Performance Disparities Between Accents in Automatic Speech Recognition

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ABSTRACT
Automatic speech recognition (ASR) services are ubiquitous, transforming speech into text for systems like Amazon’s Alexa, Google’s Assistant, and Microsoft’s Cortana. However, researchers have identified biases in ASR performance between particular English language accents by racial group and by nationality. In this paper, we expand this discussion both qualitatively by relating it to historical precedent and quantitatively through a large-scale audit. Standardization of language and the use of language to maintain global and political power have played an important role in history, which we explain to show the parallels in the ways in which ASR services act on English language speakers today. Then, using a large and global data set of speech from The Speech Accent Archive which includes over 2,700 speakers of English born in 171 different countries, we perform an international audit of some of the most popular English ASR services. We show that performance disparities exist as a function of whether or not a speaker’s first language is English and, even when controlling for multiple linguistic covariates, that these disparities have a statistically significant relationship to the political alignment of the speaker’s birth country with respect to the United States’ geopolitical power.

CCS CONCEPTS
• Computing methodologies → Speech recognition; Phonology / morphology; • Social and professional topics → Geographic characteristics; Race and ethnicity; Cultural characteristics; • General and reference → Evaluation; Empirical studies.

KEYWORDS
bias, automatic speech recognition, natural language processing, artificial intelligence, machine learning, accent, dialect, english language, speech, fairness, audit

1 INTRODUCTION
Automatic speech recognition (ASR) services are a key component of the vision for future human-computer interaction: a way for people to interact with the next generation of devices and services in a seemingly more natural and efficient manner. However, many users are familiar with the frustrating experience of repeatedly not being understood by their voice assistant [16], so much so that frustration with ASR has become a culturally-shared source of comedic material [5, 30].

Bias auditing of ASR services has quantified these experiences. English language ASR has higher error rates: for Black Americans compared to white Americans [24, 44]; for Scottish speakers compared to speakers from California and New Zealand [43]; and for speakers who self-identify as having Indian accents compared to speakers who self-identify as having American accents [29]. It should go without saying, but everyone has an accent – there is no “unaccented” version of English [26]. Different Englishes are spoken around the world, as a first language and a second language, due to colonization and globalization. While some English accents may be favored by those with class, race, and national origin privilege, there is no technical barrier to building an ASR system which works well on any particular accent. So we are left with the question, why does ASR performance vary as it does as a function of the global English accent spoken? This paper attempts to address this question quantitatively using a large public data set, The Speech Accent Archive [46], which is larger in number of speakers (2,713), number of first languages (212), and number of birth countries (171) than has been previously used to audit ASR services, and thus allows us to answer richer questions about ASR biases. Further, by observing historical patterns in how language has shifted power in the past, our paper provides a means for readers to understand how ASR may be operating today.

Historically, accent and language have been used as a tool of colonialism and a justification of oppression. Colonial power, originally British and then of its former colonies, used English as a tool to “civilize” their colonized subjects [22], and their accents to justify their lower status. English as a lingua franca today provides power to those for whom English is a first language. People around the world are compelled to promote English language learning in education systems in order to avail themselves of the privilege it can provide in the globalized economy [39]. This spread of English language may be “reproducing older forms of imperial political, economic, and cultural dominance”, but it also exacerbates inequality...
along neoliberal political economic lines [39]. A relevant example for our readers is that publishing is a key measure of research output for academics, but due to the dominance of English in research publications, researchers whose native language is not English face increased barriers to publication [41], including editing costs [17]. In short, the dominance of the English language around the world shifts power in ways that exacerbate inequality. ASR has the potential to further expand the power of the already powerful.

American English is and has historically been used as a nationalist tool in the United States to justify white conservative fears that immigrants pose an economic and political threat to them and has been used to enforce the cultural assimilation of immigrants [26]. We note that “Standard American English” is a theoretical concept divorced from the reality of wide variations in spoken English across geographical areas, across race and ethnicity, and across age, class, and gender [26], even within the United States. As stated in a resolution of the Conference on College Composition and Communication in 1972, “The claim that any one dialect is unacceptable amounts to an attempt of one social group to exert its dominance over another” [26]. The social construct of language has real and significant consequences, for example allowing people with accents to be passed over for hiring in the United States, despite the Civil Rights Act prohibiting discrimination based on national origin [27]. Accent-based discrimination can take many forms — people with accents deemed foreign are rated as less intelligent, loyal, and influential [25]. Systems based on ASR automatically enforce the requirement that one code switch or assimilate in order to be understood, rejecting the “communicative burden” in which two people will “find a communicative middle ground and foster mutual intelligibility when they are motivated, socially and psychologically, to do so” [26]. By design, then, ASR services operate like people who reject their communicative burden, which Lippi-Green reports is often due to their “negative social evaluation of the accent in question” [26]. As Haleyon Lawrence reports from experience as a speaker of Caribbean English, “to create conditions where accent choice is not negotiable by the speaker is hostile; to impose an accent upon another is violent” [25].

Furthermore, we are concerned about discriminatory performance of ASR services because of its potential to create a class of people who are unable to use voice assistants, smart devices, and automatic transcription services. When technologists decide that the only user interface for a smart device will be via voice, a person who is unable to use the device at all. As such, ASR technologies have the potential to create a new disability, similar to how print technologies created the print disability “which unites disparate individuals who cannot read printed materials” [47]. The biased performance of ASR, combined with the assumption that ASR works for everyone, creates a dangerous situation in which those with particular English language accents may find themselves unable to obtain basic services.

Given that English language speakers have a multitude of dialects across the world, it is important to consider the ability of English language ASR services to accurately transcribe speech of their global users. Given past research results [29, 43] and the United States headquarters of Amazon, Google, and Microsoft, it is perhaps not surprising that our results show that their ASR services will transcribe with less error for people who were born in the United States and whose first language is English. We expected that performance of ASR systems can be explained in part by the year of onset, the age at which a person first started speaking English, which is known to be highly correlated with perceived accent [8, 11, 34]. But beyond this, based on the nationalist and neoliberal ways in which language is used to reinforce power, we expect that the discrepancies in ASR performance can be explained by the power relationship between the United States and speakers’ birth countries. That is, for the same age of onset of English and other related covariates among speakers not born in the United States, we expect that speakers born in countries which are political allies of the United States will have ASR performance that is significantly better than those born in nations which are not aligned politically with the United States. This paper tests and validates these hypotheses on ASR services from Amazon, Google, and Microsoft by utilizing a data set with significantly more speakers than those which have previously been used for the evaluation of English ASR services.

2 RELATED WORK

2.1 Audits of Automatic Speech Recognition

Our work builds on a small but impactful body of literature investigating the disparities in performance of commercially available English ASR services.

Gender, while frequently evaluated, has been inconsistently associated with English ASR performance, with English ASR performing significantly better for male speakers over female speakers [43], female speakers over male speakers [14, 24], or with no significant performance difference being found [29, 44].

Evidence for the impact of race and geographic background (especially as it relates to accent and dialect) on ASR performance is clear. Speakers from Scotland were found to have lower English ASR performance than speakers from New Zealand and the United States [43], while speakers who self-identified as speaking with Indian English accents had transcriptions with higher error rates versus speakers who self-identified as speaking with American English accents [29]. Finally, ASR services consistently underperformed for Black speakers in comparison to their white counterparts [24, 44].

There are multiple aspects of spoken English which are affected by the particular accent of the speaker, including both: a) how words are pronounced (pronunciation of phonemes, intonations, pitch contours, stress patterns vs. syllable) [26], and b) what words are used and how sentences are structured. By studying unstructured speech, researchers obtain a view of the discrimination experienced by speakers in transcription accuracy as a function of multiple aspects of accent [24]. This paper presents results from a data set that controls for word choice and sentence structure [46] so that we can focus on the impact of how words are pronounced on ASR performance.

2.2 How Language is Used to Control and Divide

Language, and in many cases specifically English, has a history of being “standardized” by those in power as a medium through which to exert influence. Examples range from English being used to rank and hierarchize those deemed “other” in the United States [26] to the deliberate introduction of variations of English in India during
British colonization in order to maintain societal hierarchies and divisions [36].

We argue the attempted standardization of the English language via the increasing ubiquity of ASR systems is another chapter in a long story of how movements to create a standard language, or in this case “Standard American English”, have been tools to maintain power.

2.3 How Technology and AI Shift Power

Auditing ASR services is just one step in building an understanding of how artificial intelligence (AI) has the potential to either consolidate or shift power in society, both on a local and global scale. Whether it be the feedback loops we observe in predictive policing [10, 40], the involvement (and experimentation) of Cambridge Analytica in Kenyan elections [37], or the significant portion of Amazon Mechanical Turk crowdwork performed by workers in India [7, 42], all of these phenomena are a part of the coloniality of power:

[T]he coloniality of power can be observed in digital structures in the form of socio-cultural imaginations, knowledge systems and ways of developing and using technology which are based on systems, institutions, and values which persist from the past and remain unquestioned in the present [31].

Through our audit of English ASR services (with recordings from speakers born in many different countries) in combination with a historical analysis of the ways in which language and power have been closely intertwined, we both bring attention to and report evidence demonstrating the coloniality of ASR as it currently exists today.

3 HISTORICAL CONTEXT

ASR services operate in a worldwide context in which languages are not simply transparent forms of communication. Rather, they encode dense conflicts over status, power, and discrimination. Language has shaped the trajectory of social power. Mohamed, Png, and Isaac suggest using “historical hindsight to explain patterns of power” and align future development efforts with our ethical goals [31]. In this vein, we provide examples from colonization to globalization that provide historical parallels to the current context in which English-language ASR services operate and impact speakers today.

3.1 Standardization of Language

During the onset of European nation building and European colonialism, there were many conflicts over language, resulting in some languages becoming standardized. Linguistic dominance and linguistic imperialism are neither inevitable nor universally beneficial, and as we discuss in this section, the history of the standardization of language has always perpetuated more and greater disparities.

Globally dominant languages such as French, Spanish, Portuguese, and English are drenched with a violent history of imposition both within their nations of origins and then, through the colonial encounter, upon vast and disparate areas of the world. For instance, the notion of a standard French was used to force national belonging upon groups within the area we today recognize as France, people who themselves had scant investment in the metropolitan-based needs of an emerging centralizing economy. The French language was used to turn “peasants into Frenchmen” within the French Republic [45]. Within France, the emergence of a standard French served the needs of a dominant class and a capitalist economy; it denied the cultural and cosmological world-view of its own people; it worked to discipline labor and extract greater profit. The history of French is only one example, for the purposes of this paper it is significant to note that technologies of standardization and centralization were deployed to override enormous linguistic diversity and economic autonomy. Regional forms of communication were dismissed as mere “dialect” and elite notions of linguistic purity were forced upon divergent cultural systems.

All of this language standardization served to centralize political and economic control. ASR systems similarly serve to standardize language — if an English speaker does not speak with the accent deemed standard, then they are not understood. They are compelled to mimic the dominant accent in order to be able to make use of the ASR, which is felt as coerced or even violent [25].

3.2 Language Enables Hierarchy

Beyond standardization, language was used historically to enforce a hierarchical power structure. Western European languages expanded throughout the world when colonial powers imposed the language of their nation of origin upon newly subjugated colonies [23]. Each of the colonial languages, French, Spanish, Portuguese, and English, “spread” to areas dominated and controlled by those European powers. French in Senegal, Spanish in Mexico, Portuguese in Brazil and English in the United States (for instance) all carry the lived impact of colonial dominance, subjugation, and control. The history of colonial language imposition perpetuated more and greater disparities. In other words, new languages and modes of communication did not open the world to a greater ease of communication, rather they created new enclaves of social power. The colonial encounter introduced new languages upon disparate areas of the world. Colonial languages perpetuated difference between ruler and ruled and those differences were consolidated into notions of “race” [1, 12].

Specifically pertinent to our discussion of United States-based ASR services is the history of the English language itself. Along with other so-called global languages, the vast reach of the English language throughout the world is intertwined with colonialism. While no transnational language is free of social bias, it is important to underline the specific matter of the dominance of the English language, historically and contemporaneously. In the case of British colonized India, for example, the British deliberately instituted English as the language of rule and governance. The switch from Persian to English as the language of the State displaced earlier regional languages, centralized colonial power, and elevated “masters” over “natives.” The existing literate ruling class immediately identified technology which are based on systems, institutions, knowledge systems and ways of developing and using technology which are based on systems, institutions, and values which persist from the past and remain unquestioned in the present [31].
across the board, the British colonial rulers deliberately and selectively shared the language only with a small group of favored subjects. In the case of British India, this was predominantly a tiny minority of urban, Hindu, upper-caste men — the very group whose knowledge base and social customs were being universalized as “Indian culture” itself [3].

Newly English educated Indians were tasked with educating the rest of the “natives” — not in English, but rather in a new, reformed, standard, “vernacular” language. Dominant castes were the ones to enter English medium schools while simultaneously being the ones empowered to standardize the vernacular. The first generation of British India’s English speaking and writing Indians were expected to “refine” the “vernacular” languages and teach those to other Indians; they did so while subtly securing their own privileged access to colonial English [4]. What this history shows is that official colonial policy created fresh hierarchies. Under the guise of introducing English to India, the British dismissed some languages as “dialect” while elevating others as “classical” [20]. In the process of introducing the language of power through a favored group of upper-caste men, colonial education and linguistic policy instantiated wide-ranging and long-term effects. The colonial language was ranked above existing regional and pan-regional languages and the latter were now standardized by the very intermediary elite beneficiaries of colonialism. English became polarized against all so-called “vernacular” languages. The entire process granted tremendous cultural and social authority to a new class of pan-regional, upper-caste elites.

The spread of English reinforced the brahmanization of Indian society [2]. The colonial policy of instituting English as the language of governance and state power further elevated the brahmin caste. Ultimately, this was a particular strand of English. Elite and dominant caste colonial subjects have written of the careful education that they received within their homes, whereby colonial tutors were imported from England to teach them the “correct” accent and cultural references, all to prepare them to participate in and shape an Anglophone world [13].

Dominant caste Indians were the selected beneficiaries of colonial English. The story of English and its history of social discrimination ensured fresh internal divisions. Rather than broadening access to the language, British India’s first English educated men underscored their acquisition by a complex process of monopolization. They used tangible as well as more obfuscated ways to deny the language to other Indians. Symbolic power reinforced visible modes of authority, and they filtered the language through existing hierarchies of religion, gender, caste, and language to prevent other Indians from accessing English [4]. This was how colonial English was quickly circumscribed, and forever ridden through with caste and gender difference. As an interest group created by colonial education and governance policy, so-called “upper caste” English educated men moved quickly to consolidate their monopoly over the language, and they did so by restricting its spread.

Colonial education policies favored one existing elite, a group that moved quickly to appropriate English. But they did so by denying it to other Indians and thereby rendering the language selective, exclusive. In other words, what seems like the spread of English through India was actually a contentious process of discrimination, of serving the administrative and bureaucratic needs of British colonial extraction, of shoring up one social group against many others, and ultimately of marginalizing the vast majority of the colonized from access to the resources of modernity.

English-language ASR services are similarly exclusive, in that they do not serve people of all English language accents. Exclusivity is useful in the marketing of products, it can be used to market not only the commodity itself, but also the identity that people can have by using it. In this regard, it makes sense that American-based technology companies would sell a product that works for one wealthy group of consumers and excludes others. This exclusivity, however, provides less control to English speakers whose accents are disfavored. We show in this study that poor ASR performance can be explained, in part, by an axis of American political dominance.

### 3.3 Historical Traces in Contemporary Times

The historical account presented here illuminates the twists and turns by which a process of economic resource extraction and political might was supported by linguistic change. It is only with hindsight that we can appreciate how the notion of a standard language resulted in the hardening of ranked social categories and, as in the case of India, the favoring of one group of caste privileged men over millions of others. Existing social categories were exacerbated by the adoptiveness by which some could switch to a new and culturally dissonant language of expression. The “ability” to access, learn, and then communicate in English deepened long histories of power: both between ruler and ruled as well as among colonial subjects themselves. Access to the colonial language of power in each colony fomented hierarchies that have continued through the decades.

It is undeniable that the differences of colonialism have magnified under globalization and neoliberalization. Today, differentials in education, health and safety map onto access to English [35]. The language continues to be restricted to those who are not born into dominant caste families. Contemporary Indians have chronicled their determination to learn English in recent times, and their tenacious battle against towering structural hurdles. Crucially, as so many testimonies evidence, those hurdles are augmented by visible as well as obscured structures of caste discrimination [9, 38]. English remains out of reach, or at the very least, heavily restricted for the majority of Indians and in particular for those born to socio-economically underprivileged families.

Today India is named as the country with the widest circulating English language press; a desired target for the erstwhile Facebook as well as Amazon Prime and Netflix. The discussion above on the colonial era illuminates otherwise obscured aspects of the contemporary neoliberal era. India’s status as the leading market for English language content and its touted call-center capabilities is actually produced by a fairly recent colonial-caste history of discrimination. The story of English within India is one of a selective differentiation; it is riddled with the social codes of religious and caste power. Rather than dismiss this as a matter of past concern, or as a story from another part of the world, it is significant to recall the prominence of caste-privileged Indians in contemporary United States-based industry: the medical, software and academic fields in particular.
The notion of a standard language enables social disparity. The United States’ own history as a former English colony has elevated this particular language as the language of rule within America. Historically too, as research on education policy during the American occupation of the Philippines makes evident, the language was used to subjugate, in fact to racialize, colonized people. Education manuals brought to the new colony directed teachers to scrutinize the accent, body language, and sentence structure of “Oriental” students, and to use English language lessons to introduce students to a vocabulary of hygiene and cleanliness [28]. Standard American English was very much a tool for imperialism and racism.

Within the United States, its own citizens have demonstrated that American English is fraught and deeply contested. The language is laden with hierarchy and power; there is no single or value-free language, accent, or sentence structure. Even for those born in the United States, English is qualified by deep rooted social perceptions, by the language spoken at home, and most distressing of all, the shadow of war from decades past. The poet and essayist Cathy Park Hong writes powerfully about her battle to claim English; this despite being born and raised in Los Angeles [19]. For her, the inherited trauma of past genocide unleashed by the United States in Korea, the struggle to maneuver between competing sentence structures from disparate languages, and the manner by which her “Asian” appearance encodes social expectations of the meaning of her words, all shape every aspect — quotidian and formal — of her grasp over “English”.

Given the place of the English language in the history of white settler expansion in the United States, and drawing on the examples from France, British India, the Philippines and South Korea above, we stress that the disparities in English ASR performance we find and their connection to a United States-based worldview is no coincidence. Under the surface of a standard English lie terrible histories of appropriation and conquest, and of structural discrimination, bias, and racism.

4 MATERIALS AND METHODS

In order to quantitatively study the performance of ASR as a function of the variety of English language spoken, and particularly as a function of its relationship to a United States-based power structure, we need to tailor our methods and data sources appropriate to the task. We need a large data set of spoken English with speakers with a variety of first languages and from many nations, annotated with speaker information. We need to submit the audio from this data set to the dominant English-language ASR services in operation. We describe the setup of this analysis in this section.

To stay relevant with the published research on ASR bias, we select from among the five ASR services evaluated by Koenecke et al. [24]. The top three performing in their extensive tests were Google, Amazon, and Microsoft’s cloud-based ASR services. All three companies are notable not just as cloud service providers but in the consumer product space in which their ASR services are implemented as part of their own devices. Recordings were transcribed using the three companies’ respective speech-to-text APIs in 2021.

4.1 Word Information Lost (WIL)

To evaluate the correctness of the ASR service transcriptions against the elicitation paragraph that speakers read, we use a metric specifically designed for the assessment of ASR known as word information lost (WIL) [32, 33]. WIL is derived from an information theoretic measure of the mutual information between two sources. In short, for our case, it is a distance between the elicitation paragraph and the transcription for a speaker. The WIL is given by:

\[
WIL = 1 - \frac{H^2}{(H + S + D)(H + S + I)},
\]

where \(H\) is the number of hits (matching words), \(D\) is the number of deletions, \(I\) is the number of insertions, and \(S\) is the number of substitutions between the elicitation paragraph and the transcription.

Compared to another commonly used metric, word error rate (WER), WIL offers distinct advantages:

1. WIL is defined from 0 (all information preserved) to 1 (no information preserved), whereas WER is similarly bounded by 0 but has no upper bound.
2. WIL is symmetric between deletions and insertions, unlike WER, which, especially at high error rates, weights insertions more than deletions [32, 33].
3. The inaccuracies of WER are more severe at higher vs. lower error rates [32], which can be problematic for its use in linear regression studies.

Particularly in the context of our transcription task and the resulting analyses, the advantages of WIL make it the better metric by which to compare ASR performance.

4.2 Speech Accent Archive

Our recordings come from The Speech Accent Archive, a collection of recordings of speakers born across the world and with different first languages all reading the same text [46]. Full details on the methodology used in the recording collection and processing are available in Section A in the Appendix. After answering demographic questions, speakers were presented with the elicitation paragraph in Section 4.2.1 and allowed to ask questions about words they did not understand before reading the paragraph once for the recording.

4.2.1 Elicitation Paragraph. The elicitation paragraph below was crafted by linguists to include many of the sounds and most of the consonants, vowels, and clusters that are common to English [46].

Please call Stella. Ask her to bring these things with her from the store: Six spoons of fresh snow peas, five thick slabs of blue cheese, and maybe a snack for her brother Bob. We also need a small plastic snake and a big toy frog for the kids. She can scoop these things into three red bags, and we will go meet her Wednesday at the train station.

The methodology for recording, demographic information collected, and careful construction of the elicitation paragraph means that The Speech Accent Archive contains a wealth of information that is particularly well-suited to analyzing how English ASR services perform across a wide variety of people from across the world.
Further, the use of a constant text allows us to produce results that control for particular aspects of accent. Since all speakers read the same paragraph, any disparity in ASR performance will not be a result of word choice or sentence structure. We can use this feature of the data set to narrow in on ASR disparities that result from the manner of speaking the same words across different English language accents.

4.2.2 Speaker Information Collected. The information on speakers collected at the time of recording includes their age, sex (recorded, unfortunately, as a single binary male/female variable), country of birth, first language, age of onset of English speaking, and whether the speaker’s English learning environment was academic or naturalistic. Age of onset is particularly useful, as it has been shown to be correlated with perceived accent [8, 11, 34]. This speaker-level information is integrated into the regression performed in Section 5.2.

4.2.3 Data Description. Our data set includes 2,713 speakers with an average age of 32.6 years, and an average age of onset of English speaking of 8.9. Our speakers represent 212 first languages across 171 birth countries. Table 1 shows the top ten first languages represented in our data set by the number of speakers.

| First Language | Number of Speakers |
|----------------|--------------------|
| English        | 620                |
| Spanish        | 212                |
| Arabic         | 164                |
| Mandarin       | 128                |
| Korean         | 94                 |
| Russian        | 79                 |
| French         | 74                 |
| Portuguese     | 62                 |
| Dutch          | 51                 |
| German         | 40                 |

Table 1: Top Ten First Languages in Data Set with Number of Speakers

We note that at the time of recording, 2,023 (74.6%) speakers were either current or previous residents of the United States. By default, most ASR services that would be used on and by these speakers while they are in the United States would likely be configured to use the United States English dialect for transcription. For some of our results, we also use this dialect as the default. In addition, in Section 5.3, we conduct analyses using the “best of” all transcription service dialect settings, and show that the results are primarily the same.

5 RESULTS

5.1 Group-Level Analysis

In Figure 1, we compare WIL across ASR services grouped by whether a speaker’s first language was English. While overall performance differs between services with Microsoft performing best followed by Amazon and then Google, all services performed significantly better ($p < 0.05$) for speakers whose first languages was English. On average across all services, WIL was 0.14 lower for first language English speakers. By service, the size disparities followed overall performance, with a difference of 0.17, 0.14, and 0.10 for Google, Amazon, and Microsoft, respectively.

In Figure 2, we highlight mean ASR service performance for the ten first languages for which we have the most data, as described in Table 1. The order of performance found in Figure 1 is maintained across services — across all ten first languages, Microsoft performs the best, followed by Amazon, and then by Google. We find that all the ASR services perform best for those whose first language is English, followed by Dutch and German. The worst performance is on speakers whose first languages are Mandarin, Russian, Spanish, Korean, or Arabic.

Figure 1: Word Information Lost by ASR Service and English as the Speaker’s First Language. For each service, WIL is significantly lower when English is a first language.

Figure 2: WIL vs. First Language (showing the top 10 first languages by number of observations). Average WIL performance across all speakers (shown as vertical dashed lines) shows service performance, from best to worst, is Microsoft, Amazon, and Google.
5.2 Speaker-Level Regression
Motivated by the results in Section 5.1, we construct a linear regression to understand what factors have a significant effect on the performance of ASR services. As discussed in Section 3, the way a person speaks English has and continues to be a basis for discrimination by those in power, and so we include covariates to understand how this discrimination may transfer to ASR services. We want to know if ASR performance is correlated with how the speaker is perceived from a lens of United States global political power. As a broad single measure for this political power, we encode if the speaker’s birth country is a part of the North Atlantic Treaty Organization (NATO) as of January 2022. This avoids encoding each country as a separate regression variable (of which there are 171), and avoids having to develop a measure of United States political power in each country.

Specifically, we include about each speaker our analysis:
- Age and age of onset of English speaking;
- Sex;
- English learning environment;
- If their first language is Germanic, as a measure of first language similarity to English, with the list of Germanic languages coming from Glottolog [15];
- If their birth country is a part of NATO, for the reasons described above.

We create a nested covariate for English and the United States in the Germanic first language and birth country in NATO covariates respectively to avoid English and the United States being the drivers of any detected effect.

In order to satisfy the assumptions for linear regression, in particular the normality of the residuals, we perform a square root transform on our response variable, WIL. The diagnostic plots for the regression assumptions can be found in Section B.

5.2.1 Regression Results. The results of the regression are shown in Table 2 under the headings Amazon, Google, and Microsoft.

We find multiple covariates that have a significant effect across all three services. These statistically significant findings include:

1. WIL significantly increases with a later age of onset of English speaking. As described in Section 4.2, age of onset is correlated with perceived accent.
2. Speakers who learned English in a naturalistic environment have a significantly lower WIL over speakers who learned in an academic one.
3. WIL significantly decreases with speaking a Germanic first language, above and beyond the effect on WIL of English as a first language.
4. Finally, being born in a country that is a part of NATO but is not the United States, even while controlling for all other covariates, is associated with a lower WIL.

The final result suggests that a person’s birth in a country proximate to the United States’ geopolitical power does improve how ASR services perform on their speech. This result holds for all of the services tested.

Some covariates are only significant for certain services - ASR services from Amazon and Microsoft perform significantly worse on males than females. Google performs significantly better for those that speak English as a first language, and both Google and Microsoft perform significantly better for those born in the United States.

5.3 Transcriptions Using Other English Settings
As explained in Section 4.2.3, a majority (74.6%) of the speakers in the data set were or had been residents of the United States at the time of recording. Thus, when not stated in the above analyses, we used the United States English setting of all of the ASR services, as this was likely the settings which would be used on or by them.

However, ASR services do offer more settings for English. It is reasonable to ask how much using all of the English language settings available for a transcription service could improve WIL. We decided to understand this question for the service with the worst overall performance and largest disparity in performance as show in Figure 1.

We transcribed the recordings using all available English settings that Google supported. Specifically, we try these English settings on Google’s ASR service: Australia, Canada, Ghana, Hong Kong, India, Ireland, Kenya, New Zealand, Nigeria, Pakistan, Philippines, Singapore, South Africa, Tanzania, United Kingdom and the United States. To give Google the best opportunity for improvement, for each speaker we took the lowest WIL across all settings’ transcriptions. Note that while this is guaranteed to offer the largest improvement, it is unrealistic to do in practice, since it requires knowledge of the ground-truth transcript. We refer to this as Google All Settings.

A comparison to Google’s original performance is offered in Figure 3, where Google refers to transcriptions generated only using the United States English setting, and Google All Settings refers to WIL generated using the method directly above.Originally, we saw that for Google, first language English speakers had a WIL that was on average 0.17 lower than first language non-English speakers. When using the technique for Google All Settings on both first language English and non-English, we notice that a significant disparity of a similar size (0.14) still exists. In fact, even when we only use the United States English setting for speakers with a first language English and allow first language non-English speakers to take the lowest WIL from all settings, the disparity is still a considerable 0.10.

We also note that the significance of the factors in the linear regression did not change when compared to Google’s original transcription performance. This result is displayed in Table 2 under the column Google All Settings. This shows that not only did the performance disparities not fundamentally change, but also the effects that we noticed persisted, suggesting that even Google’s attempts to adapt their technology to different global settings are subject to the same biases we highlighted originally.

6 DISCUSSION
Across all three ASR services tested (Amazon, Google, and Microsoft), we find significant disparities in performance between those whose first language is English and those whose first language is not English. Moreover, we find that these disparities are
connected not only to the age at which an individual began speaking English, the environment they learned it in, and whether or not their first language was Germanic, but also whether or not their birth country is a part of NATO, a representation of political alignment with the United States. When, with one of the services tested (Google), we again transcribed recordings using all of the available English language locality settings, we saw all of our significant results remain the same, implying that the current set of international English language models offered does not solve the inherent problems of bias we observe in ASR.

6.1 Foresight for Future ASR Development
The historical use of language to maintain power via multiple colonial and post-colonial means can help us to model how ASR’s performance gaps are operating today. Perhaps more importantly, these mental models allow us to have “foresight and tactics” [31] for how we should address the problems of ASR in the future.

We provide one example of how these lessons may apply to discussions of how ASR will evolve in the future. Academic researchers and industry service providers have made claims that the problems are temporary. For example, Amazon claims “As more people speak
to Alexa, and with various accents, Alexa’s understanding will improve” [16]. As another example, researchers state about the ASR racial performance gap: “The likely cause of this shortcoming is insufficient audio data from black [sic] speakers when training the models” [24]. However, historical hindsight has not indicated that services will improve in this manner or without deeper structural changes in ASR services. First, by selling products that work for one accent above others, technology companies make speakers of other accents less likely to adopt their products. Members of groups who are historically subject to disproportionate state surveillance may be more hesitant to consent to contribute data towards AI technologies [21]. Both problems operate as a feedback loop to keep disfavored speakers out of future ASR service training data. Further, ML algorithms may naturally tend to discriminate against a smaller group in the population because sacrificing performance on that group may allow reducing average “cost” on the population as a whole, even if the training data represents them in proportion to their population [48]. Finally, ground truth labelling is likely to be less accurate for members a disfavored group, and incorrect labels will be fed back into training of future systems [6]. Whittaker et al. describe an example in computer vision for autonomous vehicles — the more video of people in wheelchairs used in training, the less likely it was to label a person backing their wheelchair across the street as a crosswalk as a person [47]. Instead, historical hindsight indicates that the problem is more systematic, related to the more fundamental nature of the use of standardized language to divide and provide the benefits of control.

6.2 Conclusion
This paper extends the results reported in prior English language ASR performance audits. In part, we provide an audit of ASR using a much larger data set containing speech from a large number of countries of birth as well as a large number of first languages. The quantitative results show how ASR services perform on speakers whose first language is English vs. those for which it is not, and how ASR services perform compared to each other. More critically, we find that, controlling for several related covariates about first language (including if the first language is in the same language family as English), and the age when someone started speaking English, all ASR services perform significantly worse if the speaker was born outside of a NATO country; in effect, in a country further from United States geopolitical power. We argue that this has historical parallel in the ways in which language has been used historically to maintain global power. By explaining these parallels, and by providing quantitative evidence for the effect, we hope that researchers and developers hoping to reduce disparities in ASR services will be better able to identify the systematic nature of the problems.

ACKNOWLEDGMENTS
The authors thank Abigail Lewis for her helpful insights on quantitative analysis, the stargazer R package [18], and The Speech Accent Archive [46].

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A SPEECH ACCENT ARCHIVE RECORDING AND VIZUALIZATION

A.1 Data Collection

Subjects were sat 8-10 inches from the microphone and recorded individually in a quiet room. They were each asked the following questions:

- Where were you born?
- What is your native language?
- What other languages besides English and your native language do you know?
- How old are you?
- How old were you when you first began to study English?
- How did you learn English (academically or naturally)?
- How long have you lived in an English-speaking country?

Subjects were asked to look over the elicitation paragraph and ask questions about any unfamiliar words. Finally, they read the passage once into a high-quality recording device.

A.2 Data Processing

All recordings were initially converted into the mp3 file format and then subsequently converted into the formats necessary for transcription by each of the respective services. This was done to help control any effects which might arise from files being originally recorded in lossy instead of lossless formats. Audio files were submitted to the respective APIs for all three services. The providers and the returned transcripts were then concatenated into a single string for each speaker. Across all services, only once did a service fail to return a transcription, and this occurred only for a specific triplet of service, speaker, and transcription dialect. Transcripts were then cleaned using the following process:

1. Semicolons were converted to spaces.
2. Characters were converted to lowercase.
3. Hyphens and forward and back slashes were replaced with spaces.
4. All currency symbols, ampersands, equals signs, octothorpes, and percent signs were separated by spaces on both sides.
5. The string was split on spaces to create words.
6. Punctuation at the end at beginning of words was replaced with spaces.
7. Leading and trailing spaces were stripped.
8. Words that were only spaces were deleted.
Words exactly equal to the characters "3", "5", and "6" were converted to "three", "five", and "six", since these exact numbers appear in the elicitation paragraph as written in Section 4.2.1 and would be correct transcriptions.

Spaces were added back in between words and recombined into one string.

After putting all transcripts and the elicitation paragraph through this process, WIL was calculated using the jiwer Python package [33].

B CHECKING REGRESSION ASSUMPTIONS

Before looking at the results of our regression, we evaluate the regression assumptions via diagnostic plots in Figures 4, 5, 6, and 7. Due to the square root transform which we performed on WIL (our response variable) in Section 5.2, the diagnostic plots show that our regression assumptions are satisfied, although there are some outliers to investigate. We analyzed each labelled outlier from the plots by hand, first by checking the speaker data to make sure there are no anomalies, and then by listening to the recording to ensure there are no audio issues. Having done this, we proceed to interpret the results of the regression as described in Table 2.
Figure 5: Checking the Regression Assumptions for Google

Figure 6: Checking the Regression Assumptions for Microsoft
Performance Disparities Between Accents in Automatic Speech Recognition

Figure 7: Checking the Regression Assumptions for Google All Settings