Algorithmic Language Management: How do language technologies affect linguistic practices and beliefs?

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Abstract

Language technologies such as machine translation, automatic captioning, and text and speech generation are embedded in an ever-growing range of digital devices used by millions of people every day in contexts as diverse as schools, homes, hospitals, and offices. While many of these technologies are not new, they are newly pervasive and, in part due to improved capabilities, subject to enormous hype and debate. What is largely missing from this conversation, are theoretical and empirical investigations of how language technologies affect the linguistic, interactional and social contexts in which they are adopted – answers to the deceptively simple question: 'What do language technologies do to language?' Researchers working on language and society, including linguists working on all aspects of human language structure, development and use, sociologists working on labour, technology or language, and computer scientists working on designing and evaluating language technologies, can fill this gap. In this paper, I suggest theoretical and methodological approaches to analysing language technologies, drawing on scholarship from (socio)linguistics, philosophy, and human-computer interaction. By situating language technologies in their historical, political, ideological and technical contexts, I show why these complex socio-technical systems are not just an interesting, but an important topic for researchers interested in language, technology, labour, or power.

1 Introduction

For many people, including myself and likely most readers, 'language technologies' are a mundane part of everyday life. This is perhaps best illustrated with a (fictional but plausible) account of a morning at an academic conference in an unfamiliar city. Before embarking on an all-important search for coffee and breakfast (and the conference venue), I might speak to my smartphone, asking 'assistant' Siri what the weather will be like and request a list of coffee shops and automatically translated customer reviews. Having located the cafe with the help of turn-by-turn directions provided by a friendly voice, a machine translation app helps me navigate the menu. While waiting for my coffee, I scroll through a feed of algorithmically curated social media videos with automatically generated captions and translations. Later on, I search the web to follow up on interesting references, though I need to clarify the spelling of the author's name as the automatic captioning at the keynote talk did not transcribe it properly. Other people's daily interactions with language technologies may include dictating a text message while waiting at a traffic light in a car, using a screen reader to listen to a report, anxiously searching for information about a medical problem, using a large language model to formulate a polite but firm email at the office, and engaging with a customer service chatbot.

Of course, this account, which admittedly almost reads like an advertisement for a smartphone, reflects a type of engagement with technologies which is common and mundane *only* in very few places around the world. It presupposes many privileges including an expensive smartphone, internet connection and the availability of robust language technologies to support automatic speech recognition, speech synthesis and natural language processing. Despite these significant biases and limitations, recent years have seen an immense proliferation across a wide range of technical, geographic and linguistic contexts, making them an increasingly important part of digital infrastructure. Under the wider umbrella of 'artificial intelligence', many current language technologies are the subject of enormous hype – characterised by exaggerated claims about positive and negative 'transformative' effects – propagated by industry, academia, popular media, and many governmental institutions (Markelius et al. 2024).

While language technology research (and 'artificial intelligence') has always been adjacent to linguistics, there is less engagement between these fields than one might expect. Regardless of the historic, institutional and epistemological reasons for this distance, this engagement is now more important than ever, as language technologies are moving into high-stakes contexts such as hiring (Sloane et al. 2022) and policing and immigration (Ozkul 2023), while also transforming 'language work' – from translation to teaching, writing to customer service – and creating new types of work, in particular related to the curation of language data. As a result, what is changing is not just how language is used but also how we think about language(s). I suggest that these changes in practices and beliefs related to language(s) can be conceptualised under the umbrella of "algorithmic language management", drawing on Bernard Spolsky (Spolsky 2004; Spolsky 2019).[1]

The article is organised as follows: in Section 2, I provide relevant technical and theoretical background; in Section 3, I situate modern language technologies in their intellectual, historical and social context, focusing in particular on the myths underpinning their development and the ways in which they can reproduce structural inequities; in Section 4, I illustrate how the framework of 'algorithmic language management' can be applied to analyse how language technologies affect linguistic practices and beliefs; finally, in Section 5, I point out future areas of research.

2 Definitions: language, technology and language technologies

2.1 On language technologies and 'artificial intelligence'

Recent decades have seen the development of a rich field exploring the ways in which digital technologies enable communication. Social media platforms (boyd and Ellison 2007) have been of particular interest as they enable quantitative studies of language variation and change (Strelluf 2019), qualitative multimodal analyses of linguistic and semiotic enregisterment (Tebaldi 2020; Ilbury 2022), and investigations of community norms (Are 2021; Cervi and Divon 2023; Calhoun and Fawcett 2023). By contrast, I am interested in 'language technologies', which I define as digital technologies which automatically process language completing tasks like translation between different varieties, summarisation, transcription, and generation of text and speech.

People encounter language technologies technologies in many different ways. Machine translation tools can be directly accessed through an app or website, or be almost imperceptibly integrated into a browser or social media user interface. Automatic speech recognition tools are embedded in smart phones, smart speakers and wearables to record and action voice commands, and enable (live) transcription of video and audio. In addition to enabling the automatic generation of text, large language models are also used to process natural language queries and formulate responses, which might then in turn be 'voiced' using speech synthesis. What unites these technologies despite their disparate application contexts is a focus on processing natural language[2], and, increasingly, a handful of central machine learning techniques.

In marketing and popular discourse, what I describe as 'language technologies' is now often

[1] I am indebted to many scholars across different fields who have thought and written and talked about language, society and technology and its intersections for much longer than me. Special thanks to my friend and colleague Stephen Joseph McNulty, who has first drawn my attention to language policy and has been integral to the development of many ideas in this paper.

[2] "Natural language" here is opposed to "formal language" (e.g., programming languages).

called ‘artificial intelligence’ (AI). I resist using this term here on purpose and will only use it in quotes. While the concept and field of research on ‘AI’ has a long lineage (Smith 2019; Pasquinelli 2023; Natale and Ballatore 2017), the term is often used to obfuscate, rather than clarify (Katz 2020; Crawford 2022; Goodlad 2023). Firstly, there is a fundamental confusion around the precise notion of ‘intelligence’ invoked (Weizenbaum 1976; Smith 2019; Goodlad 2023). This is compounded by the way ‘AI’ gestures to a rich tradition of narratives around intelligent machines spanning thousands of years in the Western literary canon alone (Cave et al. 2020). It is also not a precise technical term, as, in today’s usage, it collapses a number of different techniques across a wide array of application contexts. As science and technology scholar Lucy Suchman puts it, “interventions into the field of AI controversies that fail to trouble and destabilise the figure of AI risk contributing to its uncontroversial reproduction” (2023, p. 1). Here, I trouble this “figure of AI” by drawing out its ideological underpinnings and historical lineages which shape and even constrain if and how it can support human flourishing. In the next section, I explore the material foundations of language technologies.

2.2 On materials: Algorithms, data, hardware

How people understand, perceive and interact with technologies is often more interesting than, and quite unrelated to, how they “actually” work (Kempton 1986). For example, many social media users have rich “folk theories” around the inner workings and behaviours of “the algorithm” which recommends or curates content which are not necessarily reflective of the complex algorithmic systems operating ‘under the hood’ (Karizat et al. 2021). Crucially, these theories can still have significant effects on individual and group behaviour and the discursive construction of a technology (Seaver 2019; Calhoun and Fawcett 2023). Nevertheless, a rudimentary technical understanding of modern language technologies is required to ground the analysis which follows.[3].

Many of the most popular current language technologies, including most large language models (LLMs) and state-of-the-art automatic speech recognition (ASR) systems, share similar algorithmic architectures, datasets and hardware. For example, many LLMs are ‘pre-trained transformer models’ (Vaswani et al. 2017). They are ‘pre-trained’ on an enormous amount of text data such as a section of the web data repository Common Crawl (Baack 2024), and can be adapted for specific use cases. Transformer models predict token sequences based on complex contextual representations of meaning. Like other neural language models, they leverage several layers to compute

[3]As an accessible primer on current techniques in natural language processing, I highly recommend Jurafsky and Martin’s continuously updated draft of the third edition of their textbook Jurafsky and J. H. Martin (2013), which can be found at `https://web.stanford.edu/~jurafsky/slp3/`. I refer to this draft as well as primary literature in this section. See also Vallor (2024) for an accessible, non-technical introduction.

these meanings (hence: deep learning), and, unlike some others, can take preceding and following contexts and estimates of their relative importance into account. This makes transformers more computationally efficient and better at modelling natural language than previous architectures. While the innovations in the design of the algorithmic architecture are fundamental to the success of these models, so is the availability of large text datasets and sufficient computational resources. These models can be used for machine translation and transliteration, text summarisation and generation of natural language and code based on prompts. Examples of pre-trained transformer models include Open AI's GPT models, Meta's Llama models and Google's Gemini, PaLM and (older) BERT models. Historically, ASR models required transcribed speech data, increasing the cost as transcription is a laborious, skilled task. Modern model architectures, such as the conformer , developed by Google (Gulati et al. 2020), and wav2vec developed by Meta (Baevski et al. 2020), can be pre-trained with very large datasets of untranscribed speech. For example, Y. Zhang et al. (2023) (Google), train their multilingual speech recognition model on 12 million hours of (untranscribed) audio sourced from YouTube, 28 billion (unrelated) sentences sourced from the web, and about 100,000 hours of transcribed audio (also from YouTube).

Finally, language technologies are, of course, also material objects and the result of complex processes (Taffel 2022), consisting of rare minerals which are dangerous to mine and handle and plastics which are not biodegradable among other materials (Crawford 2022). These materialities are obscured when language technologies are embedded in multi-functional digital devices like smart phones or computers, but more obvious when we consider that 'state-of-the-art' models are pre-trained using thousands of graphic processing units (GPUs) (e.g., Llama 3 Team 2024). As a result, the data centres in which pre-training and deployment happens, require a lot of space, materials, power and water (Crawford 2022; S. Luccioni et al. 2024). To match demand, new, bigger data centres are built around the globe, in particular in regions with favourable regulatory contexts, where they can disrupt the local power grids and affect retail and wholesale prices, and draw significant amounts of water for cooling (Saul et al. 2024; Olivo 2024). Importantly, even as many Big Tech companies focus on renewable energy, sudden increase in demand is often met with fossil fuels (Olivo 2024) and nuclear energy. This matters especially as we witness (and perhaps participate) in the integration of LLMs into any number of existing processes where they simply do not add sufficient value, for example internet search (C. Shah and Bender 2022) and the creation of art (Goetze 2024).[4] Overall, the extremely resource-intensive production of 'artificial intelligence' naturally favours an oligopolic structure, with a very small number of large players being able to afford the infrastructure required, as explored in more depth in Section 3.2.1.

[4] As Taffel (2021) puts it succinctly in the context of yet another massive drain on energy and water, "in an ecologically sane society, bitcoin does not exist". Perhaps the same is true for generative models.

2.3 On management: language policy and technocracy

The ways in which language technologies shape language use and ideologies are still empirically and theoretically under-explored. As discussed in more detail below, research does suggest that successful and unsuccessful interactions with voice user interfaces affect how users feel about themselves and their language (Wenzel et al. 2023; Mengesha et al. 2021; Leblebici 2024). There is a common assumption – not yet fully borne out by empirical research – that availability of high-quality language technologies affects the status or popularity of language varieties. Unquestionably, since language technologies mediate everything from internet search to content moderation and personalised content recommendation, their availability in a language can enable its speakers to participate in digital life. Language technologies are also embedded in high-stakes decision making processes such as algorithmically supported hiring and job performance reviews (Sloane et al. 2022) and asylum application assessment (Ozkul 2023). Notably, most of the tools are developed, maintained and deployed by for-profit businesses using opaque model architectures and proprietary datasets. In addition to creating technical and legal barriers to effective and impactful auditing (I. D. Raji and Buolamwini 2019; Costanza-Chock et al. 2022; Metcalf et al. 2021), this also means that important decisions relating to language such as the selection and curation of language data, system quality control and any constraints on system behaviour are taken by private, corporate actors. It is this decision making, and its impacts on language communities, that requires more scrutiny.

Bernard Spolsky's framework of 'language policy' provides a useful starting point for analysing language technologies and their impacts on the sociolinguistics context because it recognises the inter-related nature of practices, beliefs and management. In work with Elena Shohamy (Spolsky and Shohamy 1999), 'language policy' is conceptualised as consisting of language practices, language beliefs and language management. Elaborating on this theory, Spolsky defines these interrelated components simply as "the habitual pattern of selecting among the varieties" (language practice), "the beliefs about language and language use" (language beliefs or ideologies), and "any specific efforts to modify or influence that practice" (language management) (2004, p. 5). Traditional domains of this notion of "language policy" include national and supra-national institutions and organisations, workplaces and educational institutions as well as families, neighbourhoods and religious groups (Spolsky 2004; Spolsky 2021). Recent revisions to the framework (Spolsky 2019; Spolsky 2021) furthermore highlight the role of individuals in their "self-management" and acknowledge the differential status of different types of actors. As we discuss in Markl and McNulty (2022), we can furthermore understand the role of specific individuals and groups within language technology development in terms of language policy, for example through the concept of "language policy arbiter" (D. C. Johnson and E. J. Johnson 2014).

Of course, the question of how to 'manage' social life was (and continues to be) a pre-occupation not just of sociolinguistics, but the social and human sciences more broadly. As Geoghegan (2023) chronicles, the development of a structuralist, cybernetic account of all aspects of human life was one of the defining endeavours of 20th century academic research. This focus was specifically driven by the quest for technocratic approaches to 'problems' as different (or similar, as the cyberneticians would argue) as therapy, welfare and warfare (Geoghegan 2023). Technocracy, as Geoghegan frames it, is about "a politically motivated valorization of the technical as a supposedly nonpolitical and neutral tool of governance" (2023, p. 15). In the context of sociolinguistics, this technocratic impulse manifested in the field of 'language planning' in the 1950s and 1960s (Ricento 2000). During this period, numerous nations around the globe established formal independence from European imperial states. Many of these nascent states comprised multiple linguistic, cultural, and ethnic communities, raising complex practical and theoretical questions about the creation of official standardised language varieties to be used in administration, government and education. Linguists strongly influenced by structuralist approaches prominent across multiple fields at the time (Geoghegan 2023), and holding (explicit or implicit) commitments to 'modernisation' and Westernisation, acted as experts to 'solve' these 'problems' by creating complex national policies granting official status to indigenous and colonial languages, developing writing systems and compiling dictionaries (Ricento 2000; Heller and McElhinny 2017). In other words, linguistic experts directed the selection of particular varieties which they then standardised and promoted in various domains via national policies, a process, of course, paralleled by the work of technical experts in the development of computing technologies elsewhere (Geoghegan 2023; Ensmenger 2012; Hicks 2018).

As it happens, the technocratic approach to 'language problems' often re-established the very power hierarchy the decolonisation process was supposed to destabilise, promoting colonial languages to 'high-status' domains (O'Regan 2021, p. 128). Over the course of the twentieth century, intellectual currents like post-structuralism and Marxism, reached both language policy and, to some extent, technology studies. Within language policy, it sparked significant debates and drove the development of new theories and methods (Ricento 2000). Critical investigations of how technologies are created and how they affect society, have, of course, been a core focus of sociological and political theory for hundreds of years (on Marx, see e.g., O'Regan 2021, 21ff), but have only coalesced into a (still broad) field of science and technology studies in the 1970s and 1980s (Rohracher 2015; Pinch and Bijker 1984).

2.4 On use: (Dis)affordances and valences of language technologies

To complicate our understanding of technologies and analyse their origins and impacts, we need to map how they are and can be *used*. Here I focus on the "affordances" and "valences" of technologies. Though it has a longer history, the concept of "affordances" was popularised by Don Norman: "An affordance is a relationship between the properties of an object and the capabilities of the agent that determine just how the object could possibly be used" (Norman 2013, p. 11). As Sara Ahmed points out in her discussion of "use", what is self-evidently "usable to some is unusable to others" (Sara Ahmed 2019, p. 59). To take an example used by Norman, and discussed by Sara Ahmed (2019) and Costanza-Chock (2020): a door affords entry into a building – though only for those who can climb the steps up to the door, have a key for the lock, and are able to push it open. For everyone else, the door might disafford entry – it closes off a particular space. Crucially, these disaffordances may or may not be intentional – a physically strong person designing a door may not consider that its weight might act as a barrier to entry (Sara Ahmed 2019; Shew 2023). To further extend this example, a door might also afford things beyond enabling or disabling access to a building. For example, a wooden door may afford knocking (to ask permission to enter), slamming (to express emotions in argument), scratching (to express desire to go out for a pet), leaning (to rest while waiting for a locksmith), and so on.[5] We can distinguish between normative and non-normative, expected and unexpected uses through the concept of "valence" introduced by Bush to capture how the design of object can "push or pull behavior in definable ways" (Bush 1993, p. 197). She provides the example of a gun as a "technology that is designed for killing in a way that ice picks, hammers even knives [...] are not" (Bush 1993, p. 197). While other tools can be used as weapons, firearms have a unique valence towards violence. In a less extreme example, cars have a valence towards individuation in contrast to trains (Bush 1993, p. 197).

In summary, the notion of affordance allows us to capture all the intended, expected and normative uses of language technologies, as well as the unintended or subversive ones. Valence is useful because it describes the overall tendency of a technology. Considering what is afforded and disafforded, to whom and at what cost shows how existing inequalities are reproduced in technology.

[5] Norman (2013) also famously discusses the importance of 'signifiers' in design which should indicate affordances to users – it should be obvious, without signage, whether a door is opened by pushing or pulling, for example.

3 Policy: steering language and technology

The design, biases, capabilities and limitations of language technologies meaningfully shape interactions between humans and between humans and machines, and, in this way, intervene in the existing sociolinguistic context. To understand these interventions, we need to look 'upstream' and examine the wider social, political, and historical contexts shaping technology development and deployment. To do this, I will first highlight the discursive and ideological context in which modern language technologies are being developed, before turning to the ways in which they materially reproduce economic and social inequities.

3.1 Myths about technology: Inevitability, Utopia, Dystopia

Writing in 1983 from the United States, feminist scholar Corlann Gee Bush identifies three dominant discourses about technology which still resonate today: technologies as tools, as threats or as triumph (Bush 1993, p. 195). Crucially, all of these are too simplistic in her view. As she puts it: "we must analyze these assumptions and unthink them, making them simpler by naming their complexity" (Bush 1993, p. 195). She highlights that the myth of technology as triumph (over other nation states, disease, death, nature, etc.) is powerful and, of course, in part true but also obfuscates considerable damage (environmental, social, cultural), This encourages a highly polarised context where critics frame technology as a fundamental threat, glossing over real and genuine positive impacts (Bush 1993). The limitations of this "polarized thinking" are, then as now, "obvious" (Bush 1993) – though that does not mean it is not commonly employed in discussions relating to 'artificial intelligence'. Specifically, I want to explore three notions in these discourses: inevitability, utopia, and dystopia. Making them "simpler by naming their complexity", requires a digression into the history, culture and political economy of 'artificial intelligence'.

3.1.1 'AI' is not inevitable: the myth of magical progress

The inevitability of 'artificial intelligence', or any technology for that matter, is a fallacy. Technologies are created by people in complex, slow and usually collaborative processes. Both process and outcome are shaped by the wider social and political contexts (Winner 1980; Haraway 1988). While utopic and dystopic visions diverge in the details, both frames presuppose that change is imminent, and, at least to some degree, inevitable. In recent years, national governments around the world have formulated 'AI strategies' and regulation in response to and anticipation of development and deployment of new language technologies (among others) by the private sector (Lagerkvist 2020; Bareis and Katzenbach 2021). This 'anticipatory frame' forecloses the possibility of refusing, decommissioning and undoing technological interventions (Hoffmann 2021a;

Hampton 2021; Ricaurte 2022), and, perhaps naively[6], takes Big Tech at their word that everything will indeed change.

Resisting this narrative of rupture is important. As Androutsopoulos (2006) highlights in an introduction for a special issue on Computer-Mediated Communication (CMC) of the Journal of Sociolinguistics, some of the influential early research on CMC exaggerated the impact of the specific affordances of digital communication forms (e.g., emails, SMS) on language use and erased significant context-specific variation. In discussing the role of new language technologies, we need to be careful not to fall into this trap. Just as there is no (one) "language of CMC", but rather many different computer-mediated discourses (Androutsopoulos 2006, p. 421), communities and individuals interact with a wide range of language technologies in different ways producing a multitude of social and linguistic effects.

At this point (in the early 2020s), it is entirely unclear if language technologies will 'live up to the hype'. While mainstream and business media and to some extent even scientific papers have been adopting a euphoric tone in repeating bold proclamations by Big Tech companies and (well-funded) start-ups that LLMs such as Open AI's GPT models will radically transform the global economy (Brennen et al. 2018; Cools et al. 2022; Roe and Perkins 2023; Markelius et al. 2024), there is now a growing sense that this transformation will mostly consist of worse, more precarious working conditions for writers and artists. Even as new LLMs are released, evaluating or even defining their capabilities remains an unsolved challenge (D. Raji et al. 2021; Birhane and McGann 2024; Grill 2024). What is already clear, however, and indeed has been since before this most recent explosion in popularity of LLMs, are the significant risks and harms associated with all points of the development and deployment lifecycle (Weidinger et al. 2022; Suresh and Guttag 2021; Bender et al. 2021). The challenge of meaningful, grounded evaluation is not limited to LLMs, either, but extends to automatic speech recognition (Sanabria et al. 2023), machine translation (Moghe et al. 2023), and speech synthesis (Le Maguer et al. 2024).

3.1.2 'AI' won't end us: the myth of existential risks

In discussions about the 'risks' of 'artificial intelligence' there are two perspectives, perhaps best understood as two essentially non-overlapping research communities. One of these communities is focused on the risks and harms of currently-existing technologies such as the language technologies discussed here. In general, researchers, activists and practitioners in this group, myself included, are concerned with harms of bias, discrimination and exploitation, and are, broadly speaking, guided by a commitment towards values of equity, justice and fairness. This community starts from the assumption that current technologies are, at best, flawed but can be im-

[6] Consider how often you have heard bold proclamations that fully autonomous vehicles are 'just five years' away.

proved, or, at worst are irredeemable and should thus not be deployed. As with any community of researchers, how to best approach, prevent, mitigate and understand the risks and harms produced by 'AI' is highly contested within this space (see e.g., Laufer et al. 2022; Birhane et al. 2022; Widder et al. 2022; Hampton 2021; Birhane 2021). I discuss some of the most pressing harms of current language technologies in Section 4, focusing on global inequality, poor working conditions and automation, and environmental impacts.

This is contrasted with what Shazeda Ahmed et al. (2023) refer to as the "epistemic community of AI safety". In the last twenty years, this community has coalesced around some key ideas including 'effective altruism', 'longtermism', 'artificial general intelligence' and 'existential risk' (Shazeda Ahmed et al. 2023). Gebru and Torres (2024) understand these ideas as part of the 'TESCREAL' bundle of ideologies (Transhumanism, Extropianism, singularitarianism, cosmism, Rationalism, Effective Altruism, longtermism). While a detailed discussion of these ideologies, their origins and impacts are outwith the scope of this paper[7], I will briefly discuss how they relate to 'AI safety'. Firstly, it is important to note that this community is largely concerns with future risks and harms which could arise if 'artificial general intelligence' (AGI) is developed. AGI is distinct from currently existing technologies which, in essence, are very good at recognising patterns in structured or unstructured data (sometimes referred to as 'narrow AI' or 'weak AI'). While exact definitions of AGI differ, they agree that this class of technologies would have to be more autonomous and flexible (Gebru and Torres 2024; Shazeda Ahmed et al. 2023; Vallor 2024). As philosopher Shannon Vallor puts it succinctly: "AGI is what you envision when you imagine holding a conversation with an android like Data from *Star Trek*" (2024, p. 22). Whether developing AGI is possible is deeply contested among researchers (Shazeda Ahmed et al. 2023; Vallor 2024). Even if it was, there are strong disagreements whether current generative models (such as LLMs and image generation models) are anywhere near the right path to AGI (Vallor 2024; Shazeda Ahmed et al. 2023). Effective altruism, longtermism and concerns about existential risks are all rooted in utilitarianism, an ethical framework according to which the ethical value of an action directly relates to its impact on total wellbeing (Shazeda Ahmed et al. 2023; Gebru and Torres 2024). The highly influential Centre for Effective Altruism states: "effective altruism is about using evidence and reason to figure out how to benefit others as much as possible, and taking action on that basis" (MacAskill 2019).[8] This orientation towards "science-aligned", "welfarist" and "maximising" action (MacAskill 2019) can manifest in very complex calculations about the most

[7] I direct interested readers to Gebru and Torres (2024), which is an excellent and foundational analysis of these beliefs and their connection to eugenics. Shazeda Ahmed et al. (2023) furthermore document how online discussion forums, competitions and very large amounts of private funding provided by some of the wealthiest and most influential actors in the tech industry contributed to the development of the "AI safety epistemic community". For a very accessible yet deeply researched introduction to effective altruism and longtermism, see Thorn (2023).

[8] For a more precise definition, see MacAskill (2019).

effective (and financially efficient) way to, for example, reduce global Malaria deaths. Longtermism is a distinct but related movement which prioritises the long-term well-being of humanity – crucially this “long-term” is not defined in decades but centuries, millennia and even millions of years (Shazeda Ahmed et al. 2023; Greaves and MacAskill 2019). At this point, the well-being of currently-existing people is weighed up against the potential well-being of future people (Greaves and MacAskill 2019). Coupled with a firm belief in the possibility (or inevitability) of developing AGI, harms by unsafe or rogue AGI as well as harms that could have been prevented by life-saving AGI-based technologies become a core concern and an ‘existential risk’ to humanity (Greaves and MacAskill 2019). It is this reasoning that shapes a lot of research and engineering in ‘artificial intelligence’ research today. Though the wider belief system sketched out by Gebru and Torres (2024) may be alienating to outsiders it is very influential the ‘artificial intelligence’ space.[9] Open AI, who develop the GPT language models and the DALL-E image generation models, are explicitly committed to “developing beneficial AGI safely and responsibly” (Open AI 2024b) and state that “[they] believe [superintelligence] could arrive this decade” (Open AI 2024a). Several key figures associated with the company, which works in close partnership with Microsoft, including founder and CEO Sam Altman and former chief scientist Ilya Sutskever are strongly committed to (some version of) the TESCREAL beliefs (Gebru and Torres 2024). Beyond Open AI, billionaire investors such as Peter Thiel (current CEO of defence and intelligence technology firm Palantir), Elon Musk (current CEO of Tesla and X) and Sam Bankman-Fried (disgraced founder of cryptocurrency exchange FTX, convicted for fraud in 2024 (Sherman et al. 2024)) are only some of the most recognisable people associated with TESCREAL (Gebru and Torres 2024).

There are, of course, real existential risks facing humanity right now. We are experiencing unprecedented changes in the climate triggering a cascade of irrevocable and escalating chain reactions in the Earth’s ecology as a direct result of human activity (Intergovernmental Panel on Climate Change (IPCC) 2023). As discussed in Section 2.2, the development and deployment of language technologies also consumes vital resources further contributing to ecological destruction (Saul et al. 2024). Additionally, the discourse of ‘long-term’ risks associated with AI based on a speculative future, takes up vital discursive space (and funding!) which could be used to discuss more immediate harms such as climate crisis (Dauvergne 2020; Schütze 2024) or harms directly resulting from inhumane labour practices in curating data (see Section 3.2.2) and discriminatory system outcomes (see Section 4.1.3). It is important to note here that while I contend that ‘AI’ will not ‘end humanity’ anytime soon, thousands (or more likely millions) of people are already experiencing significant harm because of it. Workers involved in content moderation, system evaluation and data annotation have reported severe and life-changing psychological harms

[9] It is also worth noting that the quasi-religious undertones in discussions of AGI have not gone unnoticed by commentators and critics, as discussed by Gorcenski (2023) and Williams (2023).

as a result of inadequately supported exposure to traumatising content (e.g., child sexual abuse materials) (Perrigio 2023; Gebrekidan 2024). High-stakes decision making systems relating to credit and banking, child protection and safeguarding, welfare and insurance, and policing and warfare have enormous unintended (and intended) negative consequences for millions of people around the world (Eubanks 2018; Suchman 2020; Angwin et al. 2016). Even if concerns about the capabilities of 'AGI' in a hundred, a thousand or a million years are warranted, there is much more immediate work to be done right now to ensure that people across the globe will (still) have access to food, water, shelter and community in the not-so-distant future.

3.1.3 'AI' won't save us: the myth of the technical fix

As Gebru and Torres (2024) point out, "AGI utopia and apocalypse [are] two sides of the same coin" (n.p. 2024). This is in part because AGI is framed as inevitable, and in part due to a (however misguided) belief that AGI could save humanity from genuine existential risks such as climate collapse. Utopic thinking around 'artificial intelligence' is not limited to AGI, however. In recent years, calls for "language technologies for all" have gained prominence in corporate, academic and global policy circles (e.g., UNESCO). As briefly discussed in Section 2.2, current 'state-of-the-art' language technologies such as large language models require an enormous amount of data to train. Languages for which this kind of data is not available, usually due to a confluence of factors including global and local inequalities, linguistic discrimination and cultural differences to the Western norm such as primarily oral storytelling, are referred to a 'under-resourced' or 'low-resource'– a label which encompasses languages with tens of speakers and those with millions of speakers (Bird 2020; Bird 2022). Under-resourced languages are of particular commercial and scientific interest to language technology developers. Products for hitherto unsupported languages obviously open up new markets – including not just the immediate applications of, say, machine translation and captioning, but also web localisation, social media, search and advertising. Building robust and usable language technologies with small(er) datasets is also a significant and potentially lucrative engineering challenge. Overall, claims that communities would benefit from more widely available and better language technologies are fairly uncontroversial, especially in the context of what Bird (2022) terms "contact languages" which act as lingua francas within "cultural areas". These languages tend to be standard varieties used in trade or communication between linguistic groups whose primary languages are "local" languages – primarily oral languages spoken by small, indigenous or other minoritised communities (Bird 2022). Many of these languages are considered endangered, usually as a direct or indirect result of violent conquest, settler colonialism, displacement, and attempts by dominant social groups and states to suppress and eradicate indigenous cultures (Chiblow and Meighan 2021; Mahelona et al. 2023).

Coupled with the hegemonic status of English (O'Regan 2021) and, to some extent, other colonial languages, this legacy threatens and harms hundreds of millions of minoritised people globally. While language technologies may support these communities in building networks of solidarity, sharing their cultures and knowledge, and participating in global labour markets, carelessly built technologies for local languages are unlikely to meaningfully contribute to the fight to pass on indigenous cultures (S. Zhang et al. 2022; Bird 2022; Schwartz 2022). Regardless of the type of language, inclusion in large-scale language technologies is not an unalloyed good, and understanding who benefits from them is essential. A much-cited but still extremely illustrative example are Māori language technologies. Māori organisation Te Hiku Media has, in recent years, built a number of language technologies for Māori using data compiled with support from their local communities. Crucially this project is led by indigenous people to benefit indigenous people. It sits in stark contrast to the 'massively-multilingual' approach to endangered and under-resourced languages pursued by developers like Google, Meta AI and Open AI. The latter's automatic speech recognition system 'Whisper' has drawn particular critique from Te Hiku, as it included Māori despite the communities explicit and public request not to use Māori data (Mahelona et al. 2023; Marx and Mahelona 2023). Māori has also been incorporated into Google Translate and Meta AI's machine translation system.

It is essential to resist a naive narrative that endangered and minoritised languages (and their communities) can be 'saved' by technological innovation (alone). While language shift can probably be exacerbated by lack of technological support, reversing it likely requires broader structural changes and significant input by the affected language community. Without deep engagement, and, ideally, leadership from the language community in the development of technologies, it is very difficult to build things that actually benefit the community and very easy to build things that are, at best, useless for the community and benefiting someone else, and, at worst, directly harming the community (Schwartz 2022; Bird 2020). While some of the research into large-scale multilingual systems by Big Tech is welcomed by language communities and has real, immediate, material benefits for them, approaches which consistently do not meaningfully involve communities, rely on low-quality training data and, ultimately, cede no power to communities at all, are not enough. Having discussed the foundational myths of 'AI', I now turn to some of the ways language technologies reproduce existing power structures.

3.2 Encoding systemic oppression

Scholars, practitioners and activists have long traced the ways in which 'artificial intelligence' and algorithmic systems more broadly relate to and reproduce systemic oppression. Batya Friedman and Helen Nissenbaum published a foundational analysis of "bias in computing systems" almost thirty years ago (Friedman and Nissenbaum 1996). Since then, countless studies have demonstrated the fundamental insight that science and technology cannot be disentangled from the social and political contexts in which it is created (see Haraway 1988; Winner 1980). Since the widespread adoption of algorithmic systems in domains such as information retrieval and communication (e.g., internet search and social media), public service access (e.g., welfare systems), banking and insurance (e.g., credit scoring and fraud prediction), and policing and warfare (e.g., 'predictive policing', object and person recognition), there has been a growing body of incisive critiques documenting harmful logics and outcomes. This area of work, carried disproportionately by women and, especially, women of colour, has shown decisively that algorithmic systems re-produce systemic oppression (Noble 2018; R. Benjamin 2019b; R. Benjamin 2019a; Chun 2024; Eubanks 2018; O'Neil 2017). By definition, machine learning systems can only make future predictions based on past data, making them fundamentally conservative. In practice, the existing data is also always partial, not just in the sense that all data necessarily is partial (Haraway 1988), but in the sense that data about and by historically marginalised groups is underrepresented (Guyan 2022; Onuoha 2016). Shaky foundations notwithstanding, algorithmic models are applied to extremely complex social processes to make automatic decisions, often lending a futuristic veneer of science, rationalism, and objectivity to deeply discriminatory systems (Fourcade and Healy 2024; Chun 2024; R. Benjamin 2019b). This is especially true when the type of demographic data that people would be able to discriminate upon (e.g., race, age, gender, disability) are redacted in the decision-making process. As both social theorists and marginalised people have long known, it is impossible to disentangle any data related to life experience (e.g., language, interests, address) fully from one's social position (Fourcade and Healy 2024). As a result, algorithmic systems will construct some "post-demographic" (Fourcade and Healy 2024) category to discriminate by if necessary. Crucially, the critical scholarship suggests that algorithmic discrimination is in many ways *more pernicious* than human discrimination because of the way blatantly discriminatory outputs are legitimised through science and technology – if bias is located with an individual human, a framing which already individualises structural oppression (Hoffmann 2019), then a computer cannot be biased.

Paola Ricaurte frames this in terms of "hegemonic AI" and identifies "three epistemic processes: datafication (extraction and dispossession), algorithmisation (mediation and governmentality) and automation (violence, inequality and displacement of responsibility)" (2022, p. 727). These epistemic processes emerge as part of the larger structures of capitalism and empire they re-entrench. Understanding these epistemic processes, and their roots, is extremely important at this juncture where language technologies are being enthusiastically adopted by public institutions and businesses from universities to hospitals. Until the recent rapid proliferation of LLMs, language technologies evaded the kind of critical scrutiny that has long been applied to automated decision making systems in high-stakes contexts. Perhaps this was due to the relatively limited performance of these systems, or due to their absence from life-or-death decision-making. However, as researchers interested and invested in communities and their languages, we need to take seriously the way seemingly harmless tools intervene in sociolinguistics contexts and the legacies they bring with them.

3.2.1 *Controlling 'AI': corporate capture*

Given the sheer scale of data and computing power required to develop, train and maintain models like these, it is unsurprising that large multinational corporations and, to a lesser extent, start-ups funded by venture capital are the dominant actors in this space (Jacobides et al. 2021). As of 2024, they include Microsoft, Apple, Google, Meta and IBM alongside Open AI, Anthropic, Cohere and Mistral. Key software and hardware infrastructure such the popular Tensorflow platform (developed by Google), the Pytorch python toolkit (developed by Meta) and cloud computing platforms (e.g., Amazon Web Services, Microsoft Azure) is also directly tied to these large developers (see also Vlist et al. 2024). While much of this software is freely available under an open-source license, and the hardware openly sold, as Whittaker (2021) puts it, "[t]hese companies [...] make the water in which AI research swims."

Of course, as Whittaker (2021) also points out it is not fair or accurate to say that all researchers (including academic researchers) supported by corporate funding and research infrastructure are somehow compromised. Especially in academic contexts, these resources are foundational to projects ranging from basic computer science research and dataset compilation, to computational social science. It is also important to acknowledge that universities are not (and never have been) neutral institutions existing outside of empire or capitalism. Nevertheless, infrastructure and funding steer the overall direction of the field (for example towards larger models) (Whittaker 2021), and can threaten academic integrity (Mohamed Abdalla and Moustafa Abdalla 2021). Even projects which are explicitly framed as an alternative to industry-driven research, such as the open-access LLM BLOOM (BigScience et al. 2022) funded by the French government and built by a team of over 75 academic researchers across the world still require an expensive, large-scale effort.

In addition to setting (or at least, significantly shaping) the 'AI' research agenda and related debates (Brennen et al. 2018), a handful of corporations have an enormous competitive advantage in this space. Most obviously, they have the financial resources and space required to purchase, maintain and deploy the required computing infrastructure. This is coupled with unparalleled access to proprietary training datasets which dwarf public ones, and the ability to attract and retain workers with the necessary skills. Following Rikap (2022) we can understand this infrastructural power as the result of intellectual monopolies which are further re-entrenched as platforms collect rent (money, data) from these tools, knowledge and datasets (Sadowski 2020). This approach is supported by a general trend towards financialisation which allows venture capitalists to invest based on speculative future profits (Tricot 2021; Kampmann 2024; Fourcade and Healy 2024). As contemporary observers and historians have pointed out, the desire for centralisation, and the facilitation of large-scale bureaucracies lies at the heart of the development of modern computing (Weizenbaum 1976; Hicks 2018; Eubanks 2018; Katz 2020; Pasquinelli 2023). Combined with today's neoliberal commitment to privatised public services, tech companies play increasingly important roles in developing and maintaining what is, in effect, public technical infrastructure.[10] The over-reliance on a small number of providers for core services such as cloud computing (Vlist et al. 2024) creates significant risks by introducing single points of failure which could affect millions or billions of people. However, even avoiding monopolies, a fully market-based approach to infrastructure (be it physical or digital) is risky because it leaves crucial (and expensive but potentially unprofitable) maintenance to the private sector.

3.2.2 Making 'AI' work: Labour and automation

Computing technologies obscure and, in the long-term, displace or, more commonly, significantly alter human labour processes (Levy 2022; Gray and Suri 2019; Atanasoski and Vora 2019). As Pasquinelli highlights in their history of artificial intelligence this motivation lay at the heart of some of the earliest computing technologies such as Charles Babbage's famous Difference Engine which was invented specifically to "mechanise the mental labour of of clerks" (2023, p. 47). Importantly, and perhaps less obviously to an outside observer, computing technologies, and, in particular, modern language technologies, require a very large amount of labour. This labour consists of the design and operation of software and hardware and the preparation of datasets. While software and hardware design (and to some extent, operation) tends to be performed by highly-paid, highly-trained workers (e.g., tech workers at some of the aforementioned companies and within academic institutions), the production of hardware and data is overwhelmingly outsourced to low-paid workers (Gray and Suri 2019). Electronics manufacturers and tech companies outsource this production to a wide range of territories including the (post-socialist) EU, the Middle East, South East Asia, and West Africa taking advantage state investment and lax labour

[10] States are, to this day, crucial funders of computing infrastructure development delivered by private companies (to states or private businesses). The apparent contradiction between Silicon Valley's commitment to free markets and the state has long been noted, most famously perhaps by Richard Barbrook and Andy Cameron in their prescient landmark essay 'Californian Ideology' (Barbrook and Cameron 1996). In the forthcoming (and posthumous) 'Cyberlibertarianism: The Right-Wing Politics of Digital Technology', David Golumbia locates this the right-wing, libertarian politics at the heart of modern digital technologies. [Author's note: will add reference after publication in Oct 2024.]

protections (Sacchetto and Andrijasevic 2015; McElroy 2024; Perrigio 2023).

Necessary datasets include text and speech recordings produced and/or annotated by people (Gray and Suri 2019; Crawford 2022; Tacheva and Ramasubramanian 2023). Not all labour involved in the compilation of datasets is explicitly intended to build language technologies. For example, the large text datasets on which LLMs are pre-trained are usually derived from the web (A. Luccioni and Viviano 2021; Dodge et al. 2021; Baack 2024). As a result, most of the people who 'contributed' data to these corpora have not consented to, and are likely even unaware of, its use in machine learning. It almost goes without saying that these users (likely including all of us) have not been compensated or paid for this data. While the indiscriminate scraping and reusing of texts from social media and collaborative projects like Wikipedia may be legally and ethically acceptable, materials protected by copyright pose a more complex challenge. As early as 2016, a number of (published) authors complained about Google's use of their texts which they had uploaded to an ebook hosting website (Lea 2016). These books had been compiled two years earlier into BookCorpus, which was later shown to include copyrighted materials and author information and has been used extensively to train commercial and open-source (large) language models (Bandy and Vincent 2021). With the recent popularisation of models which can generate text or images, many artists and writers have objected this use of their labour (Goetze 2024). Their concern is not just the lack of compensation for their immediate contribution, but also the long-term risks to their livelihood and craft as generative models 'learn' to produce text and images in their style (Goetze 2024).

Beyond this language data, many language technologies also require metalanguage data, such as transcription (automatic speech recognition) and annotation (sentiment analysis, chatbots), and a type of work which law scholar Veena Dubal calls "digital piecework" (Dubal 2020). To create sentiment analysis tools (which predict a positive or negative sentiment for a string of text for, e.g., large-scale analysis of product reviews) or content moderation algorithms (which predict a 'toxicity' score for a string of text, e.g., on social media), manually labelled examples of the different categories are required (e.g., 'toxic' or 'positive' language). Miceli and Posada (2022) show that the tasks, instructions and general working conditions associated with this kind of data work are deeply problematic. Tasks include highly contextual text annotation (e.g., identifying sexual content or hate speech) often according to pre-defined taxonomies shaped by the cultural and legal context of the client (e.g., the social media platform) which may be unfamiliar to the annotator. As a result, the work is not only difficult, but the produced datasets may not be of particularly high quality which can have negative repercussions not just for the end product but also the workers who may not be offered more work. Miceli and Posada (2022) also draw attention to the frequent use of aggressive "warnings" to workers (e.g., "accurate responses are required. Otherwise you will be banned."), coupled with constant performance evaluation. In addition to this hazard of precarity, annotation work can also be distressing or uncomfortable (Miceli and Posada 2022). Workers have drawn attention to the significant harms they experience when reviewing social media content for illegal and harmful materials (Spence et al. 2023; Steiger et al. 2021; Gebrekidan 2024). With the advent of LLM-based chatbots, a similar type of annotation task has gained prominence. Since LLMs are very difficult to directly constrain (because of their huge training datasets and their opaque, multi-layered architecture), model behaviour is optimised through a process called reinforcement learning: annotators assign positive or negative scores to system outputs, with the aim of decreasing the probability of unwanted outputs. In practice, this means that annotators have to read or look at disturbing or violent imagery, not unlike content moderators. Recent investigations have documented the significant psychological harms caused by this work (Gebrekidan 2024; Rowe 2023; Perrigio 2023) which furthermore takes place in already stressful and precarious working conditions. Muldoon et al. (2023) interviewed workers at "impact sourcing" company Sama (explicitly founded to "reduce poverty and create secure jobs") in Kenya and Uganda, who describe close surveillance and long hours annotating data in the context of short-term contracts, low pay and gender-based harassment.

Overall, the currently dominant paradigm of language technology development exploits workers involved in the production of data and hardware. This is particularly egregious given that some, if not most, of the corporations and start-ups profiting from the current boom in language technologies are some of the most highly valued and profitable in the world and could therefore, arguably, afford to pay a fair price for the data which forms the 'raw material' for their products. Alternative approaches are, of course, possible. In addition to the Māori language technologies discussed above, organisations like Masakhane NLP and Mozilla champion a collaborative and equitable approach to creating, sharing and working with language data in ways which benefit and respect language communities (Nekoto et al. 2020; Ardila et al. 2020). While labour issues have long been sidelined in discussions around 'tech ethics' (though see Hicks 2018; Ensmenger 2012), recent ethnographic work has explored the specific ways that partial automation undermines worker agency (Levy 2022). Detailed studies of labour practices in data work, including a "worker's inquiry" led by workers themselves, form the foundation of a robust challenge to exploitation and insufficient protection from physical and psychological harm (Data Workers' Inquiry 2024).

3.2.3 Putting 'AI' to work: Enduring empire

Katz (2020) argues that the history of 'artificial intelligence', as "contested and nebulous" a concept this may be, has always been bound up with empire. While ideas and stories of intelligent machines and machines capable of processing and producing language have a much, much longer history stretching back to antiquity (Bareis and Katzenbach 2021), Katz (2020), like most historians, traces the history of the concept as used today back to the Dartmouth Summer Research Project on Artificial Intelligence 1956 organised by John McCarthy at Dartmouth College, New Hampshire, USA.[11] In the years that followed, research under the umbrella of 'artificial intelligence' was generously funded by the US military via the (Defense) Advanced Research Projects Agency[12], especially at the Massachusetts Institute of Technology and Stanford University (Katz 2020, 24ff).

However, while the research was well-funded, the slippery and vague operationalisation of 'intelligence', let alone deeper philosophical questions about the feasibility and desirability of developing 'intelligent' machines, drew serious critiques from the start, most infamously from philosopher Hubert Dreyfus (1979), computer scientist Joseph Weizenbaum (1976)[13], and, arguably most consequentially, mathematician James Lighthill who authored a damning report about the merits of the research efforts in the 1970s (Lighthill 1973). Katz (2020) argues that the vague and contested nature of the research area nevertheless allowed researchers to position their research as useful for military applications, drawing funding from (D)ARPA. Machine translation and automatic speech recognition were two extremely valued research areas building on cryptography during the Cold War, with significant funding being directed not just to computer scientists and engineers but also linguists (Heller and McElhinny 2017; Golumbia 2009; Paullada 2021; Geoghegan 2023).

Going beyond the specific notion of 'empire' as a state, Tacheva and Ramasubramanian suggest that "the entire lifecycle of AI algorithms, as well as the associated material, knowledge, data, logistical, labor, and political, cultural, economic, and ideological infrastructures behind them" can be understood to "[function] as empire" (2023, p. 2). This particular framing captures the ways in which the quest for dominance in the 'AI space' is not limited to nation states *or* corporations, empire *or* capitalism, but rather operates at multiple levels (national, multinational, supra-national), with multiple centres across the globe (Tacheva and Ramasubramanian 2023). Whether it is rhetoric invoking an "arms race" between the United States, China and Russia (Katz 2020), or ambitions by the United Kingdom to "lead the world over the next decade as a genuine research and innovation powerhouse" and a "global superpower in AI" (HM Government 2022),

[11] The term "artificial intelligence" was first used in the funding proposal for this two month summer workshop – in which McCarthy (alongside Marvin Minsky, Nathaniel Rochester and Claude Shannon) proposed that "an attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves." They added, perhaps a bit too optimistically: "We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer."

[12] The agency changed its name several times since its creation in 1957, and has been known as DARPA since 1996.

[13] John McCarthy responded to Weizenbaum (1976) in a withering review which also received an equally sharp response from Weizenbaum (Kuipers et al. 1976).

'AI' is framed as an aspect of geopolitical power extending beyond any single nations' borders.

Finally the logic of empire also endures in the fundamental tendency of language technologies (and those working with them) to view language as data (Bird 2020; G. Benjamin 2021). This is part of a larger process of datafication in which all aspects of human life are constructed and then captured as data (Vallor 2024; Fourcade and Healy 2024; Ricaurte 2022), and can manifest in what Birhane (2020) terms "algorithmic colonisation". Today, academic institutions and large technology corporations seek in this way to extract (language) resources to develop tools, services and research which, ultimately, benefit them at least as much as they benefit the communities they're supposedly serving, both in terms of financial and cultural capital. As Hoffmann (2021b) highlights, discourses of "inclusive" and "ethical" development can be used by technology corporations (and academic institutions) to position themselves as responsible and "doing good" (see also Green 2019). Furthermore, Sadowski (2019) argues, in modern capitalism, data is not *like* capital, but rather it *is* capital as it is essential to (especially language technology) production. At the same time, as Fuller Medina argues: "language data is patrimony" (2022, p. 2). This framing raises important questions regarding the "ownership" of not just linguistic data but language varieties more broadly, which are particularly acute in language technology development. As discussed in Section 3.1.3, some communities actively resist this algorithmic colonisation and the ideology of language as 'data' to which anyone (or no-one) can lay claim to.

4 Management: Producing language(s), nations, speakers

Spolsky (2004) defines language management as "any specific efforts to modify or influence [language] practice". Given the inter-related nature of practices and beliefs in his model, I interpret this definition to also include changes to beliefs which may consequently affect practices.

4.1 Practices: (dis)affording interaction

There are many ways to distinguish language technologies, but here I will discuss 'interlocutors', which are designed for people to directly engage with, and 'intermediaries', which are designed to mediate between people. I will then discuss how 'biases' limit the affordances of both types for marginalised groups, and explore the ways even 'unbiased' technologies can foreclose other types of social interactions.

4.1.1 Eliza, Alexa, Siri and Sky: Language technologies as interlocutors

Some language technologies are intended to afford interactions between humans and machines. One of the first programmes of this type was called ELIZA, developed by computer scientist Joseph Weizenbaum in the 1960s.[14] It used a simple rule-based system to model Rogerian psychotherapy, generating follow-up questions based on previous input (Natale 2021). Despite being unsophisticated, ELIZA became a hugely influential artefact as it enticed people to engage in personal interactions with an interlocutor they understood not to be a person (Natale 2018; Natale 2021).[15] What lesson we are supposed to draw from ELIZA was and to some extent remains contested. For some, it demonstrated the potential of human-like machine intelligence and automated psychotherapy, while for others (including Weizenbaum himself) it playfully highlighted the fundamental difference between humans and machines (Natale 2018; Weizenbaum 1976). Thirty years later, Clifford Nass, Jonathan Steuer and Ellen R. Tauber presented a set of experiments which showed that even "experienced computer users" approach interactions with (desktop) computers as "social" interactions in a paper titled 'Computers are Social Actors' (CASA) (Nass et al. 1994). Nass and Moon formalised CASA as a framework to understand human-computer interaction, highlighting the tendency of users to "mindlessly [...] overuse human social categories, applying gender stereotypes and ethnically identifying with computer agents [...] [and] exhibit [...] politeness and reciprocity" (2000, p. 81). This behaviour, they argued, is not due to a "sincere belief that the object has human characteristics" or a genuine emotional attachment to the computer but simply "mindless" social interaction triggered by some social cue (such as a voice) (Nass and Moon 2000, p. 93).

Since then, voice user interfaces (VUIs)[16], have become common in personal and business computing, especially in 'high-resource' languages such as English. Furthermore, while the 'social affordances' of early systems such as ELIZA and even the desktop computers used by Nass and Moon (2000) were very limited, modern VUIs are explicitly and purposefully designed to afford personalised social interaction between human and machine (Gambino et al. 2020; Natale 2021). Amazon's voice assistant Alexa embedded in smart speakers among other devices, is, according to its developers, "here to make [our] life easier" (Amazon n.d.). Similarly, Apple's Siri allows us to "get everyday tasks done with just [our] voice" (Apple n.d.). Their affordances go be-

[14] The programme was named after the Cockney flower seller Eliza Doolittle in George Bernard Shaw's play *Pygmalion*. As Natale (2021) discusses, this choice of name is important as ELIZA, the programme, made use of several different "scripts" using specific linguistic registers to play a role, just like Eliza, the flower seller.

[15] The most frequently repeated anecdote about ELIZA relates to Weizenbaum's (female) secretary asking him to leave the room while she talked to ELIZA 'in private' (Natale 2018). Regardless of its veracity, this anecdote perpetuates the narrative of humans being easily deceived, and the image of a naive female secretary trusting ELIZA with her relationship woes might be particularly memorable because of the way it draws on sexist stereotypes.

[16] I use VUI as an umbrella term here, in the literature other terms such as intelligent personal assistants, and virtual assistants can also be found.

yond processing simple verbal commands and triggering certain actions. What these tools really afford is "assistance" and "help" in our daily lives (or so we're told).

The design of a machine 'interlocutor' shapes how people interact with. Even a disembodied voice invokes a particular type of person through accent, prosody, voice quality, register and paralinguistic features such as laughter (Abercrombie et al. 2021). It is perhaps not surprising that the use of coherent, 'human-like' language, and in particular, spoken language by a machine invites both mindless and self-conscious social interaction. Based on both cognitive biases and experience, we cannot help but assume that human language originates from embodiment and experience similar to ours. As Natale (2021) argues, this "banal deception" is a central feature of VUIs, and generally makes human-computer interaction smoother and more enjoyable. However, human-like (but non-human) interlocutors also bring real risks. Setting aside the privacy risks (discussed in Section 4.1.2), voice and text-based user interfaces can engender unwarranted trust by users. The limitations of language generation systems (such as large language models) are well-documented but some of the riskiest system outputs, such as the production of misleading, factually incorrect, radicalising, or hateful language are notoriously difficult prevent, notice and correct (Weidinger et al. 2022). It is also as yet unclear what the psychological ramifications of deep emotional attachments to increasingly popular artificial 'companions' could be (Xygkou et al. 2023; Kneese 2023).

'Interlocutors' like VUIs and text-based chatbots might also have broader impacts on cultural and linguistic practices. As several studies, including one commissioned by UNESCO (West et al. 2019), have noted, VUIs designed to help 'manage' the domestic space are frequently constructed as feminine personas with a traditionally feminine name and, per default, a synthesised voice based on the voice of a female voice actor. VUIs like Alexa, Siri, and Open AI's short-lived 'Sky'[17] have also been found to respond in deferential, bashful and even flirtatious ways to users, even if presented with sexual comments (e.g., "I'd blush if I could") (Cercas Curry and Rieser 2018). This design, which builds on a long tradition of 'female computer voices' in science fiction (Faber 2020), reproduces and normalises misogynistic gender roles and gender-based violence.

4.1.2 "Eradicating language barriers", monitoring employees: Language technologies as intermediaries

Language technologies can also act as intermediaries between people. Machine translation tools which translate speech or text into a different language variety, are a prototypical example. In this context, languages are often framed as "barriers" preventing interactions. Discussing their 'No

[17] 'Sky' caused controversy due to the resemblance to actor Scarlett Johansson who had explicitly denied permission to have her voice used for the model. Open AI states that "The voice of Sky is not Scarlett Johansson's, and it was never intended to resemble hers" but has removed the 'Sky' from its products.

Language Left Behind' project, Meta AI argue that machine translation research "[is d]riven by the goal of eradicating language barriers on a global scale" (NLLB Team et al. 2022). Google Translate, probably the most well-known machine translation application, uses the tag line "Connect with people, places, and cultures without language barriers" [18]. In practice, machine translation tools are used to support a wide range of crucial interactions, including activities by non-governmental organisations (Angelucci et al. 2023) and urgent communication between patients and healthcare professionals when there are no interpreters available (Mehandru et al. 2022; Valdez et al. 2023). Or, rather, they can be used in these ways by some people. Those who stand to benefit the most from accurate translation, such as migrants navigating a new environment in an unfamiliar language (Liebling et al. 2020) or seeking information and community in a crisis (Sum et al. 2023), often aren't adequately supported, as discussed below. Accurate automatic captioning of multimedia content and live speech can afford access to information, knowledge and communication. However, as with machine translation, current technologies may be inadequate for people who would most benefit from accurate and full real-time transcription such as people who are Deaf or hard of hearing (Lacerda Pataca et al. 2023). Technologies supposedly designed *for* a particular group, also need to be designed *with* or better *by* that group, as captured in the disability activism slogan "nothing about us, without us" (Costanza-Chock 2020). If the aim of a technology is to afford interactions, understanding exactly how this interaction should unfold, who is involved and what their needs for any technological support are, is essential.

Following marketing discourse, the valence of machine translation could be describe as "accretionary" if we assume that they primarily push people towards more communication with more different people (Bush 1993). Similarly, automatic speech recognition tools are embedded in a wide range of tools affording everything from cheaply and efficiently transcribing and captioning multimedia content, hands-free interaction with computing devices, and speech-to-speech translation, but they also, importantly can afford a wide range of what we might consider to be a illiberal applications, such as a large-scale surveillance (Beek et al. 1977). These valences matter not only because the underlying motivations for development and research shape institutions, practices, standards but also because they endure. Today, automatic speech recognition tools are used for surveillance of inmates' phone conversations in a large number of prisons and jails in the United States (Asher-Schapiro and Sherfinski 2021). While calls with lawyers, doctors and spiritual advisors are not monitored according to a 2023 report from Florida (Garcia 2023), a Reuters investigation reported in 2021 that keyword searches included 'abogado' (lawyer) and discussions of COVID-19 outbreaks in prisons (Asher-Schapiro and Sherfinski 2021). While this type of surveillance of incarcerated people and their contacts is not new, automatic speech recognition enables an unprecedented scale: a contract between the provider Leo Technologies and

[18] `https://translate.google.com/about/`

the State of Florida promises to analyse up to 50 million minutes of speech in one year (Garcia 2023). Large-scale and real-time monitoring of phone calls is also applied in some workplaces, especially in customer service (Christl 2023). What has changed in call centres is, again, not the fact of monitoring or quality control but its scale (Broek 2002). Christl (2023) highlights that employees in call centres are monitored by software which 'assesses' their interactions with customers in real time, assigning scores for "empathy" and "friendliness" and searching keywords, in addition to more traditional metrics such as call volume and duration.[19] In addition to the inherent limitations of a crude sentiment analysis system according to which an interaction is either positive or negative, the algorithmic, black-box nature of these proprietary software tools limits workers' agency and scope for recourse. With an ever-larger percentage of all white-collar work being mediated via digital communication platforms, coupled with the rise of remote work, we see this type of surveillance expand rapidly (Roemmich et al. 2023; Masoodi et al. 2021).

Pervasive algorithmic decision-making is not just opaque (as human decision making also often is), but absent complex chains of accountability (Metcalf et al. 2021; Metcalf et al. 2023) it is difficult to challenge. This is clearly dangerous where systems are deployed in inherently unjust ways, but can furthermore be compounded by *bias*, which I discuss below. Even if we are happy with *what* the technologies are for, we need to ask *who* they are for.

4.1.3 Language technologies for whom? Language variation and algorithmic bias

Because affordances are relations between objects and their users, technologies do not afford the same things to all user groups. In the context of language technologies, these affordance gaps are often discussed as instances of "predictive bias": disparities in terms or error rate or outcomes for different user groups (D. S. Shah et al. 2020). This includes, for example, a higher error rate in an automatic speech recognition or machine translation system based on speakers' language variety, ethnic background, age, or gender, and the reproduction and amplification of harmful stereotypes in generated or translated text. Sociolinguistic theory and data have been integral to documenting and, perhaps most importantly, contextualising these biases and linking them to linguistic discrimination, and concrete real-world harms (Blodgett et al. 2020). In a foundational study, Koenecke et al. (2020) demonstrate that commercial automatic speech recognition systems for US English exhibit significant racial bias, performing worse for speakers of African American English (AAE), in particular Black men, than white speakers of Mainstream US English. Through careful experimentation with speech data from a sociolinguistic corpus, they show that these disparities appear to be triggered by subtle differences in prosody and pronun-

[19] Christl highlights 'emotion recognition' providers Cogito and Callminer, both of which are used at call centres today (including at large insurance companies) and have received initial funding by (D)ARPA and a CIA venture fund (2023, 38 ff.)

ciation, which can further be compounded by lexical, semantic and pragmatic variation between and within varieties (Koenecke et al. 2020; J. L. Martin and Tang 2020). Similarly, Wassink et al. (2022), Chan et al. (2022) and Choe et al. (2022) apply (socio)phonetic methods to understand, not just document, algorithmic bias in speech recognition. Linking this to user experience, Mengesha et al. (2021) and Wenzel et al. (2023) show that this 'degraded performance' not only constrains how AAE speakers can use technologies supposedly designed for speakers of English in the United States, but also meaningfully impacts their wellbeing and self-esteem. Beyond voice technologies, large language models have a notorious tendency to reproduce and amplify harmful stereotypes based on race, gender and sexuality, religion, age, and disability (e.g., Abid et al. 2021; Cheng et al. 2023; Gadiraju et al. 2023; Zhao et al. 2023; Harrison et al. 2023).

Most language communities around the world do not have access to robust language technologies. As discussed in Section 3, however, this does not mean that communities do (or should) uncritically embrace efforts to develop them. 'Fixing' racial biases in automatic speech recognition could, as Mengesha et al. (2021) and Wenzel et al. (2023) show, have a positive impact on marginalised communities. The very same system could, however, also facilitate 'better' surveillance of some of the most vulnerable members of these communities (e.g., incarcerated Black men in the United States (Asher-Schapiro and Sherfinski 2021; Garcia 2023)).

4.1.4 Foreclosed alternatives

A subtle, less obvious impact of language technologies is the fact that they foreclose alternative solutions to real social problems. For example, communication between patients and healthcare providers is extremely important – and usually inadequately supported if they do not share a language. However, machine translation is not the only, or best, solution to this problem. Machine translation tools are actually quite ill-suited to this particular task. Biases based on accent, dialect, age, emotional state and health status can disadvantage already vulnerable patients. Patients might also have well-founded concerns about their data privacy when discussing or disclosing sensitive information about their health. While these issues can also affect medical interpreters, they can offer reassurance, clarify understanding, and, importantly, translate between cultural contexts. Even if all current limitations of machine translation could be overcome, a hospital visit in an unfamiliar linguistic and cultural environment would still leave patients stressed and vulnerable – all without addressing the more fundamental challenges of mismatched expectations, knowledge and goals between patients and usually overworked healthcare providers which often prevents effective communication (Mehandru et al. 2022). To address these deeper challenges, we might want to train and hire more medical and cultural interpreters, doctors and nurses to facilitate better interactions, rather than just translation. A more extreme (and much more far-reaching) example of this tech-solutionist approach are attempts to fully automate aspects of healthcare provision such as counselling and cognitive behavioural therapy (Kretzschmar et al. 2019). Arguing that these tools make mental healthcare "more accessible" forecloses the possibility of employing more professionals or building strong networks of mutual support and further individualises health and wellbeing (Meadows et al. 2020). It arguably also misunderstands what it means to care for one another as humans, by outsourcing the emotionally difficult task of listening, empathising and supporting to machines (Vallor 2024; Weizenbaum 1976).

4.2 Beliefs: Ideologies about language and technology

As discussed in Section 4.1.3, performance differences between language varieties are well-documented in range of technologies, with generally best performance for high-resource standard varieties. In Markl and McNulty (2022), we argue that we can understand the language technology design process as a kind of language policy process. Design considerations such as "which language varieties should this machine translation system/VUI/large language model support?" build on, and reinforce existing beliefs about language varieties and their speakers. Spolsky (2004) defines language beliefs simply as "what people think should be done" in relation to language. Crucially, as Gal and Irvine put it, "statements about language are never only about language – and they are never only statements" (2019, p. 1). That is, questions such as "what kind of language should be used in school/at home/at work/in parliament/in the media/in this smart phone/on this social media platform?" are also asking about who should be included and prioritised in different spaces. Some of the beliefs, assumptions, ideas, priorities and practices underlying the design of technologies can be glimpsed by looking very closely. While users can resist and subvert the 'intended' uses of technologies, their design "pushes" (Bush 1993) users into a particular type of interaction and behaviour and naturalises ideological constructs. Below I discuss three examples of language ideologies reproduced in language technologies: 1) English as 'the language' of technology and modernity, 2) naturalised mappings between nations, languages and speakers, and 3) speakers as markets according to linguistic and economic hierarchies.

4.2.1 Ideologies about languages: English and technology

The hegemonic role of English in today's global capitalism is an enduring legacy of colonialism which technology continues to perpetuate (O'Regan 2021). While large language technology developers now support a growing number of (high-resource) languages, English continues to be conflated with 'natural language'.[20] In commercial applications, which languages are supported

[20] Computational linguist Emily M. Bender famously disrupted this practice by popularising the 'Bender Rule' which requires authors to state which language varieties they are working with (Bender 2019).

relates to ideological, financial and practical considerations such as target markets and available datasets. Who is considered to be part of a target market and whose language is adequately represented in datasets is the result of a long history of political and economic choices. So-called 'high-resource' languages such as (some varieties of) English, Spanish, French, Arabic and Mandarin Chinese have this privileged status for a number of complicated reasons which have nothing to do with the languages as such and everything to do with where and by whom they are spoken. English is by far the highest-resourced language, with a huge variety of meticulously annotated speech and text datasets covering a large number of genres, and state-of-the-art commercial and open-source tools (Held et al. 2023).

This material inequity affects perceptions and beliefs by users too, who construct English as the 'native' or 'original' language of these kinds of technologies. As an Turkish-speaking Apple user puts it in Leblebici (2024): "You are Apple, why are you speaking to me in Turkish?" Languages other than English may be perceived as "culturally inappropriate", especially if users are aware of the specific cultural origins of a particular device or brand (Leblebici 2024). This default preference for English is not limited to VUIs. Earlier work shows that users perceive English to be a more effective medium in engaging with smartphones and social media than lower-resource languages (such as Hindi or Tamil) due to inadequate localization and poor adaptation to multilingualism (Karusala et al. 2018).[21] As Leblebici (2024) also points out, new capabilities are almost always introduced in English first and users may be reluctant to switch to a different language later on.

4.2.2 Ideologies about languages: nations and multilingualism

Another way that implicit and explicit beliefs about language(s) and their users are expressed in language technologies is in the way language varieties are named, categorised and mapped onto specific territories and markets. This classification and naming is a mundane part of product description and marketing which spells out who a particular tool is intended for while usually also assigning a value to language varieties and, by extension, their speakers. Categories and names encoded in technology, are not neutral (Bowker and Star 2000), especially when the 'object' of classification is language (Schneider 2019).

As an example, we can consider Siri. Users can select from about 40 language varieties to 'recognise', most of which originate in Europe.[22] For pluricentric languages, these varieties are ex-

[21] As Karusala et al. (2018) highlight, many digital devices are furthermore specifically designed for Latin characters, making text input in other scripts more difficult and features such as spell-check (in English) can make it harder to transliterate non-English languages in Latin script.

[22] As of summer 2024 – all analyses of this type of software and hardware is bound to provide only a snapshot at a particular point in time as products are updated continuously.

plicitly distinguished in terms of nation states, for examples as "English (United States)", "French (Belgium)", "German (Austria)". The selection of the language variety constrains the possible options for language generation: if any variety of English is selected as input, the different output options are "American", "Australian", "British", "Indian", "Irish", "South African" – each of which is exemplified by several different voices (based on different voice actors) varying in gender and region.[23] While input and output variety are 'matched' by default, it is possible to 'mismatch' them within a named language (e.g., US English command and Australian voice response) but it is not possible to 'mismatch' between different languages. Since 2024, selecting "English (India)" enables users to "[use] English mixed with Bangla, Gujarati, Hindi, Kannada, Malayalam, Marathi, Punjabi, Tamil, or Telugu" and configure responses to be in English, Hindi or a mix of the two languages (Apple Support 2024).

What is interesting about these different affordances is that they position some types of linguistic practices as 'default' (each language variety comes with a default voice) and some as impossible. Furthermore, even where design disrupts long-standing monolingual defaults in language technologies (Schneider 2022), only very strictly defined types of multilingual interaction in specific territories (India in this case) are afforded. Users are therefore discursively constructed as residing in a particular territory or nation state, speaking a particular language or set of languages which likely matches the official languages of that territory. It is important to acknowledge that many of the constrains discussed here likely have pragmatic, technical reasons to simplify the design and guarantee high-quality outputs. As discussed by participants in Leblebici (2024), using Siri in Turkish to navigate a map of Germany (or vice versa) can be difficult because the system 'expects' placenames to be pronounced in a particular way (and likely also uses the language as a 'hint' when searching through all possible placenames). What is important to recognise, however, is that 'pragmatic', 'technical' and 'default' choices are still choices, and, as such can be subject to critical analysis, challenge and change. Crucially, we do not just see a "mirroring" of existing language ideologies but a re-entrenchment and perpetuation of them as they are "encoded" into language technologies. Gal and Woolard (1995, p. 129) name "translation, the writing of grammars and dictionaries, the policing of correctness in national standards, the creation of linguistic and folklore collections or academies" as practices which (re)produce "bounded" and "naturalised" languages. Language technologies modelling a specific "variety" encode this variety in a similar way to grammars and dictionaries, delineating the "boundaries" of lexicon and variation based on the training dataset. Where speakers interact with them, they also perform the function of "policing", where variation outwith the "boundaries" is not recognised, as discussed below.

[23] The subtle difference in terminology between "English (Australia)" and "Australian" is potentially also indicative of a distinction between dialects and accents, though this is not entirely clear from looking at the options alone.

4.2.3 *Ideologies about speakers: markets and hierarchies*

Of course, all 'languages' constructed as named and bounded entities, comprise numerous different repertoires, styles and varieties arranged in complex multidimensional hierarchies of power and status (Schneider 2019). Considering 'English', the 'default' varieties we observe in language technologies are Mainstream US English (MUSE) and Standard Southern British English (SSBE). These varieties are not just associated with the standard or mainstream as the terminology suggests, but also, and more fundamentally, express (proximity to) whiteness and capital (O'Regan 2021). In commercial settings, groups of speakers, language communities, are reframed as 'markets'. This is sometimes explicit, for example in a post on the Amazon Web Services Machine Learning blog celebrating Amazon's tools which supposedly enable businesses to "easily expand their product across borders and into new geographical markets by offering fluid, accurate, multilingual customer support and sales" (Tran and Wilkes 2022). Other times, the value of different markets to developers is only implicit. To return to the example of Apple's Siri, the fact that of the about 40 varieties offered, 9 are varieties of English highlights the central importance of English-speaking markets for the company. This includes comparatively small markets like Ireland and New Zealand, alongside larger ones like the United States, India, South Africa and the United Kingdom. Given Apple's status a high-end electronics manufacturer, the over-representation of European language varieties is perhaps unsurprising, but still expressive underlying beliefs about different speaker groups.[24] These ideologies are, of course, self-perpetuating, as groups whose languages are not supported are less likely to adopt the technology, as they are well aware that they are not designed 'for them' (Mengesha et al. 2021). How persistent exclusion from language technology design affects the status of language varieties is still unclear. On an individual level, Mengesha et al. (2021) and Wenzel et al. (2023) have shown that users can experience being 'misunderstood' by language technologies as micro-aggressions which negatively impact their self-esteem and reinforce internalised linguistic discrimination.

5 Directions: theoretical, empirical, practical

In this article, I have tried to provide the historical, technical, political and social context of language technologies necessary to ground future theoretical and empirical research on the intersections of language technologies with society. I have also gathered relevant theoretical tools

[24] In addition to French (Belgium, Canada, France, Switzerland), German (Austria, Germany, Switzerland) and Spanish (Chile, Mexico, Spain, United States), it also supports Arabic, Chinese ('Cantonese - China mainland', 'Cantonese - Hong Kong', 'Mandarin - China mainland', 'Mandarin - Taiwan'), Danish, Dutch (Belgium and Netherlands), Finnish, Hebrew, Italian (Italy and Switzerland), Japanese, Korean, Malay, Norwegian Bokmål, Portuguese (Brazil), Russian, Swedish, Thai and Turkish.

and frameworks. I propose that we can use the overarching framework of 'algorithmic language management' to study how language technologies engage with and reconfigure their sociolinguistic contexts – affecting language practices and language beliefs. To study these effects we can consider affordances and valences of different technologies, trace their histories and examine policies and discourses surrounding them. To close this article, I provide some suggestions for future work.

5.1 Expanding theoretical frameworks

There are numerous theoretical questions to be explored at the intersections of language, communication and language technologies. Some of the most pressing, in my view, concern the reproduction of language ideologies and practices and fundamental concerns about the nature of language data, its role in the language technology ecosystem and economy and its relation to language communities.

5.1.1 Who are the new language managers?

There is much more work to be done to understand how, why and by whom decisions related to language are made in language technology development. The powerful role of (very large) corporations is particularly interesting here, as analyses of corporate language policies have usually focused on workplaces and employees. Today, corporate language policies can affect millions or even billions of people across the world as they engage with a particular tool or platform. In addition to empirical research investigating the decision making process (e.g., through ethnographic fieldwork), we also need to develop theoretical accounts of this power and its impacts.

5.1.2 What is language data and who does it belong to?

While there is a rich literature exploring the commodification of linguistic identity and linguistic skills, data-hungry language technologies turn linguistic data into a valuable resource. This creates new types of linguistic markets and new types of linguistic labour. It also raises old questions about who, if anyone, can own a language variety. These questions intersect with more recent debates about data sovereignty and algorithmic colonisation, and are particularly urgent in the context of endangered, marginalised, and under-resourced language varieties.

5.2 Gathering empirical evidence

Rather than uncritically dismissing or embracing language technologies, researchers working on language are uniquely well-positioned to develop sophisticated analyses which will broaden our understanding not only of technology and how people engage with it, but also language and interaction. Empirical research is needed at all stages of the language technology lifecycle – from design to deployment. Three particularly interesting and, at this point, under-explored, lines of research concern the adoption and adaptation of language technologies in specific sociolinguistic contexts, the ways in which language technologies reinforce linguistic discrimination, and the ways in which they reconfigure language work.

5.2.1 How are language communities adopting and adapting language technologies?

Theories, methods and perspectives focused on the social, linguistic and political complexities of language would perfectly complement the ongoing research on the adoption and adaptation of language technologies by researchers interested in design, human-computer interaction and user experience. In addition to exploring how particular tools are adopted and used 'in-the-wild', this work also intersects with the existing interest in new media and the ways in which linguistic behaviours are structured by platform design.

5.2.2 How do language technologies reinforce linguistic discrimination?

As language technologies are embedded in high-stakes contexts such as education, employment, healthcare, policing and immigration, the expertise of scholars working on linguistic discrimination is essential. We can draw on the rich literature on linguistic discrimination, and on ethnographic and experimental methods to understand how institutions make use of language technologies, and assess whether they reproduce existing patterns of discrimination. The ability to link system behaviours to real-world harms is an essential part of challenging discriminatory systems in many contexts. However, researchers working on language, society and power are also well aware of the limitations of this king of 'evidence' in the face of injustice. Their insights and experience are crucial in challenging illiberal use of language technologies.

5.2.3 How are language technologies reconfiguring language work?

The implementation of language technologies is already changing workplaces – from schools to call centres – and creating new types of work and tasks. Of particular concern are the ways in which language technologies are negatively affecting the social and economic value associated with some types of work, and altering work processes to the detriment of workers. Some tools may also greatly benefit some workers, for instance through the automation of tedious tasks. The development of language technologies also creates new types of language work related to the creation of data and evaluation of systems. This work, in addition to being difficult, is often also dangerous in ways which are not well-recognised. Linguists, sociologists and psychologists are particularly well-placed to contextualise the challenges of this work.

6 Conclusion: Building a multi-disciplinary research community to support language communities

The theoretical and empirical questions investigations above, can support practical work with language communities. In this paper, and all my work on language technologies, I have tried to draw together scholarship from different fields concerned with language, technology and society. I strongly belief that a multi-disciplinary approach is essential to any critical analysis of language technologies. This is easier, and more fruitful, in the context of multi-disciplinary teams. Beyond leveraging skills, methods and knowledge of each team member, this also forces the kind of dialogues we urgently need if we are interested in protecting language communities from intended and unintended harms of existing language technologies, and supporting them in developing, maintaining and deploying better ones.

Language technologies, like all technologies, are not inevitable, and they are neither all good, nor all bad. They are always shaped by and expressive of politics. However, what those politics are, and whether and how we choose to engage with technologies, is up to us.

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