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Finding the Human in an Era of Machine Intelligence: A Flat Ontological Analysis of Generative AI and Language Learning



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Abstract

Amid the optimism of generative Artificial Intelligence (gen-AI) in language education, there remains a weak connection to learning practices. The emergence of gen-AI has preceded considerations of how it should be applied in teaching and learning. However, while gen-AI has been justified in terms of the possibilities to enhance learner agency by expanding opportunities to engage with language, such as through the generation of content or the translation of texts, it can also take power away from learners. How can learners be self-determining in light of how choices become increasingly guided by Artificial Intelligence? In this paper, I conceive the arrangements of humans and software as an assemblage of complex and dynamic social, and technical processes. Drawing on a flat ontology, where all agents (human and non-human, material and subjective) have equal ontological status, I argue that learner agency has its origins in the messy and lively interactions between heterogeneous actors. In particular, I consider active and passive affects as being part of the same process: active when we bring something into effect ourselves, passive when our self-determination is changed not by our own power, but through external forces acting on it (such as gen-AI). From this, I explore the constraining and enabling potential of artificial intelligence. Finally, I extend this discussion to the emergence of learner agency.

Keywords: flat ontology, artificial intelligence, language learning, language education, learner agency, socio-materialism

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Introduction

Advances in generative artificial intelligence (gen-AI), particularly large language models (LLMs) such as Chat GPT, offer the potential to shape language learner agency. Some argue that gen-AI promises efficient tools which can enhance language learning opportunities (Son, et al., 2023; Rusmiyanto, et al., 2023). However, many worry that gen-AI may undermine the validity and reliability of student work or lead to over-reliance on quick, AI-generated answers (Maier, 2022; Anderson & Rainie, 2024; Darvishi, et al. 2024). Although the long-term impacts of gen-AI are difficult to predict, what is certain is that language learning is now taking place in a very different environment, and there is a need to understand how learners can be independent and self-determining in light of how language learning becomes increasingly entangled and interdependent with machine intelligence.

In the absence of a strong empirical basis, language learning practices that incorporate gen-AI may fall back on essentialist views of agency, particularly by reducing agency to individualist justifications which elide the contexts from which agency is achieved. However, language learning is highly social and language learning practices are deeply embedded within complex relations of individuals, institutions and technologies. The way language learners engage with the world depends on how they are situated within it and language learner agency is inevitably conditioned by other things. As Williams (2019, p. 118) observes, an increased technicalization of society results in more relations with a greater diversity of actors, affording greater potential for interaction. This complexity has an impact on individual capacities, but as learners become entangled in mutual cooperation and compromise with various forms of artificial intelligence, they might not increase their autonomy. In this paper, I offer a relational account of gen-AI in language learning to explore the impacts of the emergence of machine intelligence. First, I outline a *flat ontology*, a philosophy of the social sciences which holds that all actors (human and technical) are equally significant and interconnected, before providing an analysis of gen-AI in language learning.

Literature Review

Artificial Intelligence has long held potential for language learning, for example chatbots for error correction, translation software, language learning apps and the efficient marking and administration of assessments (Dodigovic, 2005; Huang, et al., 2022; Chen, et al., 2020; Pikhart, 2020; O’Grady, 2023; Zheng, et al., 2024). A particular emphasis has been on the auxiliary powers of artificial intelligence, with chatbots often characterized as learning assistants or coaches and AI justified in terms of its speed, scale and efficiency for marking and assessment (O’Grady, 2023; Poole & Coss, 2024). However, for the most part, the application of AI remained peripheral to mainstream language education.

The innovation that emerged with the introduction of ChatGPT 3.5 in November 2022 was in generative artificial intelligence (gen-AI), a form of machine learning trained to simulate content in the form of text, images, music and video. This involves a number of processes and technologies including, machine learning, deep learning, natural language processing (NLP) among others. An important feature of gen-AI is its ability to learn directly from input (examples, data and experience) often through a feedback loop where an output is generated and compared to an ideal or correct response (Gutiérrez, 2023). This is fed back into the model which helps it improve its performance. One outcome of machine learning is that gen-AI can accurately translate language combinations it has never been introduced to based on its initial training data (Johnson, et al., 2017, p. 343). Other applications include the ability to summarize long texts, generate content and have a natural-seeming conversation. These new capacities have developed quickly and surprisingly and have had a sudden impact on many aspects of language education.

These powers now go well beyond assistance to the point that many acknowledge the agency of machines (Markauskaite, et al., 2022; Anderson & Rainie, 2024). Agency is a primary concern in social and educational theory, and it is well recognized that learners are best placed to make decisions about their own learning. Agency is a particularly important idea in language education, reflected in concepts such as learner autonomy, self-regulation and self-determination, and it is often used to justify choices about language learning and teaching (Larsen–Freeman, 2019; Mercer, 2011). Since gen-AI is so recent, there has been little research into the relationship between gen-AI and learner agency. Agency is often framed as an active power (Darvishi, et al., 2024; Gašević, et al., 2023). However, an emphasis on the capacities of humans elides the capacities of the machines. Responsibility for work that is produced is typically assigned to the human, with the influence of the machine being reduced to “personalised nudges” or recommending systems (Darvishi, et al., 2024).

But the human-technical dichotomy is not reducible to a single actor; the human is *always* situated within a technological context (that is, we always use technology to produce work), and the technical *always* comprises humans exercising agency. As the philosopher Bruno Latour (1986, p. 276) argues, there is a danger that “social scientists (conflate) the effect for the cause, the passive for the active, (and) what is glued for the glue”. There is a need to account for the influence of machine intelligence and wider influences on human agency, not in terms of their separate powers, but in their emergent capacities that result from their “working together” (Bennett, 2010; Archer, 2021). Godwin-Jones (2024, p. 9), in a speculative argument on the impacts of gen-AI in language learning, recognizes the relational nature of agency, which is “emergent and distributed, arising from iterative interactions between human user and AI”. It is this shared concept of agency that is explored in this paper. To this end, the research questions are:

1. Who are the major actors involved in the gen-AI ecology?
2. How are the powers of these actors distributed?
3. What forms of agency emerge?

Theoretical Framework: A Flat Ontology of Learner Agency

A flat ontology is a philosophy of the social sciences which holds that non-human actors (such as technology) are as important to the functioning of a social structure as humans. It is associated with a range of methods and approaches, for example, new materialism (Nail, 2019), assemblage theory (DeLanda, 2016; Bennett, 2010), actor-network theory (Latour, 2005), *thing*-ethnography (Michel-Villarreal, et al. 2023), scale theory (DiCaglio, 2021) and object-oriented ontologies (Harman, 2018), all of which share an emphasis on socio-materiality and non-human agency. A flat ontology aims to avoid essentialism (the presumption that things have inherent characteristics) by levelling, or flattening, the hierarchy between agents. That is, all actors (human or non-human, material or subjective) have an equal ontological status where none is privileged over the other. Actors can consist of anything or anyone that has a causal power, from teachers, dictionaries, bookcases, opinions, chairs or search engines. Actors combine to form an *assemblage* with its own capacity to act (DeLanda, 2016). An assemblage can be anything from a language classroom, a trading network, a zoo, a swimming team or a multi-national corporation. In each case, agency is being exercised at different strata: first by each individual actor, and secondly, through the collective endeavor of the assemblage (Johri, 2022; DiCaglio, 2021). Everything is interconnected and each actor can be a member of multiple assemblages, raising the potential for any actor to influence any other actor. It is important to acknowledge that a flat ontology does not deny the existence of hierarchies, just their presumption, and it is often a useful way of revealing asymmetry between different actors.

A flat ontology opposes any essentialist separation of powers between actors, instead viewing these connections as ways they affect each other (Alanen, 2017). As human and technical actors exercise their capacities to act, others necessarily have to accommodate them (and vice versa) (Kisner, 2021, p. 83). Therefore, in any interaction, actors always have to trade off to various degrees. The organizing power of non-human actors such as artificial intelligence is a key aspect of modern technical societies, and human agency is increasingly (at least partially) dependent on technical processes. Although gen-AI does not have the capacity for responsibility or intentionality that humans do, it has its own powers which can radically alter relational arrangements in language education, for example by orienting practices towards the management of the technology rather than to supporting teaching and learning (Williamson, 2017b; Ali & Hamid, 2023; Matthews, 2024). A flat ontology allows us to unpack the influences of various actors in complex social forms, with the aim of revealing their effects on each other. Locating agency involves not separating off the capacities of each actor, but by understanding how their powers work together (Bennett, 2010).

Active and Passive Affects

A useful way of exploring the *working-together* of diverse range of actors is to distinguish between an agent's active and passive affects. The concepts of active and passive affects have their roots in Enlightenment thinking, particularly John Locke, who observed that active power is only realized in relation to the passive properties of its object, for example, for fire to be able to melt gold, gold must have the capacity to be melted (the active power is dependent on the passive affect, Alanen, 2011). An active affect is the ability for an actor to act in a certain way. Active affects not only refer to physical powers, but also to mental ones, such as the ability to reflexively adapt to a situation, or to reject a power acting on us (Archer, 2007; Alanen, 2017). Passive affects, meanwhile, are ways of acting that can be attributed to another agent, or no agent at all, for example when a learning platform tracks student data and makes it visible, then learners' actions become guided by the data (Fricker, 2007, p. 12; Williamson, 2017a; Matthews, 2024).

The concept of passive affect was extended in the twentieth century (particularly by writers such as Michel Foucault and Pierre Bourdieu) to explain the coercive power of practices embedded in social institutions, such as prisons, mental hospitals and schools, where power is not exercised directly but through indirect mechanisms such as surveillance or regulation (Christensen, 2023). In the twenty-first century, the concept has been used as a useful way of exploring non-human agency (particularly technology) within complex socio-technical systems (Latour, 2006; Bennett, 2010; DeLanda, 2010; 2016; Harman, 2018; Haraway, 2016; Fricker, 2007). Tsang and Qin (2020) observe how the technicalization of teaching and learning may result in technical disempowerment, where technical processes narrow the concept of learning (for example, gamification may reduce learning to affective responses such as fun) or reduce pedagogical practices to the working of technology. Williamson (2018) observes how online learning platforms can impose practices on to its users that they would not otherwise employ (such as competition or the ranking of student performance).

A flat ontology tells us that active and passive affects are not binary, and agency results from the interaction between an actor's self-determination and the external thing acting on it (Alanen, 2017). For example, where a language learner uses gen-AI to help them write an essay, they are at once exercising agency by making choices about their learning and being influenced by the technology. Passive power may be benign. Nevertheless, circumstances may be such that an agent cannot impose their own will, and their actions may be governed by the thing (or things) acting on it. The concept of active and passive affect provides ways in which we might understand how we can be affected by influences beyond our ability to perceive them.

Methods

This paper applies a flat ontology to review the literature on gen-AI in language learning. A flat ontology has been applied in various ways in applied linguistics. It has particularly been associated with work on translanguaging (Pennycook, 2017; Canagarajah, 2020, 2024; Gurney & Demuro, 2022). Phil Benson (2021) has applied socio-material methods to explore the design of language learning spaces. Meanwhile, in information sciences, Gutiérrez (2023) discusses how a flat ontology (specifically *actor-network theory*) can reveal new power dynamics of large language models. Kasirzadeh and Gabriel (2023) use a flat ontology to explore how large language models can align with human values. However, there is little research yet on how a flat ontology can be applied to Artificial Intelligence in language education. Here I outline the following steps for doing a flat ontological analysis (adapted from Enserink, et al., 2022; Fenwick, 2010; Harman, 2018).

First, I reviewed the academic literature on gen-AI from journal articles, book chapters and conference proceedings in educational research, social science research, linguistics research, language teaching, information systems scholarship, computer science, law and librarianship, covering a range of diverse contexts and methods. To be included in the initial review, papers required a well-defined concept of gen-AI and needed to be published after November 2022, when Open AI released its Chat GPT chatbot. This was supplemented and expanded with general web searches until saturation was reached (where no new actors emerged).

From this, I drew up a long list of actors involved in gen-AI in language education. Then, actors were grouped together depending on their causal powers to make a shortlist. Some categories were separated out into separate actors, for example the gen-AI was divided into its algorithm and corpus given that each of these have their own independent causal influences. In other cases, multiple and disparate actors were combined into a single collective (for example, the corporate ecosystem) where it was discerned that they had a common influence. At this stage, I wrote a case reconstruction whereby I set out a descriptive summary of each actor (Gerhart, 1994; Stapley, et al., 2021, pp. 28–29). Next, I identified the ways that each actor had an effect on the network, which involved coding how actors bear influence on each other. These could be one-directional relations (where an actor is dependent on another power), or bi-directional, that is actors affect each other). The codes were refined and compared until no new relations emerged. This resulted in an outline of the hierarchical and relational network of actors (see Figure 1).

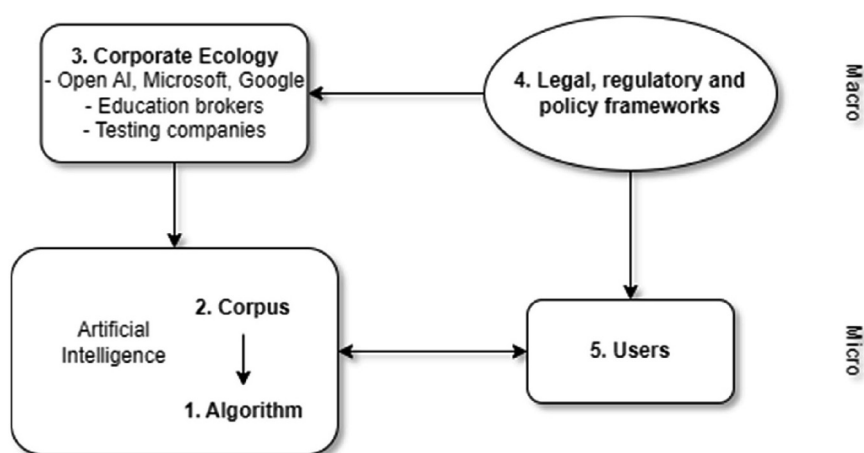


Figure 1 *The Gen-AI Language Learning Assemblage.*

A Flat Ontological Analysis of Gen-AI in Language Learning

The gen-AI language learning assemblage incorporates a complex network of diverse actors which each exercise agency at micro and macro levels. The main actors at the micro-level are the gen-AI (made up of two distinct entities, the algorithm (1) and the corpus (2)), and the users (5). The powers of the algorithm are dependent on the corpus, though combined they make up a single power (the capacity to produce human-like texts). The users and the gen-AI work together to create and translate texts through written prompts, responses and editing. The gen-AI and users are affected and shaped by other actors, principally a corporate ecology (3) and a legal and regulatory framework (4), which exert downward forces on the activity of the users.

Algorithms

There are many types of Artificial Intelligence (AI) used in language education, some that are so ubiquitous that we may not even think about them as AI, such as predictive text, spellcheckers, and autocomplete, but the form of AI that has become particularly prominent recently draws on large language models (LLMs) that can recognize, translate and generate text (such as Chat GPT or DeepL). These large language models are technically not Artificial Intelligence (that is, they do not mimic human intelligence). Instead, LLMs use machine learning to synthesize texts that humans have already written. Referring to LLMs as artificial intelligence imbues them with an authority, but there is then a danger that its internal processes are closed off and its working is not understood by users (a process known as *blackboxing*). As a result, users of LLMs may not fully understand how the algorithms they use operate or how they are affected by them, and there is a need to unpack the working of these models.

A large language model generates language by drawing on large corpora of texts, which it subjects to statistical treatment to predict a “reasonable continuation” of the next word, words, or even texts (Wolfram, 2023, p. 1). This is not necessarily the statistically most likely word, but one of a choice of potential associations that it selects randomly. In this way, such large language models appear to be creative in their application. For example, Wolfram observes the various outputs for the prompt “*The best thing about AI is its ability to ...*” (Wolfram, 2023, p. 4):

1. The best thing about AI is its ability to **learn. I’ve always liked to ...**
2. The best thing about AI is its ability to **really come into your world and just ...**
3. The best thing about AI is its ability to **examine human behaviour and it ...**
4. The best thing about AI is its ability to **do a great job of teaching us ...**
5. The best thing about AI is its ability to **create real tasks, but you can ...**

A key development in making large language models possible was the introduction of *transformers* in 2017, a software architecture designed around the idea of *attention* (an AI approximation of cognitive attention), which made it possible for artificial intelligence to process more complex sequences of words by focusing on key features of input, therefore overcoming the limitations of memory encountered in previous models, such as predictive text (Vaswani, et al. 2017). Transformers rely heavily on a concept called *self-attention*, which refers to a focus on each item in a corpus. Essentially, self-attention assigns values of a word to other items in the corpus. For example, in the sentence “*The animal didn’t cross the street because it was too tired*” (Kincher-Wonoto & Kavalier, 2019), each word is associated with the others to different degrees, but the pronoun “it” is particularly ambiguous, referring to either the animal (which is far away in the sentence) or the street (which is next to it). A transformer-based translator reads the whole sentence at once (rather than word by word), determining the relevance of each word in the sentence to the pronoun. In this way, AI directs its “attention” to the statistically most

relevant word, thereby generating a more accurate approximation of how words in a longer series of text hold together.

However, gen-AI cannot yet efficiently encode factual knowledge, which greatly reduces its reliability (Zhuo, et al., 2023). Zhuo et al. (2023) identify a particular problem in LLMs, whereby reliability is compromised by a phenomenon known as *hallucinations*, which refers to the generation of false or misleading information. In a study on the prevalence of hallucinations in ChatGPT, Zhuo et al. found 24 instances of hallucinations in a sample of 100 messages. Meanwhile, there have been concerns around ChatGPT generating harmful and convincing misinformation or presenting wrong information as the truth (Haltaufderheide & Ranisch, 2024; Meyer, et al., 2023).

Corpora

While the algorithm has the capacity to create human-like texts, its performance is wholly dependent on another actor, namely the corpus, which provides the algorithm with training data. The corpus has power over the algorithm; if there is no corpus, then the gen-AI cannot learn. Moreover, the algorithm can only produce language within the limits of the data provided. A corpus (from the Latin for “body”, corpora in plural) refers to a collection of texts organized into datasets. Each form of AI is different as the training data that is used for machine learning is drawn from different corpora that are selected by humans. For the most part, the specific make up of each corpus (that is, what texts they are comprised of) is not publicly shared. However, it has been generally reported that the most widely used gen-AI model, Chat GPT, was trained using databases that included data from research papers, books, websites (including Wikipedia), and other content from the Internet. Nevertheless, gen-AI can be trained with any corpus content (see for example the experimental AI corpus built using only the work of the philosopher, Daniel Dennett, (Schwitzgebel, et al. 2024)).

Gen-AI models draw on a machine learning technique known as self-supervised learning. This works through the use of a positive feedback loop, where the AI generates an output, which it then compares with a “correct” form. If the algorithm’s prediction is wrong, it is rejected and if it is correct, this information is fed back into the model which informs future outputs. Typically, correct forms were provided through labels being added to the data manually (“supervised learning”). However, the datasets that large language models are based on are so massive, manual labelling could never be done efficiently. Therefore, machine learning scientists have developed a way for gen-AI to produce its own feedback independent of any human, through the generation of labels from unstructured datasets. The ability for gen-AI to produce its own feedback represents a breakthrough in natural language processing, allowing more efficient synthesis and comprehension of large numbers of texts by machines. Self-supervised learning is not as accurate as supervised learning, though at scale (as supervised learning becomes more difficult), their accuracy is comparable (Geirhos, et al., 2020).

However, much of the quality of the output depends on the quality of the input training data and there is always the potential for corpora to introduce biases. Corpora can either capture negative social biases, such as gender, race or class (or any other way of categorizing society, Zhuo, et al. 2023), or it can result from a problem with the data collection methods, which may include or exclude a certain element or elements of the population. Papakyriakopoulos, et al. (2024) in a paper that involved a dataset gathered by massive web-crawling of publicly available spoken data, observed a lack of diversity in available texts. Hirmer, et al. (2021) in a paper on the development of corpora involving illiterate communities, observe how many corpora are built on data that is easy to access, and subsequently excludes most

of the world's population. Meanwhile, Weidinger, et al. (2022) also identify the potential for fake or misleading information to affect the quality of gen-AI corpus data. Chua and Chen (2022) in a paper on the development of a corpus of restaurant reviews, observe the difficulties associated with the proliferation of fake texts, written either by humans in bad-faith or by artificial intelligence, which are subsequently used in corpus data.

The gen-AI cannot yet be trusted in terms of the authenticity of its output. When the AI gets something right, it is not because it has used intelligence to figure it out, but because it is drawing on texts that already exist. Moreover, while the gen-AI can produce authentic-like output, the potential for bias or misinformation, amplified by the algorithm, means that the output can never be deemed reliable. Critics of gen-AI compare it with a cartoon, where human qualities are projected onto non-human agents, such as chatbots (Stark, 2024), while others argue that AI generated texts represent a pastiche (or a parody) of reality, where reliability and truthfulness are not among its intended purposes (Marcus, 2022). There is no conceivable way that in the short or medium term it will be possible for the algorithm or the corpus, in their current forms, to be able to produce factually correct output. The power of the gen-AI, then, does not only involve new abilities to generate, translate and synthesize texts, but it also introduces the capacity to undermine the validity of student work and assessments, directing effort away from learning and toward the management of the technology.

Corporate Ecosystem

Gen-AI language learning practices are situated within a broader corporate ecology. The key actors responsible for the development of gen-AI models and putting practices and systems in place are principally a small number of large tech companies (for example, Microsoft, Google and OpenAI), which provide infrastructure such as cloud storage, payments and social media. Allied to them are a proliferation of start-ups and other companies (such as Anthropic, Cohere, and Mistral AI), which comprise a broader corporate ecological structure encompassing data engineers, financing bodies, policy makers and educational brokers (Jacobides, et al., 2021, Williamson, 2017a; Ortégón, Decuyper & Williamson, 2024). A detailed exploration of this corporate ecology is outwith the scope of the discussion in this paper (see Jacobides, et al. 2021 for a comparison of the evolution of the AI ecosystem in three different regions). However, the rise of gen-AI is taking place during a time of an emerging presence of “Big Tech” in educational spaces. Concepts in educational technology such as platform capitalism (Carrigan, 2021), choice architectures (Bradbury, et al., 2013) and the datafication of education (Watters, 2021; Williamson, 2017a) all capture the organizing forces of these structures. These actors represent a diverse range of corporate entities, each with their own capacities, though collectively they share the power to organize and put AI routines in place through the development and distribution of technology.

The combined endeavors of these corporate actors have resulted in the development of bureaucratic and technical structures that involves the development of corpora, the design of the interface and the integration of AI into existing technology. Gen-AI is being integrated into language education in a number of ways, for example chatbots (Hwang & Chang, 2023; Huang, et al., 2022), language learning apps such as Duolingo, spellcheckers and proofreading systems (Ciaccio, 2023), translation tools (Khasawneh & Al-Amrat, 2023; Lee, 2023; Klimova, et al., 2023) and virtual assistants (such as ChatGPT). Products such as Chat GPT Edu are being targeted at schools and universities. Gen-AI has also been incorporated into applications in an opaque way, for example search engines, and users may not know if AI is present or what effect it has.

Gen-AI is not a neutral tool and in the absence of a strong evidence base on which to justify its presence in language education, claims about its efficacy and desirability become value-driven. The

prevailing value structure that underpins the corporate ecology is neoliberalism, an ideology which prioritizes competition, market mechanics and deregulation (Bradbury, 2019). A major critique of neoliberal philosophy is its presumption that technology equates with progress in education (Davies & Bansel, 2007, p. 249). Such positions can be characterized by a tendency towards framing justifications of gen-AI that lead to an inevitable progress, where gen-AI is in place to direct us to that end point (a teleological argument). Rensfeldt and Rahm (2023) observe that AI debates often align with “techno-optimist” discourses, which are often not intellectually defensible (Danaher, 2022; Königs, 2022). Such bullishness is evident in comments made by Bill Gates (in Huddleston, 2023), who argues for chatbots in every classroom, and popular education writer Angela Duckworth, who argues that:

We know that GPT is the ultimate cheating tool ... (but) AI is not coming. AI is here. And it cannot be banned (Duckworth, 2023).

Comments such as these reveal a discourse of the inevitability of Gen-AI, often couched in terms of progress, seeking to normalize its use as part of everyday life. These justifications are being made within the context of an “AI race” whereby companies compete for dominance (Cheng & Liu, 2024). But, as Duckworth acknowledges, there is no escape from the technical structure – we cannot reject it. Despite the emancipatory promise of gen-AI, the reality may be more dispiriting, and there is a danger of it serving as a vehicle for corporate power (McQuillan, 2023, p. 60).

Legal, Regulatory and Policy Frameworks

As a result of these concerns, there has been a turn towards the ethics of artificial intelligence, particularly involving discussions about plagiarism, academic integrity and intellectual property rights (Cheng & Liu, 2024). A review of the literature of legal, regulatory and policy frameworks related to gen-AI reveals a stratified regulatory structure. At the macro-level there exists a global framework of guidance, involving global institutions such as the World Economic Forum and UNESCO, and regional powers, such as the European Union (Council of the EU, 2024; International Association of Privacy Professionals, 2024). Some jurisdictions have expanded existing data protection laws to cover gen-AI (for example, in the UK). In other countries, there have been specific laws put in place to regulate gen-AI (for example, Malaysia, Manap & Abdullah, 2020; and Brazil, Schirru, et al., 2024). Otherwise, ethics is mostly voluntary.

Meanwhile, at the micro-level, schools, institutions and departments must grapple with the day-to-day realities of AI use. The main concern is around the potential for work to be produced that is not the learner’s own. In a paper on the integrity of algorithmically driven writing tools, Gustilo, et al. (2024) observed significant concerns about gen-AI’s impact on academic integrity and creativity, specifically how it may compromise the trust that underpins the academic process. Bozkurt (2024, p. 2) observes that the disruptive power of gen-AI necessitates the reconsideration of what exactly constitutes student work arguing for responsible and transparent use of gen-AI. In a paper on the plagiarism detection rates of texts written by ChatGPT, Talon, et al. (2023) found that there was significant potential for gen-AI texts to avoid plagiarism detection software. Many institutions have completely banned any use of gen-AI, while others call to embrace it (for example, Lim, et al. 2023).

The principle of autonomy underpins much of the ethics around how gen-AI is used. A flat ontology is not a flat ethics, that is, although AI has agency, it is well-established that its user is ultimately responsible (Calderonio, 2023). There is a consensus that autonomy is realized through transparency; the greater the transparency, the more clearly responsibility can be assigned. It is important that the responsibility for the work produced, whether it is produced by humans or gen-AI, acknowledges

the extent of AI use. One of the main ways that transparency is achieved is through “transparency statements”, where learners have to state how and to what extent they have been assisted by machine intelligence (Tang, et al., 2024). Other institutions use gen-AI detection software (in a similar way to plagiarism detection software), but there are debates to what extent this is possible, particularly the dangers of false positives (Dalalah & Dalalah, 2023). Another issue is related to the opacity of data sources used in corpora. Large chatbots, particularly Chat GPT, do not share their sources, so it is impossible to know how to trace original texts or how content creators can have the right to withdraw their content.

Users

Artificial intelligence is already being used widely in language education. Huang, et al. (2023), in a review of the literature from 2000–2019 identify a number of ways in which gen-AI has been applied, including automated writing evaluation (AWE), intelligent tutoring systems, automated error correction and language and vocabulary learning. Liang, et al. (2023) in a study of AI in language education between 1990 and 2020 observed that research tended to focus on the capacity for AI to analyze texts for language accuracy, particularly its role as an “intelligent tutoring system”. Since late-2022 and the advent of the widespread use of large language models, gen-AI has offered opportunities for self-directed learning (Li, et al., 2024), conversation practice (Bozkurt, 2023) and customized and personalized learning (Creely, 2024). One popular avenue for research is data-driven learning, where there seems to be a good fit between corpus data and texts as data for gen-AI (Crosthwaite & Baisa, 2023; Curry, et al., 2024).

However, the human is still primary in the language learning process and an understanding of active and passive powers allows us to consider how external pressures contribute to an individual’s capacity to act autonomously. Different interactions result in the emergence of different strategies with which to engage with the new possibilities and constraints. While there remain many research gaps, the literature reveals a number of ways that agency can be conceived. First, are pro-active users, often justified by ideas which prioritize the active power of individuals to shape learning. These include early adopters, techno-optimists, AI-evangelists and others who express a positive disposition towards AI. In a scoping review of empirical studies of gen-AI in language education, Law (2024) reviewed 41 studies between 2022 and 2023, observing that the majority ($n = 28$) positively evaluated its implementation (while only one expressed negative views). Notwithstanding the potential for research bias (that is, people who have a positive disposition towards gen-AI are more likely to pro-actively research it), there seems to be a great deal of enthusiasm around the practical benefits of gen-AI. However, in the absence of a strong evidence base for gen-AI, such positions may fall back on essentialist views of technology.

Second, others have taken a more critical disposition, often rooted in perspectives which grant primacy to the passive powers of technology in shaping learning conditions. This may be characterized by rejection, non-use or resistance of gen-AI. For example, a report on the future of human agency in an era of AI, captured a range of viewpoints from experts on how AI might shape society (Anderson & Rainie, 2024). In particular, there are concerns about the expansion of corporate and government presence in the choices of individuals. Selwyn (2023) warns against the “there is no alternative” message, and instead argues for the “resistance and reimagination” of AI in education, to fulfil real learning needs. Meanwhile, Shew (2020) observes a tendency for AI to slip into ableist discourses, particularly around assistive models of AI (despite AI never being developed with assistance in mind). These claims may be based on reasonable fears of the limitations and rapid adoption of gen-AI in education. However, there is also a danger that the practical benefits of a reasonable use of gen-AI is overlooked.

A third type of agency can be conceived as a form of disorientation, whereby learners are using gen-AI in non-optimal ways. The rapid emergence of gen-AI has been too fast to prepare for making it more difficult for people to exercise effective governance over their practices, resulting in gen-AI being used in ways that do not align with what we know about how languages are learned. Lan and Chen (2024) outline some of the challenges that arise through the widespread use of gen-AI in language learning. They observe how students may treat gen-AI as a more advanced search engine, where users view AI tools as a way of getting quick answers. Another issue they identify is where learners over-rely on gen-AI to complete learning tasks. Karataş, et al, (2024), in a qualitative study of university language students observed challenges concerning the use of gen-AI as a shortcut for student work and an over-dependence on the technology.

A fourth, more speculative form of agency may be imagined as the entanglement of human and machine agency, where the relationship can be conceptualized as *co-agents* (Archer, 2021) or as joint cognitive systems (Jones, et al., 2018). Gourlay (2023) proposes a “more-than-digital” view of this relationship, acknowledging the role of both humans and machines in the production of work, where gen-AI can be compared with other technologies, such as GPS navigation or calculators, which amplify human intelligence. However, since gen-AI cannot be relied on to produce factually accurate texts, there remain concerns that there is very little for it to offer beyond its capacity to produce coherent language (Jiang, et al., 2024), and its potential as a tool for language learning may be exaggerated.

Conclusion

This paper reveals a complex ecology behind the emergence, implementation and development of practices related to the use of generative artificial intelligence in language education. First, a flat ontology has allowed a better understanding of the way that gen-AI affects language education from every day and mundane interactions to capacities that have the potential to reshape practices. Second, it has allowed us to explore the agency of non-human actors, particularly the passive powers of technological and corporate actors in shaping language learning practices. Third, it has allowed us to think about the “working-together” of human and machine intelligence, where language is not produced by either machines or humans, but through the cooperation, interaction and intermingling of their agencies. There has been a mix of enthusiasm, skepticism and curiosity about the potential of gen-AI, though its practical application remains contested. Although the gen-AI has the potential to offer new opportunities for language learners, there remain significant concerns about the validity and reliability of the texts produced by gen-AI which may undermine trust in the academic process. There are concerns too about its rapid adoption and how practices are being imposed onto users without full consideration of their merits. It is important that all language teachers begin to develop an understanding of the capabilities of gen-AI, since it is certain to have a significant effect over almost all aspects of language education in the coming years.

The contribution of this paper is to highlight the complex nature of language learner agency and to emphasize that agency is not only an active power on the part of the individual, but instead an emergent phenomenon with its origins in the interactions between multiple, disparate actors operating at micro- and macro- levels of influence. In particular, this paper demonstrates that there is no inevitability or endpoint in the development of learner agency, and the imposition of new practices may lead to agency being exercised in non-optimal ways. These findings are at odds with much of the prevailing research literature, which emphasizes the emancipatory powers of technology (Darvishi, et al., 2024). However, the paper supports a strongly relational view of language learning, which recognizes that agency is exercised within the enablements and constraints of what is available and possible (Godwin-Jones, 2024; Canagarajah, 2020). The evidence of the transformational power of gen-AI remains thin, but this is no reason to become cynical about its place in language education. Nonetheless, there is a need

for more empirical research on the relationship between human and non-human agency as we become more entangled and interdependent with machine intelligence.

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