model* of deaf cultural and linguistic identities contrasts with a *medical model* of deafness, which presumes that the defining characteristic of deaf people is not language or cultural affiliation, but a sensory deficit. Historian and disability scholar Kim Neilson notes that "when 'disability' is considered synonymous with 'deficiency' and 'dependency,' it contrasts sharply with American ideals of independence and autonomy" [147]. The medical model lends itself to the idea that any deficits must be fixed, and often looks to hearing people to help deaf people in this effort. Alternatively, the sociocultural model lends itself to the idea that society is unjust and must be fixed, and looks to deaf and hearing people to work collaboratively for social justice. It takes an asset-based perspective on deaf identities, and sign languages are often held as one of the most treasured cultural artifacts.

Societal injustice, discrimination, and prejudice on the basis of hearing is what deaf culture scholar Tom Humphries termed 'audism' [84]. Two common forms of audism include 'phonocentrism', the idea that speech is superior to signed and written language, and 'linguicism', discrimination based on language. Examples of audism include ridicule of sign language (e.g., memes mocking sign language interpreters in televised emergency announcements), eugenic practices (e.g., forced sterilization [127] and gene therapy [152]), and police violence (e.g., when a deaf person does not respond to spoken police commands, or gestures to indicate they cannot hear [122]). Audism can occur on an individual basis, and is also systemic. Examples of systemic audism include the routine failure of education systems to ensure all deaf children have access to a usable first language [85], widespread under- and unemployment [67], and the pervasive lack of communication access in medical [113], legal [35], professional [161], educational [143], and other critical settings. These types of oppression can be compounded for multiply marginalized groups (e.g., deaf people of color).

Vitality and endangerment of sign languages is a growing concern. As Snoddon and De Meulder, two leading deaf scholars in Deaf Studies and Deaf Education, argue, "It may well be that all of the world's sign languages are potentially endangered" [171]. Linguistic research on sign languages did not exist until the 1950s [185] and 1960s [176], but research since has enabled formal documentation and preservation of many sign languages. There are also advocacy efforts in many countries to officially recognize a national sign language [51]. Though linguists have argued that a critical mass of deaf signers is necessary for a sign language to survive [29], deaf people often have restricted access to sign language. Over 95% of deaf people are born to hearing parents who generally do not know a sign language at the time of birth [88, 141], and ongoing efforts within professions serving deaf children discourage families from signing with children [68]. This lack of signed language within the family coupled with lack of auditory access to spoken language puts many deaf people at risk of language deprivation [74] and delayed acquisition of a first language, which has lasting effects on language proficiency [134]. The prevalence of language deprivation in deaf people is also a major difference between most spoken and signed languages – the majority of deaf signers may not be completely proficient in a signed language, even if it is their primary language. While late-exposed deaf signers outnumber early-exposed deaf signers, they may also experience discrimination within some deaf communities due to the relatively privileged social position of fluent signers and in particular people from multi-generational deaf families [117]. To complicate matters, a number of constructed systems for manually expressing a spoken language have been taught to deaf children [23, 46, 71], often in lieu of a naturally evolved signed language. Many signers blend these manual systems with a signed language [77]. Sign languages with small populations face additional threats in part because of their community size, limited access to resources, and globalization of sign languages with more users like ASL.

2.3 Deaf-Related Technologies

AI-enabled sign language technologies may be powerful tools that offer significant benefits to deaf people. At the same time, as with any powerful tool, AI-enabled sign language technologies pose risks of (unintended) harmful consequences. Our goal here is not to draw conclusions about relative risks and benefits of various technologies, but to describe a brief history of deaf-related technology, and point out some common benefits and pitfalls so that teams might learn from history and be better equipped to proceed thoughtfully.

Many technologies have been invented with deaf people in mind, some more widely adopted than others. One class of inventions is systems for conveying language. Text-based examples include the deaf-invented TTY [118], a device that was widely used to transmit typed signals over telephone lines until it was replaced by text pagers, which were in turn replaced by smart phones. Closed/open captions, first conceptualized by a deaf person [115], also convert speech into text (e.g., historically on movies or TV, and more recently via smartphones), and videophones allow signers to connect with one another, or to connect with hearing people via interpreters. Another class of innovations involves converting sound to other modalities. Some such devices are not widely used (e.g., vibrating barrettes [4], and vests

[59]), while others have wider adoption (e.g., flashing lights tied to doorbells or baby monitors, which are currently being replaced by smart home systems or smartphone apps). Another class of innovations is those designed to make deaf people hear (e.g., now-common hearing aids and cochlear implants, and earlier innovations including ear trumpets, airplane diving, tonsillectomies, and bloodletting) [194]. Some technologies were originally designed for deaf people but have gone on to be used primarily by hearing people – for example, Alexander Graham Bell is credited with inventing the telephone while in pursuit of technology that would help deaf people communicate [34].

Technology can play a critical role in the preservation and revitalization of sign languages. For example, in the early twentieth century, the National Association for the Deaf (NAD) undertook an initiative to videotape examples of ASL [178]. Many sign languages have been increasingly well-documented as technology for recording, viewing, and sharing videos has become widely accessible. The internet, videophones, and social media have enabled communication across long distances and to broader audiences than had been previously possible. AI-enabled sign language technology may further support efforts to preserve and revitalize sign languages by enabling deaf people to interact with computers and other people using a signed language rather than a written or spoken language. At the same time, technology can be used in ways that harm deaf people. We highlight here two pitfalls that may be especially useful for technologists to be aware of: ill-conceived technological innovations and cultural appropriation/exploitation.

The first potential pitfall is a class of innovations that disability advocate and design strategist Liz Jackson calls the "Disability Dongle: A well intended elegant, yet useless solution to a problem we [disabled people] never knew we had" [183]. While disability dongles may be harmless, they can sometimes have insidious effects. One way these innovations can cause harm is by perpetuating a medical view of deaf people that focuses on (perceived) suffering (described above). The harm can be exacerbated when innovators, especially hearing innovators, are positioned as saving deaf people from perceived suffering in an effort to win resources (e.g., funding, media attention) that might otherwise be used for initiatives that deaf people believe are more pressing.

The second potential pitfall is *cultural appropriation*, the "use of a culture's symbols, artifacts, genres, rituals, or technologies by members of another culture" [164]. While cultural exchange can be experienced positively, it can also be experienced negatively as exploitation of "a subordinated culture by members of a dominant culture without substantive reciprocity, permission, and/or compensation" [164]. As the concept of cultural appropriation within the deaf community typically relates to sign language usage, it may also considered linguistic appropriation. Some deaf people consider the practice of hearing people teaching ASL to other hearing people to be a form of cultural exploitation, when the teacher's goal is to earn money and/or fame while deaf people gain little [163]. Other examples that may be considered cultural and linguistic appropriation include hearing people garnering media attention for work related to sign languages (e.g., performing signed translations of songs), or speaking on behalf of deaf people in publications or interviews with the media. Hearing people deriving monetary and professional benefit from deaf cultural symbols can be particularly offensive given workforce discrimination, under- and unemployment among deaf people [67], and active efforts to prevent deaf people from using a sign language (described above).

In addition to the risks of disability dongles and cultural and linguistic appropriation, deploying AI technologies prematurely introduces risks [91]. Early-stage technologies are by definition important and necessary steps towards more useful technologies, but premature claims about the benefits of current sign language technology can be harmful [3]. The mainstream media and public relations departments in particular may exaggerate claims. Perhaps the most well-known example of a technology that has been inaccurately marketed is the cochlear implant, a medical device designed to provide deaf people with access to sound. While cochlear implants have undoubtedly benefited many deaf people, their benefits have sometimes been oversold to the extent that sign languages have been framed as unnecessary or harmful for implantees. Cochlear implants are not guaranteed to provide access to language for congenitally deaf people [87, 131, 188], and the consequences of their failure can be dire particularly when they are used to the exclusion of everything else [73]. Other examples include sign recognition gloves and other technologies that have been celebrated in the media as sign language translation devices [6, 156, 202], even though gloves are unlikely to have real-world use as they inhibit signing ability, only capture the manual parts of sign language (i.e., ignoring the face, arms, and body), and only provide one-way translation [78]. Even advanced sign language translation technologies could be harmful if they are insufficient and discourage or prohibit people from using more effective and preferred alternatives (e.g., human sign language interpreters). Careful consideration of appropriate evaluation metrics is necessary to determine whether technologies are ready for use in applications with deaf users [93]. For example, researchers have discussed the need for appropriate evaluations of automatic speech recognition (ASR) technologies among deaf users, before deployment for producing captioning in online or real-time settings [18].

3 CONTENT

Sign language dataset content may vary widely, and largely depends on the purpose for which they are collected. The continuum ranges from resources intended for pattern recognition (i.e. for recognizing continuous signing [66, 82, 94, 200] or isolated signs [41, 89, 123] and sign language translation [36, 97]) to purely linguistic corpora (i.e. aiming at the conservation and analysis of the language [48, 110, 193]), to educational resources (i.e. video-based dictionaries [58, 112, 137]). In response to these varied use cases, many dataset properties may vary, and those properties impact FATE-related issues. This section outlines these primary properties, their main possible values, and their FATE importance (summarized in Table 1), with a focus on datasets intended for AI use.

3.1 How does the format of signed content, labels, and metadata relate to FATE?

The format of sign language data directly relates to who can contribute (i.e. who has access to the hardware/software for recording), which in turn impacts the inclusiveness of models trained on the dataset. Signing data can be captured in many different ways: 2D RGB video, 2.5D with depth or a fully reconstructed 3D view, motion capture to track individual body parts with high accuracy, sensor or cotton gloves, and other kinds of sensors (e.g. WiFi-based [132]). A number of sign language writing systems have been proposed (e.g., SignWriting [179] and si5s [14]), though none have been widely adopted, which would be required to produce a large natural written corpus.

Label or annotation format directly impacts who can label the data, which may embed certain perspectives or biases into labels or translations. Labels are required for documenting the contents of sign language data. They enable supervised learning of statistical models to estimate mapping functions between the data and labels. Primary label formats include a written language such as English (either glossed, which maintains the grammar of the sign language, or full translations), linguistic notation systems (e.g., Stokoe notation [177]), computer notation systems inspired by linguistic notation systems (e.g., HamNoSys [75]), and pure computer notation systems used for animation and recognition (e.g. gestural SiGML [56, 160]). Sign language writing systems (described above) are less commonly used for labelling. However, many notation systems are ill-suited to capturing some aspects of sign languages (e.g., depicting signs are challenging to represent), which may subsequently limit real world applications. Using complicated notation systems (e.g., linguistic notation systems vs. written gloss), many of which require sophisticated software (e.g., ELAN [186] and Anvil [96]) means that only trained labelers can contribute. This may exclude many willing deaf annotators from contributing, and limit dataset size due to cost. On the other hand, loosely aligned labels (e.g., sentence-level alignments vs. individual sign units or components such as handshape start and end) may expand the pool of qualified

Parameter	Possibilities	Impact Related to FATE
Signing Data	RGB/Depth Video (2D/2.5D/3D) Motion capture Gloves Other sensors	hardware requirements, recording setup, who can participate, dataset size, quality of resulting models, types of end applications that can be created, privacy concerns.
Label Format	Gloss systems Spoken language translation Linguistic notation systems Computer notation systems Sign language writing systems	annotation granularity, difficulty of temporal alignment, amount of data required for training, labeling process (who can label, with what software), inter-labeller agreement, dataset size (due to cost), and model quality.
Metadata	Recording setup Language Signer demographics (more below)	decisions about which datapoints to include in training, which may impact model accuracy, who the model can recognize, and in what scenarios/domains.
Signer Identity	Hearing Status Sign language proficiency Language deprivation Occupation (e.g. interpreter) Gender Race/Ethnicity Geography	who the model can recognize, and which dialects and/or accents it can recognize.
Grammatical Structure	Single isolated signs Continuous signing	what grammatical structures can be modeled, and which end applications are possible.
Vocabulary	Limited Unrestricted	how much data is needed to train accurate models, which end applications can be created.
Prompt	Prompted/scripted Unprompted/unscripted	data quantity to train accurate models, and if models will work for real-world use cases.
Recording Setup	In-lab Real-world	data quality, data quantity to train accurate models, and model real-world viability.
Post-processing	Compression Quality enhancements Privacy enhancements AI Models Aggregate statistics Simulated data	data quality, data quantity to train accurate models, privacy concerns, and who can make use of the data.

Table 1. Major parameters along which sign language datasets may vary, possible values for those parameters, and the importance of each parameter for FATE considerations.

labelers and be less costly to collect, but may introduce ambiguities and increase the amount of data needed to train accurate models.

Datasets may include metadata about contributors, content, or curation process, and may reveal sensitive information about the people in the dataset. For example, a contributor might be asked basic demographics about themselves. Typical demographics include age and gender, but may also include questions about language and hearing background (e.g., hearing status, age of sign language exposure). Metadata may be stored in digital or paper formats. Digital formats are typically used for scaled datasets.

3.2 What is the impact of including different sign language(s) in the dataset?

The language(s) that are included in sign language datasets will affect the people who can benefit from (or be harmed by) the resulting technologies. Different sign language communities may vary in both enthusiasm for sign language technologies as a whole, and in specific use cases. The field of natural language processing often considers languages as being high-density or low-density languages, a distinction that reflects the availability of electronic corpora for that language. There are a small number of natural languages for which there exist large datasets (e.g. English, Mandarin, etc.). Whether a language is a high- or low-density language has a significant impact on whether or not a language benefits from advancements in AI and linguistic technologies, as the most successful of such technologies require large available datasets upon which to train models. From a FATE perspective, it is notable that this high/low distinction reflects an inequity among natural human languages, as to the potential for AI technologies to be developed for each. While all sign languages might now be considered low-density languages, some sign languages have more financial and material resources and/or more signers and could more easily transition to high-density languages than other languages. Technology for sign languages used in parts of the world with more financial resources or greater numbers of signers may progress more quickly than technology for other sign languages. Research on AI techniques that enable models to be built on smaller amounts of data may help to mitigate inequities among high- and low-density sign languages.

3.3 How does the identity of signers in the dataset impact models trained on the data?

The identity of signers in the dataset impacts the inclusivity of models trained on the dataset. Generally, AI/ML models most accurately process content that resembles the content on which they were trained. Consequently, sign language models work best for signers who resemble signers in the training dataset. For signers, resemblance includes physical appearance (skin color, gender, etc.), which is known to introduce FATE-related issues in other domains (e.g. poor facial recognition for Black vs. white faces [170]), but also extends to other language-specific factors.

Heterogeneity of language use among signers (described more fully in Section 2) in the dataset may be important to consider. Language proficiency may vary greatly, as many deaf signers are at risk of language deprivation, limited access to language during childhood that often permanently affects proficiency. Language use also varies across signers from different sociocultural identities. For example, distinct patterns of language use have been linked to race [135], gender [130], and geographic location [62, 173]. The majority of sign language users may not be deaf, and native signers only make up a small fraction of users for most sign languages. As such, even a dataset with contributions from a representative sample of signers may include few deaf signers and even fewer deaf native signers. Metadata indicating the signers' language background (e.g., sociocultural identities, age of language acquisition, etc.) may help to tailor models for these different end users.

The ideal composition of signers within the dataset may depend upon the application for which the AI technology is being developed. Data primarily or exclusively from native signers might be optimal for generating fluent sign-language output (e.g., in signing avatars), but data from the full spectrum of signers that includes signing variation and mistakes might be optimal for sign recognition and translation technologies (i.e., to robustly and equally recognize signers from diverse language backgrounds).

3.4 How do other properties of the signed content (e.g., grammar, vocabulary, prompt, and recording setup) impact models?

Other properties of the signed content similarly impact what type(s) of signing can be modeled, and which settings the models can be used effectively. Sign language datasets typically contain either individual signed units, or longer more continuous content. Models trained on individual signed units can be used to train models of individual signs (e.g. to build a dictionary), but will not generalize well to continuous signing (e.g. to support translation), which would include phrase-level linguistic features and co-articulation effects (e.g. how one sign will affect the production of the subsequent sign). For similar reasons, datasets of individual fingerspelling units (e.g., the ASL signs representing each letter A-Z) may be difficult to use to train a fingerspelling recognizer, as fingerspelled signs comprise rapid sequences of fingerspelling units. Similarly, the domain, or vocabulary, may be restricted or unrestricted. Training on a dataset with a restricted vocabulary will enable creating models that can handle content within that particular domain, but will not work more generally. However, if an application only requires models for within a specific domain, then it may be possible to achieve higher levels of accuracy with the same amount of training data if the domain is restricted (since the dataset will contain a higher number of examples per sign or concept).

Content can also be scripted or unscripted. Scripted content may be less natural and result in less natural sign language models. On the other hand, recording scripted content may greatly increase dataset size by removing the expense of labeling the content afterwards (and thereby improve model accuracy). Recording scripted content may also prevent recording of sensitive personal content about the signer and their acquaintances (e.g., through personal stories or accounts), which may introduce privacy concerns. Language contact considerations (i.e. the impact of interacting with multiple languages simultaneously) also impacts decisions about using scripted or unscripted elicitation. If scripts for eliciting signed language are written in another language (e.g., in English), the signer's task would not be simply "reading aloud", but translating in real time. The signed language might be blended with the written language, and include grammatical structures or other elements of the written language that would not otherwise be used. Even unscripted content varies in its naturalness due to language contact. For example, if the researchers or others present are not fluent signers or have different demographics than the subject, the signer may modify their signing to accommodate them.

3.5 How can dataset processing affect FATE issues, and in particular privacy concerns?

Sign language recordings may feel very personal, as they contain not only the person signing (their face and torso), but also frequently capture their surroundings. Gender, race, culture, and religion may be identifiable, by viewing a person's face and body, and even extracted movements may reveal ethnicity and gender [19, 129]. Because of the small size of the deaf community, it may be possible to personally identify signers in videos. Privacy concerns specific to contributing to aggregated sign language datasets include misuse of videos, being recognized, showing one's surroundings, signing personal content, and discomfort about looking presentable/attractive and signing abilities [27].

Privacy concerns may extend beyond the individual contributor to other people captured in the data, either accidentally or intentionally. The background of the recording may contain revealing content, including identifying information such as a written address or religious symbols. If family, acquaintances, or strangers appear in the background of a video, then the video reveals information about these second parties. Metadata may also reveal information about second parties, for example in questions about the signer's relationship to deaf community. In addition, if a signer is contributing free-form content, they might reference family or friends, and reveal information about those people. Moreover, unlike the primary signer, second parties may not be consenting dataset participants.

Privacy enhancements may increase people's willingness to contribute to sign language datasets, and thereby increase dataset size and diversity [27]. There are a variety of techniques that can be used to address privacy concerns, including applying filters to people's faces or surroundings; implementing differential privacy querying; or sharing aggregate statistics, simulated data, or models trained on the dataset rather than the dataset itself. Exploring the effects of various privacy-enhancing techniques on people's willingness to contribute to sign language datasets is an emerging area for research, with one existing publication [27]. That initial work suggests that addressing privacy concerns may increase dataset participation, and as a result may improve accuracy of models trained on the resulting dataset. If minorities are particularly disincentivized to participate due to privacy concerns, addressing privacy concerns may increase the diversity of signers in the dataset, which could result in more generalizable (inclusive) models.

Other types of post-processing may expand the pool of people who are willing and able to use the dataset. This expanded access may in turn expand end user applications to be increasingly inclusive of sign language users. For example, dataset compression may help reduce dataset size or latency, and enable usage in memory or latency-constrained domains. Sharing models trained on the dataset may also reduce the technical expertise required to embed sign language modeling in various applications, thereby expanding the set of people who can make use of the data. In particular, such model sharing may empower deaf people without technical expertise to design, build, and sell or otherwise share applications of value to deaf people.

4 MODEL PERFORMANCE

Using collected sign language corpora to estimate statistical models leads to the question which factors influence the final model performance. Generally, the performance depends on the complexity of the task, the amount and quality of the available data, and the chosen modeling approach. Consequently, choices about what data is recorded (Section 3) and how it is captured (Section 8) both influence the model performance. However, once the dataset is finalized (i.e. collection and annotation are completed), model performance can only be improved through advances in modeling. While sign language modeling encompasses recognition, translation, and generation, sign language modeling has historically focused primarily on recognition and translation, and has been influenced by the types of modeling employed in automatic speech recognition (ASR). The choice of models has evolved over time, in part driven by the attention of the broader computer vision and machine learning research communities.

In order for a specific dataset to pique interest in these communities, it must be well prepared (i.e. made available with code to easily reproduce baseline results and get newcomers started quickly) and packaged (i.e. separated into fixed non-overlapping training, validation and testing partitions, which are essential for reproducible research). Competitions and contests, including prizes for the best performing teams, can further foster the interest and attention of the research community to focus on specific sign language-specific tasks and raise the quality of the models.

4.1 What is the historical context and evolution of AI models for sign language datasets?

As mentioned above, much work on the application of statistical models for sign language technology has paralleled that of ASR. The most influential attempts from the 1990s and early 2000s [150] used feature extraction from video [17, 70, 174, 175], motion capture, and data gloves [195, 197–199] to train hidden Markov models with Gaussian Mixtures (GMM-HMMs). GMM-HMMs are a type of generative Gaussian model [162] with hidden states, and were a popular choice for ASR at the time. Their relative computational simplicity and ability to handle both isolated signs and continuous sequences of signs without explicit segmentation made them a popular and practical choice. However, their limitations posed challenges for sign language modeling from the beginning; in particular, they force the assumption that successive outputs (e.g. sign subunits) are independent from one another, and they force all parallel articulators of sign language to be bundled together in every frame, even if not all of them are active at the same time. For instance, in one-handed signs the non-dominant hand may not be relevant, but are incorporated in HMMs nonetheless. To address some of these limitations, extensions to HMMs were proposed [30, 196], with computational and modeling trade-offs of their own (e.g., requiring more computational resources, or making further potentially invalid assumptions about the independence of sign language features). Other past work has employed hybrid classification using HMMs and other types of statistical classifiers (e.g., [60, 124]).

Another limitation of HMMs is their inability to deal with high-dimensional feature vectors in a manner that makes collecting sufficient training examples feasible. With the sheer number of articulatory features that could be extracted from video for sign language for the hands, fingers, body movements, and facial expressions, selection of the most discriminative features is an important part of the fine-tuning process for HMMs. While some attempts were made to quantitatively determine which features work best for sign languages and gestures (e.g. [15, 40, 45, 65, 100, 165, 197]), the question was not conclusively settled for sign languages. In the early 2010s, work shifted from GMM-HMMs with handcrafted features to learned features [72, 103–105]. Subsequently, Gaussian mixtures were entirely replaced by neural network-based classifiers [106–108, 119]. Since 2017 many sign language researchers employ connectionist temporal classification (CTC) [69] for sentence based sign language recognition with neural networks [8, 38, 49, 50, 204, 208]. CTC represents a special case of a full HMM [20]. Due to the shift to deep neural networks for modeling, advances in the fast-moving field of deep learning often carry over to sign language recognition as well. Convolutional neural networks with spatial [103, 158] or spatio-temporal kernels [37, 82], or most recently with stacked 2D and 1D convolutions [8, 43, 49, 50, 208] represent the current state-of-the-art in sign language recognition models.

4.2 What is the impact of data-driven vs. language-based approaches?

ASR has long relied on abstracting spoken language into sequences of phonemes, and training models based on n-gram patterns, commonly trigrams [162]. This approach has been essential for making recognition systems both more robust and scalable, since common word features can be captured in a single model, rather than creating a separate model for each word. A "whole-sign" approach with one model per sign is even less viable for sign languages, with their rich set of independent articulators. Past research in continuous sign language recognition has addressed this modeling complexity by identifying "subunits." Two diametrically opposed approaches have been proposed to identify these subunits: one data-driven approach that uses clustering to identify common parts across signs [16, 17, 159], and one that attempts to inject findings from sign language linguistics, in particular phonetics [101, 102, 197, 203]. A head-to-head comparison between these two approaches came out in favor of language-based modeling of subunits [160]; however, this comparison was limited to isolated signs and conducted with dated methods, so it is unclear whether the findings would apply to continuous recognition or with more sophisticated data-driven techniques. Indeed, on a continuous sign language recognition dataset with larger vocabulary, whole-sign units still outperform subunit based modeling: All published state-of-the-art results are based on whole-sign units [98]. Still, subunits have been shown to improve alignment [99] and seem beneficial for cross-lingual pretraining [22, 105].

Currently, it is unclear which of the two approaches, or a combination of both, will lead to systems that more closely mirror real-world usage of sign language. At the same time, there is a significant risk that data-driven approaches with insufficient input by sign language experts find themselves incapable of capturing some of the rich aspects of simultaneous feature articulation in sign languages. In particular, meaningful use of space and depicting constructions (also known as classifier predicates) can be combined in relatively unconstrained ways, and may be difficult to capture through data-driven approaches. While some preliminary work on space exists [120], depiction or classifier predicates to date have resisted treatment by machine learning techniques. If such failures occur, deaf users of resulting sign language technologies could inadvertently be forced into an impoverished, robotic and repetitive mode of signing in order to use the technology, belying their rich linguistic and cultural heritage.

4.3 What characteristics do different recognition and translation models have?

The characteristics of the collected sign language datasets determines which types of AI/ML techniques can be used. In particular, the type-token ratio (i.e. the repetitions of the classes) must be sufficiently high to accurately train many models. As a general heuristic, signs or subunits that occur at least 10 times typically start to have more robust statistical representations in recognition scenarios. Still, the wider the tackled domain and the more variable the signer appearance, sign execution, and scene, the more data is required to find good model representations. It is important to minimize differences in the training and testing data distributions. If test data is not captured in the same environment, covering similar dialects and other characteristics as the training data, there is risk that the model will not generalize to this kind of data and fail to recognize the signing.

The linguistic level being considered may also factor into decisions as to whether sufficient training data exists for modeling. For instance, we already mentioned that some aspects of sign language like depiction have not been captured well by existing modeling approaches. Another way in which whole-sign modeling without regard for linguistic considerations can fall short is by ignoring the overall speed properties of the signer's movement, which are not part of the lexicon. However, if these are considered explicitly, then training useful models may be possible [9]. However, the bigger question is whether contemporary statistical models are adequate to capture the full rich range of signed language features. Even if they are, we cannot assume that this matter will receive sufficient attention without involvement of deaf sign language experts. Perhaps more worrisome, deep learning and neural networks currently constitute a black-box approach, with limited opportunities for determining whether tackling these types of rich sign language features is a matter of providing more and/or better data, or a matter of needing to improve the underlying technology.

Continuous sign language recognition requires all signs in an utterance to be annotated. If a sign spotting task is targeted (i.e. [149, 180]), then annotating just those classes that are meant to be spotted can be sufficient. Annotations on a more fine-grained level than full sign glosses (i.e. featuring composing subunits like handshapes or mouthshapes) may allow for better temporal alignments even of sign classes with limited repetitions [99]. Also, these may represent very challenging real-world subunit classification tasks on their own, attracting interest from researchers who do not specialize in sign language. Of course, available landmarks suit to train and evaluate detection and tracking algorithms. Simple tags of when people sign and when not can help to train sign activity detection models [21]. Sign language translation can benefit most when both gloss annotations and translations are available [36]. However, recently transformer-based architectures helped to reduce the gap of systems solely trained using translations [39]. Recognition and translation systems from sign language to spoken/written language typically require a large amount of variability present in the video data to generalize to a variety of different visual conditions.

As discussed above, if the dataset lacks diversity, sign language recognition models trained on it may be insufficiently robust. In particular, they may not be able to understand signing that differs from the training data, in terms of: human appearance, language or dialect, vocabulary, or other characteristics such as register or sociolinguistic features. While there are propositions to alleviate model bias (i.e. disentangling domain-invariant from domain-specific features [24][201]), it may be crucial to have annotations that allow for measuring bias during testing and controlling for it during training.

Some statistical models, in particular neural networks intended for sign recognition or translation, also have the capacity to memorize parts of their training samples [145]. Such methods introduce unique privacy concerns, as they may allow for the personal identification of individuals (i.e. from a visual model), expose intrinsic data properties such as dialect or ethnicity [13] or their expressions (i.e. from a language model). In particular, this possibility may deserve attention in small communities where personal identification is easier. Two categories of model vulnerabilities can be distinguished: training data tracing or membership inference, and training data reconstruction [55]. Typically, having more model parameters than training samples combined with limited regularization during neural network training facilitates the model to remember its training samples [207]. As a result, limiting model parameters, increasing training set size, and adjusting regularization during neural network training may help alleviate such concerns.

4.4 What characteristics do different generation models have?

Automatic sign language generation typically means creating sign language animations or avatars (cartoon-style computer-animated characters). When considering the training of models for sign language generation, e.g. the synthesis of animations, dataset FATE concerns differ slightly. Whereas a lack of diversity in a dataset may reduce the robustness of a recognition system, from a generation perspective, homogeneity of high-quality signing may actually be beneficial for creating accurate animations with a realistic repertoire. If the sign language dataset used to train models for generation contains a mixture of geographic dialects, sociolinguistic variation, or levels of fluency (e.g. non-fluent learners), then there is a risk that the resulting sign language output generated by the system may consist of an unnatural blending of features that does not reflect a fluent language production. The risk here arises from datasets being insufficiently labeled with regard to these dimensions of variation to allow for training on consistent portions, or from researchers inappropriately merging diverse datasets when training generation models.

Even if an appropriately homogenous dataset is used to train a model for sign language generation – or to train multiple, individual models for different variations of the language – there is a risk that a generation model may be insufficiently expressive in its repertoire. For instance, in the U.S. context, researchers have documented unique linguistic characteristics of Black ASL [136]. If a dataset did not include sufficient examples of such signing, then a generation system trained on this data would not be able to produce sign language animations that are reflective of the signing characteristics of this sub-population of the language community. A human viewing the output of such a generation system may not see their own dialect of signing reflected in the output of the system. Simply changing appearance characteristics of the computer-generated avatar (e.g. skin tone) would be insufficient for producing authentic and fluent output, if the movements of the avatar did not also reflect the diversity of signing among various sub-communities.

If the datasets used to train a generation model are insufficiently small, then the resulting model may also be of low quality, which would lead to sign language output that may be non-fluent or less understandable to human viewers. As discussed in [92], the premature deployment of sign language generation technologies before they have been adequately tested among the Deaf community poses risks; specifically, such deployment could displace existing human-powered accessibility services that had previously been provided.

5 USE CASES

Sign language datasets can be used for a variety of applications: for research or for products and services. Products and services could be commercial (i.e. for profit), non-commercial, or even open source. Sign language datasets that empower these systems could also be relatively small like those supporting dictionaries, or large and diverse supporting applications that use machine learning. In this section we will explore three broad categories of possible AI/ML applications that would use sign language datasets (sign recognition, generation, and translation). We will also explore the impact that dataset quality might have on the value of the end applications and the impact the development of these applications might have on different stakeholders.

5.1 What types of AI applications might sign language datasets be used for?

Accurate sign recognition could enable many applications, though to date, accuracy has not been high enough for real-world use. As recently as 2020, one research project claimed high accuracy for a sign language recognition system using a novel glove system for input [210]. They reported high accuracy for 660 signs using 15 samples for each sign from 4 different signers. This report quickly drew criticism from deaf researchers [78] in part because techniques that use gloves or other body sensors are unlikely to be useful in real-world settings. The [210] report is typical of many sign language recognition projects that use some novel capture technique (glove, 2D or 3D camera, and other sensors) that recognizes a small number of individual signs in a laboratory setting. Whether any of these approaches can scale to thousands of signs (which would be necessary to move from recognition to translation) is unknown.

While the accuracy of sign recognition technologies is increasing, emerging applications can take advantage of imperfect sign recognition technologies. For instance, for searching for an unfamiliar sign in a dictionary, a video-based sign recognition technology may allow a user to perform a desired sign into a camera, to query the collection of signs in the dictionary. Even if the sign recognition technology is imperfect, it may still return the desired sign in the top several results, as discussed in [10]. Similarly, imperfect recognition tools can be used to analyze signing and provide feedback to sign language students, since it may not be necessary to understand all of the signs being performed in order to identify when there are non-fluent aspects to the student's sign production, e.g. [83]. Sign recognition technology, even early models trained on isolated signs, could be used in psychological, linguistic, and education research on sign languages (e.g., to aid or fully automate corpus annotation). Such corpora could in turn be used to improve models of sign recognition and translation.

Automatic sign language generation could also enable many applications, including anonymous ways of creating signed compositions and post-hoc editing of signed compositions. When synthesizing the animated sign-language character, a human who is authoring the animation may individually control aspects of the performance, but the large number of parameters necessary to articulate a human avatar over time can be a challenge. One option is to partially automate the synthesis by using pre-recorded motion elements from motion capture or 3D cameras to animate portions of the message. One advantage of re-using elements of recordings in this way is that facial expressions, body language, hand and arm movements could be based on natural human movements. One disadvantage of this approach might be that the repertoire of avatar's movements would be only those that are captured in the first place. To produce a wider variety of utterances, researchers also investigate producing 3D models of elements of sign language that are trained on motion-capture or video datasets, e.g. for producing facial expressions [90] or selecting speed and timing details [9].

Finally, example applications of automatic sign language translation might include systems that caption or create alt-text for signed videos, systems that translate written text to a signed language, or systems that enable real-time communication between people using a spoken/written language and people using a signed language. Sign language translation would likely employ either/both sign recognition and sign generation technology [26]. A complete sign language translation technology would allow two-way communication (i.e., a signed language to a written/spoken language, and a written/spoken language to a signed language). In contrast, a partial sign language translation technology might only allow one-way communication, and may be easily confused with sign recognition or sign generation. As described above, sign recognition means converting signs into some digital–and not necessarily human-friendly–representation (e.g., English glosses, HamNoSys [75]), and sign generation means converting digital representations into sign animations. One-way sign language translation takes this a step further, and means converting complete written/spoken sentences to complete signed sentences or vice versa. Some stages in the translation process could be done by hand until the entire process can be automated. Moving beyond sign recognition/generation to sign translation would likely require a large parallel corpus of both spoken/written content and signed content to support machine learning. Several companies, MotionSavvy and SignAll, have claimed to provide real-time sign language translation, the former using Leap Motion 3D camera technology and the latter computer vision technology with colored gloves. Nonetheless, sign language translation is still considered an open research problem [26].

5.2 What impact might the development of these AI applications have on different stakeholders?

There are a number of stakeholders who could be impacted by AI applications that use sign language datasets. These include: deaf people, sign language interpreters, sign language teachers and students, and hearing people who interact with deaf people professionally or socially. An example of this last group are the hearing parents of deaf children who want to learn a sign language to improve communication with their children. In addition to individual stakeholders, organizations, businesses, and government entities also interact with deaf people. These classes of individuals and entities would be greatly affected if sign language recognition, generation, and/or translation was available, accurate, and inexpensive. In this section we begin to outline some of the impacts that we foresee, but as we do not represent the full spectrum of stakeholders, more systematic work is needed to fully identify possible concerns.

Sign language AI technologies have the potential to both aid and hinder efforts to preserve and revitalize sign languages. Sign language recognition technology could offer deaf people both a way to document sign languages, and a way of interfacing with technology in a signed language, rather than through a written/spoken language like English. This type of technology would be especially advantageous to the many deaf people who prefer not to use written and/or spoken language. The advantages will only grow as automated speech recognition technologies become increasingly ubiquitous. Being able to generate content in signed languages could also promote their use and acceptance in mainstream settings. While sign language technologies could aid in preserving language as-is, they might also shape the languages themselves by encouraging people to sign in particular ways. For example, recognition of individual, simple vocabulary items or signs with mouthing of spoken words may be more computationally tractable than recognition of complex depicting constructions in continuous signing. As a result, signers using these technologies may be encouraged to use mouthing, simple vocabulary, and to avoid depicting constructions, leading some aspects of sign languages to be better preserved than others.

Automated sign language translation could also augment currently available technologies, for example by bridging communication barriers where live interpreters may be difficult or impractical to hire (e.g., at a grocery store, or in urgent situations). If they are sufficiently sophisticated, these may be an appealing replacement for human sign language interpreters, allowing deaf signers and hearing people who cannot sign to communicate without the logistical considerations of hiring a human interpreter. While automated sign language translation may lend itself to its own set of privacy concerns, it may also alleviate significant privacy concerns related to human interpreters. For example, currently a deaf person may encounter and communicate via the same interpreter at their divorce proceedings, doctor's appointment, job interview, and–because signing communities are small–in a non-professional capacity at a social gathering.

While sign language translation technologies may be intended for use in cases where better alternatives are unavailable, there is also potential for misuse. The economic model for providing accommodations differs between countries, but is often structured such that the people responsible for paying for and selecting accommodations are not deaf, do not directly use the accommodations, are not personally impacted by the quality of the accommodations, and are often unable to evaluate their quality. As a result, the paying/hiring entity may be incentivized to select the cheapest accommodation that satisfies their legal obligations, often leaving deaf people without communication access. For example, remote interpreters (video remote interpreter, VRI) are perhaps most commonly used in healthcare settings, as a quick, cheap alternative to in-person interpreters. Unfortunately, VRI can give the impression of access, while leaving deaf people functionally without access [2]. The consequences can be lethal (e.g., leaving deaf people unable to provide informed consent to medical procedures or without access to doctors' orders). The economics may similarly incentivize abuse of automatic sign language translation, and deaf people may be forced to use automated systems in lieu of better alternatives even if they fail to meet communication needs.

Not only do emerging sign language technologies present opportunities that may significantly benefit deaf people, the monetization of this new industry also presents a secondary opportunity to correct systemic injustices deaf people face. For example, profits from sign language technologies could be directed to efforts to prevent deaf children from suffering without access to language or other pressing needs. This type of compensation to deaf communities could help offset concerns about cultural and linguistic appropriation.

6 OWNERSHIP

While the public may think about or discuss "dataset ownership", the word "ownership" is ill-defined with respect to datasets, including sign language datasets. That a dataset must have a well-defined "owner" comes naturally to many people, as they navigate a physical world where ownership is typically clear and embedded in language – for example, people easily refer to "my" work, "his" house, or "their" family. As a result, various entities may make seemingly competing claims to ownership over sign language data, without sharing a definition or understanding of what ownership means or involves. For instance, when each stakeholder discusses "ownership", are they referring to the physical storage of the data, the legal liability that accompanies data management, the ability to monetize the data, control over applications of the data, or the perception at large of who the owner is?

Ownership may most appropriately be discussed as a bundle of concepts, rather than a single unified concept, in order to accurately capture its complexities as a partition of various claims among stakeholders. Failure to acknowledge the bundled concepts of ownership may result in seemingly contradictory claims, which in turn may trigger strong reactions from stakeholders. With respect to sign language datasets, deaf communities may make strong claims of ownership stemming from a sense of cultural ownership over signed language itself and a history of marginalization, which has made it difficult for signing communities to access resources related to their signing heritage. Legal constructs which societies and governments adopt are often used to navigate the more concrete aspects of ownership and to partition and enforce ownership among stakeholders.

6.1 What does ownership encompass?

The first step in discussing ownership is establishing what sign language dataset "ownership" means. More generally, data ownership "refers to both the possession of and responsibility for information" [187]. Data ownership is a complex, multi-faceted relationship between an entity or entities and information. The field of data management covers many facets of the space, including the sub-field of data governance, which refers to both governmental and

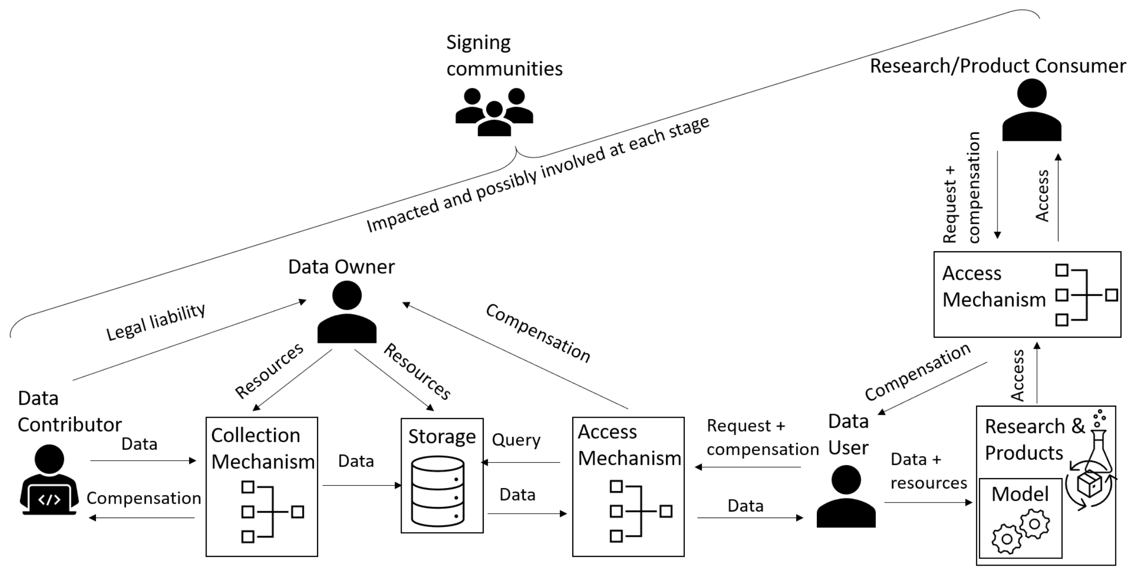

Fig. 1. Diagram of the parties who may participate in dataset creation and usage for AI applications and research, and thereby claim some form of ownership. Data format and content may vary throughout the flow. Compensation can take different forms, and can be nothing. The data owner may subcontract the collection to a third party; in that case, another entity would appear in the flow, with compensation coming from the data owner. Signing communities, and in particular deaf communities, are impacted by the collection and usage process, and may be involved at any stage.

corporate/university policy. Different models of ownership have been proposed, and entities that have been identified as potential owners include: creator, consumer, compiler, funder, packager, decoder, reader, subject, and purchaser/licenser [128]. Control over access is an important component of ownership, and is discussed in this section; see Section 7 for an in-depth discussion of access itself.

The primary difference between ownership of sign language data and other types of data is the role of signing communities. Unlike data in many other domains, sign languages themselves are largely created by and for deaf people, and are culturally linked to marginalized people. Figure 1 provides a high-level overview of the sign language data collection and usage pipeline, and the primary entities involved, who may be involved in ownership. These primary entities overlap with categories identified in existing models of data ownership, and include the data contributor, the data collector, the data user, the research/product consumer, and signing communities. These signing communities include not only deaf communities, but also sign language students and teachers, and friends and family of deaf individuals. These stakeholders are impacted by the collection and usage pipeline, and may be involved in any portion of the pipeline.

The groundwork for ownership is typically laid at the time of collection, when individual contributors' rights to their data are specified, to be carried downstream. These rights can be presented in many forms, including a consent form (when collection occurs as part of research), terms of use agreement (when collection occurs through a website or other application), and/or a video release form. These agreements traditionally release the collector of the sign language data to use that content for specific purposes, e.g. the creation of a permanent dataset for research and education. The stipulations of such agreements or statements typically apply not only to the data collector, but also to entities downstream with which the data collector shares or sells the data. Such sharing typically adds another layer of legal agreements, including various types of licenses (e.g., public license or non-commercial license) that must be signed before access is granted. In other cases, datasets may be released to repositories, e.g. Databrary [169], which has its own legal authorization process before investigators may obtain access. As laws vary from country to country, the enforceable ownership structure associated with a dataset may vary internationally.

In our experience, several primary types of ownership are referenced in typical discussions about and negotiations around sign language dataset ownership. These primary types of ownership are listed below:

- Physical ownership - involves physically managing and maintaining the data (often stored on a server), and typically includes the ability to grant access to others.
- Legal ownership - involves legal responsibility for managing the dataset, and/or the legal right to pursue any infringements on terms of usage.
- Monetary ownership - refers to the ability to monetize the dataset, for example by selling access for a profit.
- Cultural and linguistic ownership - refers to rights to the data (e.g., to collect, use, share or profit from) that stem from the cultural relationship between deaf communities and sign languages. There is no consensus on what these rights might be.
- Perceived ownership - entity who the public (or a group of people) perceives to be the actual or rightful physical, legal, or monetary owner.

It is not uncommon for two parties in a discussion to use the word "ownership" to refer to different types of ownership, leading to some level of confusion. In many cases, it may seem that two parties are competing for "ownership," but in reality they seek different types of ownership, and their desires are entirely compatible.

6.2 Who has a claim to ownership, and why?

Members of deaf communities may claim ownership to sign language datasets, as some deaf people feel a sense of ownership over signed languages themselves and any research or products built around them. As a result, deaf people may see development of sign language research and products by people outside of any deaf community as cultural and linguistic appropriation (see Section 2), particularly if deaf people do not judge their benefit from the enterprise to be equal to or greater than that of hearing people. Concerns about cultural appropriation may be lessened if a project is deaf-led, significantly involves deaf people, gives a deaf organization ownership over the data, and/or makes monetary payments or donations to deaf organizations.

Individual data contributors may also claim some level of ownership over the dataset and derived applications. In any data-collection initiative, the act of generating and contributing data may generate a linked sense of ownership. In sign language datasets, the sense of ownership may be heightened by the personal nature of sign language recordings and metadata. As described previously, sign language recordings contain people's likeness and potentially revealing background scenery, free-form content may reveal personal stories, and metadata may reveal information not only about the contributor but also family or friends. Recent legal actions have attempted to give individuals more control over personal data, e.g. through the European Union's General Data Protection Regulation (GDPR) [153].

The data collector may claim ownership to the dataset, as the collector invests significant resources in creating the dataset. The data collector adds value through curation and processing, as the value of data is partly intrinsic and partly generated through processing [128]. First, the collector must plan and organize the data-collection effort. They must also build and maintain hardware and software infrastructure for collecting, storing, and accessing the data. This process requires engineering hours, as well as financial resources to purchase or rent recording materials and server space for storing and querying the dataset. Finally, the collector must also compensate contributors for their data and time, either financially, or by designing collection mechanisms that provide sufficient compensation (e.g., through education or gamification). The collector must also consult with lawyers to create the required legal documents, and may be held legally responsible for any problems. In other domains, due to this significant burden, the data collector is typically the sole data owner, having paid data contributors for rights to their data.

6.3 What are the benefits and responsibilities associated with ownership?

While ownership may initially be perceived to be desirable, any benefits are inextricably linked to responsibilities. The primary benefits of ownership are access to the data for research and development, control over access or usage, and monetary benefit. The primary responsibilities are ensuring that usage of the dataset is ethical, fulfilling obligations to the deaf communities (and determining what exactly those are), managing legal liability, absorbing any monetary losses, and building and maintaining technical infrastructure. These responsibilities may be further complicated if ownership is shared among a large number of people (e.g., all deaf people, all people who contributed data), and may be prohibitively difficult to navigate for some potential owners.

Ownership may grant a level of control and access to the data, which brings with it the responsibility of making sure the data is handled and used ethically. In particular, the owner may be responsible for ensuring that access to the data is granted in such a way that honors agreements made with individual contributors. In addition, the owner may be expected to ensure that obligations to the deaf communities are honored (and to determine what exactly those obligations are). Furthermore, the owner will likely be held responsible for detrimental uses of the dataset. It is impossible to predict how a given technology may be used. For example, the creators of the internet envisaged as an oasis of open information exchange, but in actuality the internet has also been detrimental in many cases (e.g. [111]). Nonetheless, the owner will likely be held responsible for any detrimental usage. The repercussions can take many forms, including law suits, damaged public image, and a damaged relationship with deaf communities.

While physical ownership ensures access to the data, it also requires building and maintenance of technical infrastructure. Datasets are typically stored on servers, and storage space is costly. Running computations on servers is also costly, including making queries to databases. Servers must also be maintained, for example updating and patching code, and running system updates as security patches and other updates are released. In particular, the physical owner will be held responsible for any security breaches of the dataset. Protecting data from security breaches is not trivial, and requires continual attention and system upkeep. As soon as an IP address is made public or a database made queryable from remote access points, it will be subject to ongoing attacks trying to access the resource. Various security measures can enhance protections (e.g., [53, 95]), but no protection is infallible. The physical owner may also be responsible for deleting data at contributors' request, or after a fixed amount of time when contributors were promised that their data would be deleted.

The owner is also typically held responsible for data misuse. When individuals (or entities) contribute data to the dataset, they typically do so under an agreement that specifies how the data will be used and protected. If the data is misused by the owner, the owner may be subject to legal, financial, or social repercussions. Furthermore, the agreement with the data contributor applies even if the data is shared with a third party (e.g., if the dataset is sold to a university or company to conduct research or build a particular application). While this third party is also responsible for upholding the data usage terms, the data owner may still be held responsible on some level for third party misuse (e.g., if it is perceived that sharing with this third party was irresponsible, or if usage terms were not clearly communicated with them).

6.4 What are the consequences of different models of ownership?

Many different models of ownership and access may be employed with sign language datasets, bestowing varying levels of benefits and responsibilities on different stakeholders. In particular, sign language data may be copyrighted by individual contributors or may exist in the public domain, and various types of licenses can be used to grant access or transfer ownership.

Individual contributors may hold a copyright to their recordings, which gives them some level of ownership over their data. By virtue of independently creating content, individual creators generally hold copyright to their content. For example, videos uploaded to YouTube [206] are typically copyrighted to the creator (unless they are re-sampled from videos copyrighted to another creator). Copyrights are a way of protecting intellectual property, and typically give the content creator exclusive rights to use the content for a limited time. After the time expires, the content typically fall into the public domain (discussed subsequently). If recordings are copyrighted by individual contributors, the dataset collector would typically obtain explicit permission from the recording contributor to use their recording(s) in the dataset, for example through a copyright license agreement.

Data license agreements may be used to grant access to a sign language dataset, and are typically granted by data collectors to third-party users. Such agreements may specify compensation for usage, describe the allowed uses of the data (e.g., including stipulations on usage established when individuals contributed their sign language recordings), and provide time limitations on the agreement and/or usage. The agreement may also include disclaimers about the contents of the dataset, and limit the legal liability of the party sharing access to the data. While some standard licenses exist (e.g., Creative Commons), licenses can also be crafted to meet the exact needs of the involved parties. They establish mutual understanding of the framework within which each party operates, enabling each party to understand their benefits and responsibilities and possible repercussions.

Alternatively, sign language recordings contributed to datasets may exist in the public domain [126] from conception. Like other material in the public domain, such recordings are available for anybody to access. Placing recordings in the public domain may be seen as a way to democratize the development of sign language research and technology. In particular, public access makes it possible for deaf people with fewer available resources to study the language and build their own technological solutions. However, democratization may also require capacity-building to ensure that deaf people have the training and expertise to make full use of the data. Public access also aligns with the research ethos of collaborating in an open search for truth. However, in expanding access, public availability also makes it difficult to prevent developments that may harm deaf people. Because deaf people represent a small fraction of the population, their perspectives may be drowned out by the hearing majority in a "democratic" system. Placing data in the public domain may also heighten privacy concerns (see Section 3), as the data becomes available for all to see and potentially misuse.

Different models of ownership also introduce different ways of economizing sign language data, as compensation structures differ across models. Economic value may be attached to various forms of human sign language knowledge, ranging from individual competency of "dictionary-level" signs and grammar rules, the ability to deduce complexity of context, history and evolution, the time spent/invested in the signing community, and the capacity to innovate. The benefits around increasing the economic value may range from direct financial compensation — at individual, local and macro levels – to the reduction of stigma associated with communicating entirely in sign language. Robust economic models may also facilitate creating mechanisms of access to resources, and the development of specific opportunities designed for signing individuals and communities in the world to thrive.

As the tech industry faces backlash against monetization of customer data, newer models of ownership are emerging with the aim of giving individuals more control of data. Many "free" services make money by selling access to customer data. For example, a large company may give access to a user's search history or social network to third-parties interested in targeting ads at relevant users, while providing the search tool to users at no monetary cost. This type of business model has drawn criticism and legal repercussions in recent years [44], in large part due to opaque processes and customers' lack of privacy and control over data they generate. To date, sign language data has not been highly monetized, with only a small number of startup companies working in this space (e.g., KinTrans[2] and SignAll[3]), though their datasets may be large. Applying such monetization models to sign langauge data more likely would likely be particularly problematic, as high transparency and explicit communication are common deaf cultural values. There also are unresolved questions about the fate of datasets if the controlling entity goes out of business – in the worst case, such data could be entangled in legal battles or lost altogether. Newer models are currently being designed to give users more control over their data, heighten transparency around ownership, and enable customers to better protect their data (e.g. [172]). However, such new models are still emerging, and have not yet been widely deployed or used to the best of our knowledge.

7 ACCESS

There are many entities who might seek access to a sign language dataset, for a variety of purposes. We outline the primary entities with vested interest, and their high-level objectives (with further details on end uses in Section 5). The identity of the entity seeking access may impact ethical considerations of granting access. In particular, deaf people may be ethically opposed to entities without strong ties to and/or membership in a deaf community having access. Additionally, because deaf communities are often marginalized, the power relationship between deaf people and the entity who seeks access may be a factor.

Additionally, deaf people having access to data may be insufficient to democratize use, if the expertise to make use of them is concentrated in the hands of relatively few hearing researchers and engineers. Access and ownership plans may need to be coupled with capacity-building plans, to position highly qualified deaf researchers and engineers to make use of the data. Alternatively, sharing trained models (e.g., through application programming interfaces (APIs)) rather than raw data may also expand inclusion. Community-based research may provide an appropriate framework for making such plans [86].

7.1 Who may desire access, and for what purposes?

Researchers may seek access to sign language datasets for research purposes, and typically request access as part of a larger university or institute. These researchers may be affiliated with public institutions (e.g., state universities), private institutions (e.g., private universities), or government research institutions (e.g., European academies). In particular, researchers seeking to develop improved AI/ML methods for sign languages require large datasets to do their work. Such researchers include computer scientists, and in particular experts in computer vision, machine translation, natural language processing, and machine learning more generally. Linguists, Deaf Studies scholars, and other social scientists may also seek access to the data, but typically not for AI-related work. The identity of the researchers or research

[2] https://www.kintrans.com/
[3] https://www.signall.us/

organization may impact ethical considerations in providing access. For example, granting access to a deaf advocacy group that supports signed language (e.g., the World Federation of the Deaf[4]) may be viewed as more ethically acceptable than to a group that has no history of deaf advocacy.

Private companies and non-profit organizations may also seek access to sign language datasets, in particular for building sign language applications. Some companies have emerged building software to recognize and translate signed language into a spoken/written language, or to render spoken/written language in a signing avatar. However, none of these services are sufficiently reliable for widespread real-world use, in large part due to lack of sufficient training data. Because access to data can give a competitive edge, companies may invest in collecting their own datasets, which they do not share or publicize. When companies seek to monetize technology, FATE issues are heightened. Questions of how embedded the company is in deaf communities, whether there is deaf leadership, participation, and inclusion, and how best to mitigate possible harms may be of increased importance.

Private citizens may seek access to sign language datasets for personal projects. Many different user groups have experience with accessibility barriers related to sign language, and so may seek access to sign language datasets. These groups include deaf and hearing signers, or non-signers who wish to interact with deaf signers. The DIY (do-it-yourself) movement [181] offers a framework for democratizing the development of technical innovations, and has been applied to and studied within the disability space (e.g., [81, 184]). Empowering private citizens to solve their own problems may result in better solutions, as the person solving the problem has first-hand lived experience with the problem and can easily experiment with different solutions.

Governments may seek access to sign language datasets for building or investing in the development of accessible services. For example, laws exist in many countries that require governments to make information accessible to people with disabilities. In some situations, providing written captions (i.e., subtitles) will satisfy these obligations, but sometimes other accommodations are necessary (e.g., sign language interpreters). Accommodations can be expensive and providers are often in short supply. Governments may find automated accommodations to be an appealing alternative, though currently the technology is inadequate, largely due to lack of sufficient training data [26]. There are many ethical issues inherent in government accessing large-scale video datasets that may contain extensive personal, identifiable information, as outlined above. Many of these issues around government access are common to any human video dataset (e.g., privacy, surveillance, etc.), so we will not review them in depth here. We note, however, that there may be unique risks to deaf people who may rely on governments to provide and protect (often expensive) accommodations.

7.2 What forms of access may dataset users obtain?

Data users may receive a physical copy of the complete or partial dataset (e.g., by download). For example, a user may purchase a copy of the entire dataset, or download a public training dataset, while a held-out test set is kept private by the owner, as part of a computer vision challenge. In receiving a physical copy of data, the data user inherits many of the responsibilities of the physical data owner. In particular, they inherit the responsibility of storing the data securely, and protecting it from falling into the hands of malicious users. In using the data, they are also bound by the agreements under which individual users contributed their data. For example, such an agreement might state that the data will only be used for research purposes, not for corporate purposes, and the data receiver is subject to that agreement in their usage.

[4] https://wfdeaf.org/

Rather than obtaining a physical copy of the data, it is possible to query a dataset for select information. This select information may include individual records (e.g., videos from a particular day or signer), or aggregate statistics (e.g., average age or signing level of contributors). Receiving only required information reduces security risks, as a data breach will not expose the entire dataset. It is also possible to limit querying access to the database in such a way that privacy guarantees can be made (e.g., no individual signer can be personally identified). In particular, differential privacy [54] offers techniques with such guarantees that may be applied. However, if entire unaltered sign language videos are included in the queried data, it may not be possible to prevent personal identification. It is also possible to restrict access to certain types of content that carry different levels of risk or sensitivity (e.g., sharing only labels, or videos but not personal demographics).

Sign language datasets may also be viewable, but not easily downloadable or queryable. For example, YouTube [206] provides access to videos for human consumption, but does not make their videos available for public download. While YouTube contains sign language videos, they are not the primary content of the site and may be difficult to find. Other sites exist that explicitly to share content in sign language videos, including many deaf news sites (e.g., The Daily Moth [7]), as well as videos shared on social media ("vlogs") and other one-off projects. It may be difficult and/or unethical to make use of such resources for ML/AI model training, as the terms of service on the site may prevent scraping and downloading the videos, and may also prevent usage for commercial purposes.

It is also possible to provide access to ML models trained on the data, but not the data itself. This type of access may be of particular use to people who do not have the technical expertise or resources to train their own models. In particular, pre-trained models may be essential to democratizing the development of sign language systems, as many DIY inventors may lack the technical expertise and resources to train their own models, but have sophisticated visions of desired systems. Providing access to trained models may also help protect individual signers' privacy, as the model is trained on aggregate data from many contributors and makes it extremely difficult if not impossible to identify individual contributors (depending on the type of model, and number of contributors in the dataset).

7.3 What obligations may accompany access?

When an entity gains access to an existing sign language dataset, they inherit some form of ownership over the data. In particular, they inherit the power to share the data (or some portion of it) with others and to decide who else gains access. They also inherit the power to conduct research and build applications with the data. As a result, the obligations that accompany access largely overlap with those of owners described in Section 6. In this subsection, we briefly outline obligations that may pertain specifically to entities seeking access to existing datasets (as opposed to the original curators or contributors), and refer the reader back to Section 6 for additional details.

Entities who obtain access to sign language datasets typically have some obligations to the entity from which the data was obtained. In particular, the data is typically shared under a certain agreement. The agreement may specify use terms for the data and limitations on sharing, which may be copied in large part from the terms of usage that individual contributors. However, there may be additional stipulations that the entity granting access adds, for a variety of reasons including limiting commercial competition. The agreement may also specify compensation that the data user owes the entity granting access.

Relatedly, parties who obtain access to data are typically obligated to honor agreements made with data contributors about how their data will be used. These obligations are typically inherited from the entity granting access to the dataset, through the agreement described above. For example, if people contributed sign language videos under the understanding that they would be used solely for research purposes, the third-party data user is obligated to honor this agreement. Such agreements may also include stipulations about data security, which the data user is obligated to adhere to as well. In practical terms, this typically means that the data accessor must invest in data storage and security, just like the original data curator/owner. Also like the original owner, a data accessor may also be ethically obligated to consult with the relevant deaf community/communities to ensure that the intended usage complies with the communities' desires, as described previously.

8 COLLECTION MECHANISM

There are many different ways a dataset can be collected, resulting in different dataset content and associated FATE issues. Consequently, it may be important to first identify the type of data that is desired, and then design the collection mechanism to achieve the desired corpus. The identity of the data collector can impact the collection effort, for example by impacting language execution, a phenomenon referred to as the "observer's paradox" [114, 129]. For sign language corpora, data collectors are often hearing and highly variable in signing fluency, which may affect the design of the collection event. Some of the primary sign language data collection-mechanisms and their implications are further explored below.

8.1 What are the FATE implications of traditional in-lab data collection?

Traditional data-collection paradigms consist of asking people to contribute data, and paying them for the rights to use the contributed data. For sign language datasets, such initiatives typically record participants in a controlled physical setting. This setup may greatly restrict who can participate and result in datasets that are not representative of the signing population at large. In particular, recruitment will be limited to people who can physically travel to the recording site, which may exclude people with disabilities and result in a geographically and ethnically biased sample. Recording also typically occurs during working hours, which may exclude working people from participating. Instead, students, retirees, and other unemployed adults may be over-represented. Finally, monetary compensation may attract a disproportionate number of people who need gig work. These potential sources of biases may result in unrepresentative datasets, and ultimately in technologies that underperform for less-privileged members of signing communities.

In-lab collection schemes also typically generate high-quality recordings that may not be representative of everyday recordings. Given the expense and time of recruiting and paying participants, in-lab collection typically employs high-quality cameras and lighting, to maximize data capture. Models trained on such high-quality recordings may not transfer well to real-world situations with low-quality inputs. The studio/lab backdrop is also typically controlled, unlike the real-world backdrops of sign language recordings input into deployed models. Finally, sign execution itself may be impacted by the controlled lab setting. Scripted content may prompt unnatural execution, and even unscripted content may be executed with extreme care, given the laboratory environment and prominent recording setup. Additionally, real-world videotaping conditions may include the use of a handheld camera, which may lead signers to modify their signs (e.g., adjusting signing to fit in the frame, producing two-handed signs with one hand while the other holds the camera). Nonetheless, with the increasingly pervasive use of technology, signers are acclimating to signing into recording devices, so their language styles may be less influenced/altered by the act of being recorded.

8.2 How might remote collection of sign language data impact FATE?

One alternative to traditional collection mechanisms is collecting videos from existing platforms that host sign language videos. Many people share signed language videos online through various platforms, including social media sites (e.g. Facebook), video hosting sites (e.g. YouTube), and personal vlogs. Such resources typically contain many students, who may post homework assignments to YouTube as part of sign language classes or may be excited to share their newfound signing abilities (e.g., a YouTube search for "ASL homework" returns hundreds of student videos [205]). Deaf signers may be a minority of posters on such platforms, but are essential to forming sign language datasets that capture high-quality signing and reflect the general signing population. However, such platforms and individual contributors may have use terms associated with recordings that prevent compiling recordings into a dataset or using them for a desired purpose, and compiling such collections without the signers' awareness may feel exploitative. Obtaining consent to use videos scraped from social media may be possible, but can be tricky. Some methods have been developed for sharing and archiving sign language videos, for example by explicitly re-consenting [157]. Signed videos are also typically not captioned or labeled, and generating labels after collection can be expensive, though accurate.

It is also possible to aggregate interpreted videos of public television broadcasts or other interpreted talks or presentations. One advantage of interpreted videos is that they can be annotated with the spoken utterances that are interpreted, for example through ASR. Alignment may still require human intervention, as interpretations typically lag behind the speaker and include errors or omissions (one study found that in a three minute real time interpretation, about 26-58% of utterances are incorrect [146]). Additionally, such datasets may not reflect deaf fluent signers or the general signing population, since they consist of interpreters, who are almost never deaf, and typically not native signers. Personal demographics of interpreters often differ from those of the general population. For example, the U.S. national professional interpreter organization is predominately white (87%) and female (86%) [5]. Recordings of interpreters also have unique composition, typically containing a plain backdrop, with an interpreter wearing clothes that make it easy for viewers to pick up on their hand movements and hand shapes. Interpreted language is also atypical and often includes unnatural pauses, lexical choices, and sentence structures. Nonetheless, some of the largest state-of-the-art datasets have been collected this way (e.g., [66]) and have helped advance the field in the absence of larger, more representative datasets.

Crowdsourcing offers another means for collecting sign language datasets. Crowdsourcing [25] refers to accomplishing work by dividing it into smaller tasks that individual people, called the "crowd", accomplishes. Existing crowdsourcing platforms (e.g., Mechanical Turk [11]) can be leveraged to collect sign language data by paying workers to record videos of themselves signing. However, few signers exist on these platforms, and even fewer who are fluent. Even with qualification specifications or tests, it may be difficult to collect sign language recordings of sufficient quality and quantity. Alternative crowdsourcing methods may help overcome these limitations of existing platforms. In particular, "organic" [109] crowdsourcing methods where people benefit non-monetarily from contributing may attract a more diverse, representative pool of contributors. For example, educational resources can be designed to collect sign language data (e.g., ASL-Search [28]), or even games.

Governments can also be powerful generators of sign language content. For instance, Brazil has passed mandates to provide sign language access to public information for their deaf citizens. In 2002, the federal government recognized deaf Brazilians as a linguistic minority with attendant rights. The community's demands for education and linguistic access led to the adoption of Convention on the Rights of Persons with Disabilities – CRPD [1], in Brazil's Constitutional Decree 6.949 in 2009 [31]. This law and further amendments (e.g., [32]) required that government communication and documents of the country must be made available in Libras. The requirement that public information be made available in Libras has resulted in its ubiquity, for example on TV, on monitors as avatars at airports, in tourist centers, at political rallies and debates. The Brazilian example shows that government mandates have the potential to greatly increase the amount and quality of sign language information that can be used for sign language datasets.

8.3 How might labels be provided for sign language recordings, and how might the labeling process impact the dataset?

Labels, or annotations of sign language recording contents, are typically added to recordings after collection. The labeling process is time-consuming and expensive, and requires skilled workers with comprehensive knowledge of the language. As a result, it is standard to hire experts to annotate the contents of recordings. Labelers themselves embody certain biases (as all humans do), and may lack awareness of signing practices in certain deaf communities. In particular, skilled workers with extensive knowledge of sign languages (e.g., people with formal education in sign language linguistics), may not match the demographics of the data contributors, and so the labels they provide may involve systematic biases. For example, a white linguist with limited experience with Black ASL may inaccurately label recordings of Black ASL signers. In many research initiatives, data is only annotated by skilled deaf signers, who represent a very small fraction of an already low-incidence population. While hiring deaf signers as coders may offset under- and unemployment issues among deaf people, equity issues may arise if (often low paying) data coding positions are selectively given to deaf people, especially if (well paid) team leaders are predominantly hearing.

It may also be possible for a crowd of less skilled workers to label the sign content. In particular, if the annotation system does not require extensive training to use, it may be possible for any signer to contribute. For example, the signer him/herself or other untrained signers could be asked to provide labels in the form of a written transcript or translation at the time of recording. It may even be possible for non-signers to contribute, if the task is decomposed sufficiently (e.g., answering "yes/no" questions about whether two signs match, or whether a certain pictured handshape appears in a video of a single sign), though the reliability of labels generated by non-signers is not known. Crowdsourced labeling tasks can also be designed to provide non-monetary rewards, for example by framing labeling as an educational exercise (e.g., [28]). Such labeling schemes fall under the category of "organic" crowdsourcing (described above), and may help diversify the labeler pool and provide longer-lasting or more substantial benefits to contributors.

Alternatively, it may also be possible to collect pre-labelled content. To do this, contributors may be prompted to sign specific content, so that the contents of the recording are known. However, signing a written script is a sophisticated task that may prevent people from contributing. Sign languages are not typically written, so prompts typically take written form. As a result, the signer must translate the prompt prior to signing. This translation task is complex, especially if the person is not completely fluent in both languages, as many signers may not be. In addition, executing a script may result in unnatural signing.

Choice of annotation or labeling system itself may also impact the dataset. Annotation systems have different properties (see Section 3), and may impact both the set of people who can contribute to the labeling process, and the types of models that can be built with the data. For example, different labeling systems enable varied granularity of annotation. For example, some systems (e.g., written translation) enable sentence-level alignment, while other systems enable individual sign alignment or even sub-sign unit alignement (e.g., handshape start and end). The label granularity places constraints on the types of models that can be trained with the given labels, and different types of models also introduce different FATE considerations (see Section 4). In addition, the level of complexity and obscurity of the annotation system may prevent some people from contributing to the labelling process. If the set of people who can contribute is systematically biased towards certain sub-populations (e.g., young, white, educated academics), certain biases may be embedded in the labels.

9 TRANSPARENCY AND UNDERSTANDING

Clear communication about the capabilities and limitations of AI research and applications may be essential to building trust with deaf communities. Perhaps because of the unique communication barriers deaf people face, a common cultural value in many deaf communities is an expectation of transparency. The standard in many deaf communities is to communicate information as directly, explicitly, and completely as possible until everyone understands, in particular when discussing information particularly relevant to deaf people. Because many deaf signers prefer not to use spoken or written language, typical channels of communication about research and development (e.g., written recruitment ads, consent forms, instructions, research publications etc.) are likely insufficient for communicating information to deaf, signing communities [138, 139]. Consequently, information on work related to sign language will often require sign language-based communication.

Each portion of the sign language data collection and usage pipeline may provide various levels of information about the process, and stakeholders may have varying levels of access to this information. Whether and how this information is shared can impact stakeholders greatly, in particular deaf communities. While publishers, companies, and researchers may be incentivized to present their work in the most positive light, misrepresenting or overstating the benefits of technologies may degrade deaf people's trust in technology and technologists. In this section, we outline types of information that may be of interest to various parties, and discuss FATE-related issues involved.

9.1 What types of information might be relevant to whom?

How a dataset will be stored and used may be relevant to individual data contributors. In particular, individuals may be interested in *who* will have access to their data, and what their ties are to deaf communities. They may also want to know what information will be collected, and how it will be stored and kept secure. In addition, contributors may be interested in which end applications the dataset will be used to build, and who will benefit from their creation. For example, will a company profit monetarily, or will they donate their proceeds to deaf advocacy efforts? And will the end application be useful for people who are deaf, even indirectly (e.g., by helping students learn to sign)? Such information may impact individuals' willingness to contribute to the dataset, and agree to various use terms. At the same time, it may be difficult to define this information at the outset of a research endeavor, and attempts to do so may be overly restrictive and hamper innovation. These competing demands may need to be balanced thoughtfully.

The end use cases that dataset users pursue may be relevant to a variety of impacted stakeholders, beyond individual contributors. Deaf sign language users are arguably the most likely to be impacted by sign language research and products, and may be most concerned with the end use case. As it is possible to create detrimental sign language applications, the community may be particularly interested in knowing not only which types of applications the dataset will be used to build, but also what types of applications the dataset might enable in the future. A number of other groups use sign languages or interact with signers and may be impacted and interested as well, including interpreters, students and teachers, and hearing people who are close to deaf people.

Information about ownership and access to the dataset may be of particular interest to deaf people. Transparency around these topics may be important in addressing concerns about power that dataset owners have to impact deaf people. As described in Section 2, deaf people have a history of marginalization and cultural oppression, and continue to fight for access to sign languages [1]. As such, deaf people may want to know to what extent deaf people are involved in the ownership and access structure, to help ensure that the dataset initiative does not further contribute to this history of marginalization.

The dataset contents may be particularly relevant to dataset users. As datasets are typically curated and used for specific AI (and non-AI) purposes, technologists typically want to know what is in the dataset before acquiring access. For example, a company looking to build automatic recognition software for fast-food drive-through restaurants may want to know whether the dataset contains people ordering food. They may also want to know what types of labels are provided to ensure that the dataset is compatible with their infrastructure and modeling plan. Dataset size and diversity is also important to know, in determining how powerful (i.e. reliable and generalizable) models built on the data can be.

9.2 How might information be made available to interested/affected parties?

For potential data contributors, information about data collection and handling is usually presented at the time of collection. In other applications this information is typically presented in text, and can take one of a variety of forms: consent form for research projects, terms of usage for websites, or other types of licenses or agreements. The text is typically several pages long, and the contributor may be instructed to save a copy for future reference if desired. In some cases, this information can be made accessible to individuals with lower literacy via sign language versions (e.g., interaction with fluent signing researchers, sign language video recordings, or a human interpreter).

Information about dataset contents are typically shared via publications (research papers and news articles) or websites. If the dataset was collected by researchers, they may publish information about the dataset in a research paper, which contains a description of the dataset and its collection process, and provides a point of reference for future researchers who use the dataset. Here too, written articles may be accompanied by sign language-based research summaries either published in the same journal or in a sign language-specific venue (e.g., Acadeafic [133]). Dataset information may also be presented through websites, which may make the data directly available if it is open-source, or may provide an access point if it is not public. For example, computer vision competitions may advertise through a webpage, which describes the dataset and objective, and may provide a training set download link. Alternatively, potential dataset users may be given a particular person's contact information, to contact about usage agreements that must be negotiated and signed before the data is shared. In addition, more mainstream publications (e.g., news sites or magazines) may pick up on dataset projects and publish pieces on them. Here too, journalists could interview deaf collaborators and/or stakeholders, embed sign language interviews in each piece, and work to minimize misinformation about these technologies.

Research on AI methods applied to sign language datasets is typically presented through research papers, though an emerging field provides new methods for making AI/ML more understandable. Sign language AI/ML research papers typically present algorithms in text descriptions accompanied by pseudocode. Performance may be evaluated and presented theoretically (e.g., through big-O analysis), or experimentally through trials and plots of results. Such papers are highly technical, and may not be accessible to general audiences. Explainable Artificial Intelligence (XAI) [166] is a subfield of AI that has emerged to help make AI methods more understandable, even to technologists developing and using such methods. XAI methods may be applied to sign language modeling, though they have not previously been explored in this context, to the best of our knowledge.

Information about (non-research) end applications are typically presented by marketing departments of companies. Due to the competitive nature of business, companies do not typically share information publicly about the datasets they use to build their software, or the AI/ML methods that they employ. Instead, companies typically advertise the capabilities of the software or hardware that they are selling, with the goal of persuading customers to purchase the systems. The customer viewing this information may be an individual (e.g., a person looking at an online sign language game) or a larger entity (e.g., a school or company looking to purchase an accessibility solution). The information presented may be tailored to the audience, who may have a variety of factors to consider in deciding whether to purchase the system.

9.3 Who may hold responsibility in making sure that information of interest is communicated and understood?

The data collector may hold responsibility for making sure that the terms of usage are communicated to potential data contributors. While these terms are typically presented in long-form text, this format may not be accessible to all potential contributors, and the collector may be responsible for providing accessible alternatives, including signed content. If the data is collected as part of a research initiative, an Internal Review Board (IRB) [12] may share responsibility for ensuring that the appropriate information is presented. The IRB is an organization tasked with ensuring that research that involves people does not mistreat human subjects. Many universities and research organizations (including some companies) contain an IRB that reviews the organization's human-subjects research projects. As human signers appear in sign language datasets, sign language dataset curation falls under the purview of the IRB. IRBs may require guidance about the unique context of sign language research [47, 76, 151].

On the other hand, data contributors may also be responsible for ensuring they understand the terms under which they are contributing. The contributor typically must agree to the terms before continuing on to provide recordings or labels. If he/she does not understand the terms, there are actions the person can take to clarify their understanding before signing the contract or otherwise agreeing. In particular, additional time can be requested to process the terms, and a contact point is typically provided who can answer questions. Communication with the contact point could happen in a spoken or signed language, according to the contributor's preference or need. Signed questions may be communicated directly to a fluent signing researcher or via an interpreter.

The data user may be responsible for communicating what they are working on, and for researching and understanding the potential effects of their actions on signers, and in particular deaf people. Some lines of research and development may be more beneficial to deaf signers than others. For example, research that promotes the standing of sign languages may be deemed beneficial to deaf signers, while research that oversimplifies sign language may not. The standing of sign language within the world can have real effects on deaf signers, for example by encouraging or discouraging governments from recognizing sign languages as languages and encouraging or discouraging schools from teaching sign languages to deaf students. As a result, researchers developing access technologies or conducting research on underlying technologies (e.g. sign recognition or machine translation) also have a responsibility to ensure that the state-of-the-art of their work is communicated clearly [91].

Data users may also be responsible for noting and communicating mission creep. Data collection efforts often focus on addressing a particular issue, with an established goal and set of associated ethics. However, mission creep may occur after task completion, as people seize additional opportunities to exploit the data resource. Re-consenting contributors for new uses may be difficult, as contributors may be difficult to contact, and may have different opinions when contacted separately at a later time. Additional mission creep challenges may occur when researchers receive permission to use the data for a second task, but do not retain expert language informants to work on the new task.

Users of end applications may also be responsible for understanding the implications of purchasing or using those end applications. For example, before a hospital purchases automatic translation software to use with deaf signing patients, they may be responsible for understanding the accuracy rate of the translation software, the topics or situations where it may fail, and the effects of usage on patients and doctors. Similarly, individual consumers may be responsible to advise parties responsible for providing access as to their communication needs and the suitability of a particular technology. In some cases, it may not be feasible for each user to fully evaluate applications, and governments may need to intervene. Legal guidance or legislation on the appropriate and inappropriate uses of technologies can be helpful. For example, guidance about the use of remote interpreters has clarified technical requirements [148], when these accommodations can be used (e.g., when it is not possible to find a live human interpreter) and when they cannot be used (e.g., when the deaf person prefers a live human interpreter and one is available for hire [2]).

10 DISCUSSION

The FATE issues we have outlined are complex, and only offer a sketch of the ethical landscape. Though there have been a number of attempts to prescribe solutions for some of the ethical issues on sign language research [76, 151], many questions specific to the ethics of sign language AI datasets remain unresolved. In this section, we discuss FATE issues that may arise as teams of innovators work together to make progress.

10.1 How can people work together effectively in this space?

Scholars have argued extensively that people from deaf and signing communities should be meaningfully involved in, and have leadership roles in, research and development [76, 151]. Including deaf people not only aligns with the spirit of "Nothing about us without us" [42], but also aligns with our personal experience that inclusion can increase work quality. For example, teams that include signing deaf members are likely to be well positioned to communicate and build trust with stakeholders who primarily communicate in a signed language. They are also poised to work together to ensure that interaction protocols are not based solely on hearing and sighted norms [76]. Deaf participation may also minimize risk of cultural and linguistic appropriation. As no single person can represent the whole deaf/signing population, including multiple deaf perspectives can be beneficial, in particular to minimize the risk of developing technology that is harmful to some deaf people. Demographic factors to consider when building a team may include: hearing status, age of deafness, sign language fluency, age of sign language acquisition, type of education, sign language(s) and variet(ies) known, race/ethnicity, geography, and socioeconomic status.

Hearing people can also contribute meaningfully to the development of sign language technology. People who are not deaf do not have the lived experience of being deaf, and cannot speak on behalf of people who are deaf, but they can learn to work with deaf communities in ways that are respectful. Cultural awareness may prevent such people from building detrimental technologies. Such education may also help ensure that innovators seek partnerships within deaf communities, who can help ensure a positive outcome, before embarking on projects that may impact the communities. Expanding the pool of people who can contribute may help improve the state-of-the-art, as a more inclusive environment may foster more ideas and enable more people to contribute their skills to challenging problems.

At the same time, people who have no experience with sign languages or deaf communities run the risk of developing useless or even dangerous technologies, due to misconceptions about sign languages and people who are deaf. For example, inexperienced people may assume that sign languages are simply written/spoken languages that are manually executed, or that there is one universal sign language. Unfortunately, sign language recognition and animation research has often been conducted by all-hearing teams without close connections to deaf people. Consequently, resulting applications have been limited in their usefulness to deaf people, and some may actually harm deaf people (e.g., technologies designed in a medical model of deafness that are intended to "fix" or "help" deaf people). Importantly, hearing people are unlikely to suffer the consequences of harmful technologies. This context may explain deaf objections to technologies that have been released so far [57, 78]. These risks can be offset with education and collaboration with deaf people.

Some people outside deaf communities may wish to initiate projects, and struggle to find deaf collaborators because of the relatively small size of the deaf population. Another barrier is that common forms of networking among hearing researchers (e.g., conferences, coffee breaks) can be inaccessible spaces for deaf people. Social media has proven to be a more accessible networking tool, though it can also be inaccessible (e.g., non-captioned audio content). Hearing people might consider joining teams that already include deaf members, rather than forging a new path. Another possibility is to seek out deaf collaborators. One risk of this choice is that deaf people may feel obligated to collaborate primarily to minimize harm to their community, and not because they find the endeavor rewarding. This risk might be mitigated by compensating deaf collaborators either with traditional incentives for collaborations (e.g., publications, salaries, career advancement, public recognition) or alternative incentives (e.g., consultant fees, advisory board memberships).

10.2 More generally, how can we make progress in this space?

If sign language AI/ML modeling can be made into a popular topic, the field may advance at a much quicker pace. With popularity comes an increased diversity of people contributing ideas and skills, and an increase in funding and human work-hours. If a core group of people with knowledge about deaf cultures is centrally-involved, including deaf researchers and engineers brought into the fold through capacity building, it may be possible to scale initiatives without losing touch with deaf communities. For example, seminal computer vision competitions could be launched to introduce sign language modeling to mainstream AI, with submissions scored according to metrics specific to sign languages and valued by deaf people. For example, a prize could be won by the team that achieves highest accuracy on the use of depiction, an aspect of sign languages that is relatively unique and often highly valued by deaf communities. Awards could also be given based on deaf leadership and involvement, or for applications judged most useful by deaf people. Such competitions could educate the larger AI community about the complexities of sign languages and their role in deaf culture, while leveraging their skills to help advance sign language modeling.

Throughout, maintaining trust with deaf communities will be essential to making progress. Collecting sign language data requires active effort in reaching out to various sign language communities worldwide. Gaining the trust of sign language communities paves the way for further contribution of large-scale data. In order to gain trust, it must be provided that there will be some kind of benefit that returns to the community as a result of this engagement and contribution of valuable dataset. The "North Star" — or the biggest potential reward that comes from such efforts -– will likely be the continuing and long-term commitment towards sign language preservation and elevation. In contrast, if sign language dataset is collected without the trust of the community, it will be considered unethical and eventually harmful to the community. The value of the data itself may be questioned, and possibly be prevented from being used for active AI/ML training use.

In particular, as developments are made, it may be particularly important for deaf communities and other stakeholders to be aware that progress is slow, and that perfection is almost never immediately attainable. In general, new technologies do not work well, but generally improve as advancements continue to be made, and preliminary applications can be constrained to limit potential harms [3]. If imperfect technologies are misused and subsequently not tolerated, it may not be possible to get past initial stages of poor performance in order to benefit from more effective iterations and developments. Accurate presentations of ongoing research in the popular press may help to manage expectations and preserve trust.

10.3 What open research areas characterize the FATE issues laid out in this paper?

It may not be possible to address all the FATE issues laid out in this paper in a way that satisfies all parties. It may also not be possible to ensure that resulting research and applications built upon sign language datasets do not harm deaf people, because it is not possible to predict all the ways that a new piece of research or technology will be used. It is even less possible to predict all the research and applications that might be made possible by the creation of a new sign language dataset. Nonetheless, progress may still be made in a number of directions.

In particular, how to create a model of ownership and access that satisfies all parties involved is an open area for research. The landscape of data licenses for AI data more generally is currently evolving (e.g., Microsoft has proposed three model data use agreements [64]), and may yield new models that can be applied to sign language datasets used for AI. There may also be other novel ownership/access structures not involving licenses that can be applied to sign language datasets. In particular, boards exist for moderating biomedical data, and it may be possible to create similar boards for moderating sign language datasets. Involving representative, deaf leaders on such a board may help protect the rights and interests of deaf people by centralizing the control-point, but will also be limited by an inability to know or to act in accordance with preferences of *all* deaf people. Public datasets may take care of the need for moderation to some extent by putting the data in the public sphere, thereby "democratizing" ownership and access. By proportion, deaf people will make up a small proportion of this "democracy" and thus have limited control. Additionally, public datasets may be particularly difficult to protect from misuse, as democratizing ownership may also distribute responsibility for managing misuse.

How to communicate relevant information is yet another area open for research. As outlined in this paper, sign language datasets are complex, as are the underlying power dynamics. Consequences of usage (i.e. resulting research and applications) are also difficult to understand and communicate clearly, especially as short-term consequences may differ from long-term ones. In particular, ownership and access are complex issues, and without understanding the complexities, people may arrive at incorrect conclusions or maintain faulty assumptions. Clear communication is particularly important in order to build trust between data contributors and data collectors and owners, between data owners and third parties who attain access to the data, and with deaf communities at large. Given the history of audism and exploitation of the deaf communities, it may be particularly important to communicate the role of deaf people and the ownership they hold over sign language data. People's understanding of initiatives shape their responses to them, which in turn can alter the course of development as technologists absorb these reactions.

More generally, the opportunity is also open to further explore the FATE landscape, in particular in relation to non-Western deaf cultures. While we have attempted to be inclusive of diverse perspectives, the picture we have painted is inevitably colored by our personal experiences. A more complete picture requires input from a broader spectrum of people who may be impacted by this emerging field. Notably, our understanding of cultural dynamics are primarily Western and U.S.-centric. The dynamics outside of the U.S. may or may not be similar.

11 CONCLUSION

Sign language datasets have the potential to be very powerful, and with that power comes responsibility. For example, owners may control who can access the data and which applications can be built, but they are also responsible for maintaining and protecting the data and for any detrimental effects of its curation and use. Sign languages are also arguably the most precious cultural artifacts of deaf communities, and play a central role in deaf cultures. Consequently, deaf people have much at stake, both to gain and lose, from applications that may arise from these datasets. Before pursuing work in sign language AI/ML, we encourage technologists to pause and consider the FATE issues that characterize the space, and make any necessary adjustments to their plans.

In this piece, we begin to outline some of the FATE issues that characterise AI work with sign language datasets, and hope that it will serve as a useful resource. In particular, we cover seven main topics in relation to sign language datasets and FATE issues, identified through our personal experiences working, studying, and living in this space and substantiated by related work: content, model performance, use cases, ownership, access, collection mechanism, and transparency and understanding. Our goal is not to provide solutions or guidance, but to provide a framework for thinking about and discussing these complex issues.

While deaf communities are unique in many ways, we suspect that many of the FATE themes identified in this piece may apply to AI datasets linked to other marginalized communities. The issues we present primarily relate to deaf signers as members of socio-linguistic cultural minorities. As a result, the outlined considerations may closely overlap with considerations of other socio-linguistic minorities. For example, it is possible that people who use unwritten indigenous languages share many of the FATE issues that we have outlined. Similarly, there may be parallels with other disabled communities. We encourage other researchers and practitioners to continue thinking about these issues, and hope that this work will contribute to an ongoing dialogue between various communities and stakeholders.

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