INTERNATIONAL LITERACY ASSOCIATION READING RESEARCH QUARTERLY

Literacy in the Time of Artificial Intelligence

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ABSTRACT

The latest mutation of Artificial Intelligence, Generative AI, is more than anything a technology of writing. It is a machine that can write. In a world-historical frame, the significance of this cannot be understated. This is a technology in which the unnatural language of code tangles with the natural language of everyday life. Its form of writing, moreover, is multimodal, able not only to write text as conventionally understood, but also to "read" images by matching textual labels and to "write" images from textual prompts. Within the scope of this peculiarly mechanical manufacturing of writing are mathematics, actionable software procedure, and algorithm. This paper explores the consequences of Generative AI for literacy teaching and learning. In its first part, we speak theoretically and historically, suggesting that this development is perhaps as momentous for society and education as Pi Sheng's invention of moveable type and Gutenberg's printing press—and in its peculiar ways just as problematic. In the paper's second part, we go on to propose that literacy in the time of AI requires a new way to speak about itself, a revised "grammar" of sorts. In a third part, we discuss an experimental application we have developed that puts Generative AI to work in support of literacy and learning. We end with some findings and implications for literacy education and with a proposal for what we will call cyber-social literacy learning.

> [He] allowed himself to be swayed by his conviction that human beings are not born once and for all on the day their mothers give birth to them, but that life obliges them over and over again to give birth to themselves. Gabriel García Márquez, *Love in the Time of Cholera*

To set a context for this paper, we will begin at the point where the personal meets the professional in literacy pedagogy. Our lives in literacy have ranged widely. We have worked in working class schools with large numbers of speakers of minority and immigrant languages, where the challenge has been to achieve social access through education but without prejudice to the diversity of heritage languages (Kalantzis, Cope and Slade 1989). We have been privileged to work in indigenous communities where extraordinarily complex languages and their profound epistemologies point to other ways of living in nature and with each other—lifeways that have long been threatened by colonial incursions (Cope, 1998). We have interrogated the literacies of power and the complex dynamics of in/equity (Cope & Kalantzis, 1993). We have explored the emerging requirements of multimodality (New London Group, 1996), translanguaging (Cope et al., 2024), and the dynamics of literacies in the plural (Kalantzis et al., 2016).

We started to think about the impacts of digital media on literacies in the plural soon after we moved from Australia to the University of Illinois in 2006 (Cope & Kalantzis, 2009, 2017). When we arrived in Illinois the people at the National Center for Supercomputing Applications (NCSA) were working on a grant application to build the world's biggest research computer. At $208 m, it would be the largest single grant made by the National Science Foundation. NCSA won the grant, and today "Blue Waters" (as it was subsequently named) stands as large as an apartment block at the edge of the campus. Beside it, a massive cooling tower

INTERNATIONAL LITERACY ASSOCIATION

Reading Research Quarterly, 2025
60:e591 | doi:10.1002/rrq.591

reminds us that computing is still an industrial enterprise that consumes a lot of energy. While Blue Waters was under construction, as literacy researchers with an interest in digital media, we mused: just about every published word has already been ingested into the universal library of the internet. What then, if the relationship of every word to every other word could be calculated? At the time, this was even too big for Blue Waters.

Well, now this has happened, more or less. It's called Generative AI. This, as we will argue in the first section of this paper, is likely a milestone in human history as big as Pi Sheng's moveable type of 1039 and Gutenberg's printing press of 1450. In the history of human meaning-making, this is 1039 or 1450 again, depending on whether you are inclined to look East or West for your historical waystations. And it's just as problematic as these inventions. This is because literacy and its means of production have been as regressive in social practice as often as they have been liberatory.

The paper that follows is synoptic and wide ranging. One of our thoughtful reviewers has suggested that perhaps it should be a book, and they are probably right. But with the sudden arrival of Generative AI we feel a sense of urgency to put together something more accessible even if the price might be to cover too much ground in too short a space. In the first section, we map the historical terrain of literacy in order to situate the arrival of Generative AI. In the second, we attempt a revised definition of literacy for the AI era, including the specifics of AI literacy. Then in the third section we speak to some of the practical prospects for Generative AI in literacy teaching and learning including some recent interventions in our research lab. We conclude with a proposal for what we call "cyber-social literacy learning"—not "artificial intelligence" where the machine is used to replicate human writing capabilities, but a scaffolded, dialectical, "cyber," or feedback relation between learners–writers and their writing support machines.

Literacy, Disrupted

"Literacy," say the authors of this entry in the latest edition of the *Handbook of Educational Psychology* is "the ability to read and write" (Kendeou et al., 2023: 553). Then, for 22 pages they tell us the conventional and excruciatingly dull ways in which schools squeeze reading and writing out of learners, using standardized assessments to show that certain kinds of disciplined intervention produce "growth" the self-fulfilling measures of test scores.

In one perspective, the study of "learning to read and write" is based on a theoretical premise so commonplace and outdated that it is hardly worth examining again. Schools do literacy because for quite a while this has been what schools have done (and mathematics, of course, the third of the three "Rs," but as we will argue shortly, literacy and mathematics are converging as textual forms). Within their narrowly instrumental frame, traditional literacy researchers work to figure out how to extract better scores on the self-imposed measure of standardized tests of old-school reading and writing. But what if there is more to literacy since the rise of digital media, and even now with Generative AI? Or do we, in the context of multimodality, need a broader concept of meaning-making?

Of course, under the flags of the new literacy studies (Pahl & Rowsell, 2012), critical literacy (Luke 2018), digital literacies (Lankshear & Knobel, 2008), and 21st century literacies (Burnett & Merchant, 2015), numerous literacy educators have long argued against narrowly instrumental orientations. However, the moment of Generative AI seems to pose challenges of a quite different kind. What happens to writing when machines can do literacy too? And what if, in the moment of arrival of AI, conventional schooling is moving into a phase of "disruption" at least (Christensen, Horn and Johnson 2008), or even a crisis of fundamental institutional form (Gee, 2013)? If this is the case, narrow definitions of literacy from the legacy model of schooling are not enough.

Literacy, Technology, and Society: A Very Short History

Briefly, to recap the prehistory of modern education, literacy in its different social contexts has forever played a tortured role both in the progress and cruelties of relentlessly unequal societies. It has defined limits for some kinds of people as often as it has opened opportunities for others.

In the human beginning, the languages of indigenous peoples were profoundly multimodal. Their mnemonics of human experience were written through the amalgam of image, song, dance, totem, sacral place, and more (Glowczewski, 2019). For at least one hundred thousand years, the synesthetic multimodality of human meaning defined us as a peculiarly self-reflexive species (Kalantzis & Cope, 2006). Here we might consider writing in the broadest terms, writing our human selves in a metaphorical sense and participating in meaning. The modes of social participation for indigenous peoples were often more egalitarian, at least compared to the persistent, endemic, and systemic inequalities of slavery, caste, and property that were to follow (Graeber & Wengrow, 2021; Sahlins, 1972).

Then came writing in the narrower form we understand today: regularized systems of repeatable, symbolic graphemes. This happened in Mesopotamia about 5000 years ago then after that, separate inventions in India, China, and Mesoamerica (Christin, 2002). The first writing was a mechanism for the maintenance of inventories of ownership and wealth. It was an instrument of state bureaucracy primarily used for the siphoning-off of surpluses. Later, it became a font of religious power that maintained the social order as an antidote to the deep social tensions generated by inequality (Goody, 1986). In its founding moments, says the that giant of the discipline of anthropology Claude Levi-Strass, "the primary function of written communication is to facilitate slavery." Writing "favored the exploitation of human beings rather than their enlightenment. …The only phenomenon with which writing has always been concomitant is the creation of cities and empires that is the integration of large numbers of individuals into a political system, and their grading into castes or classes" (Lévi-Strauss, 1955 [1976]: 392).

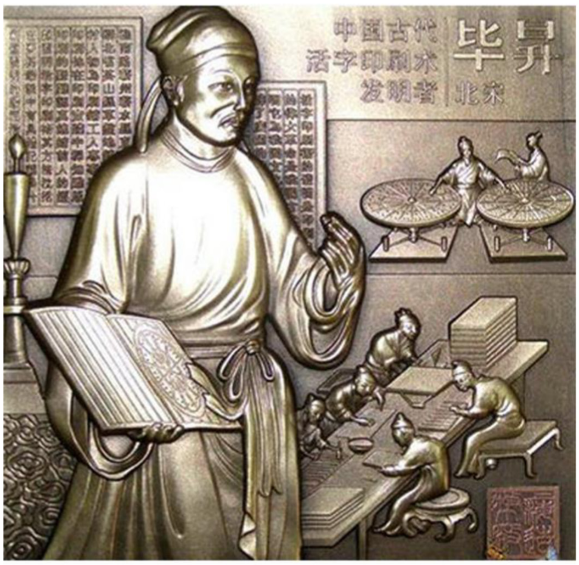
Though, of course, we have learned to love writing and reading and value the opportunities they offer. If its first effect was to support the institutionalization of radical inequality, writing also became a medium for the creation of great literature, profound philosophy, universal social memory, new knowledge, and a conduit for virtual telepresence that defies time and space. It became a medium for lyrical appeals to our better natures and a source of inspiration beckoning emancipation.

In 1039 and again in 1450, there comes the mechanization of writing (Figure 1). While Pi Sheng's invention of moveable type in China in 1039 was not applied beyond his workshop (Tsien & Needham, 1985: 201), Gutenberg's printing press of 1450 became the prototype for modern technologies of modularization, repetition, and division of labor (Eisenstein, 1979). The first properly industrial technology was a writing machine.

In its beginning centuries, the printing press served two functions, as an instrument of power and to draw illiteracy as a line of exclusion. Print literacy consolidated the power of a ruling class that depended for their power on the elite literacy of printed laws, administrative memoranda, and accounting ledgers. In Europe, the educated ruling class wrote for each other in the scientific, literary, and religious language of Latin, inaccessible to the masses (Waquet, 2001). Gutenberg's Bible was in Latin, requiring the chants of priests, the lordliness of their robes, the imagery of icons, and the grandeur of church architecture to serve as interlocutors between mystically inaccessible ruling text and popular belief. Literacy served to draw a line of social division, creating a dividing line between the literate ruling class and the illiterate masses. Books remained expensive. Literacy levels stayed low. And of course, literacy also became a vector of gender inequality (more men than women were enabled to read and write), and colonialism, ranging from the unsubtleties of colonial administration and Christian mission to the subtleties of modern programs of "development" (Street 1995).

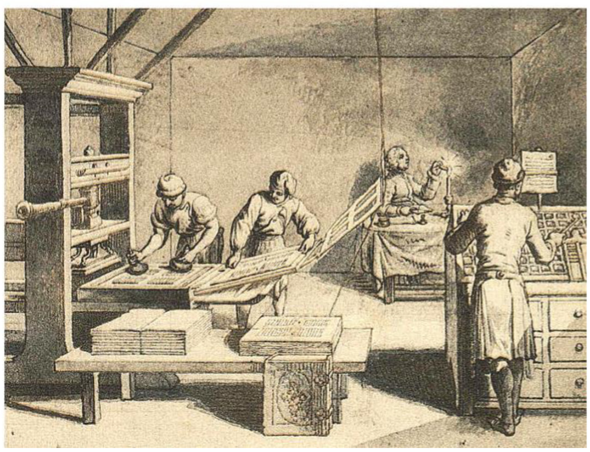
It was not until the 19th and 20th centuries that universal literacy was adopted as a social objective. This emerges in conjunction with the establishment of mass-institutionalized education. In industrial modernity, parents worked away from home, so the state committed to a new duty of care, the socialization of children. For most students, the learning objectives and outcomes of schooling were minimal. The three "Rs" of reading, writing, and

FIGURE 1
Changing our Selves by Changing our Means of Production of Meaning



The Mechanical Reproduction of Text

Pi Sheng, 1039



Johannes Gutenberg, 1450

arithmetic were taught to the basic level required for modern work, calibrated to the requirements of industrial capitalism (Bowles & Gintis, 1976). Historian of literacy Harvey Graff adds, more than minimally functional, "literacy's place was not always as a skill or technology. It was the best medium for tutelage in values and morality," shaping "properly schooled workers—possessed a number of qualities: punctuality, respect, cleanliness, discipline, subordination, and the like," contributing to the formation of a "controllable, docile, respectful workforce, willing, and able to follow orders" (Graff, 1987: 261). Behind the content of the literacy curriculum there was a moral economy of social practice.

Now that literacy had become mass, it had to regulate inequality in new ways. It did this through the ideology of opportunity—basic reading and writing for everyone, nevertheless with an insistence on the unequal distribution of educational outcomes according to school results. The redistribution of inequality reaches its scientific apotheosis with the normal distribution curve, judiciously spreading children across a numbered spectrum in which only a few can be labeled "genius," "gifted," or even "above average"; and where the majority warrant classification merely "average," or "below average," descending from there to "moron," "imbecile," or "idiot" (Goddard, 1920). The inventor of the "normal" distribution curve failed adequately to distinguish native intelligence from social conditions. It was useful to be able to rationalize social conditions as a function of intelligence and inequality as a natural state—but surely it was the social realities of literacy as much as native "intelligence" which determined one's place on the curve (Fischer et al., 1996).

For some groups positioned by race or indigeneity, the exclusions were more direct and explicit—the African–American descendants of slaves (Anderson, 1988) or indigenous or immigrant children stripped of their home languages (Phillipson, 1992). Many hoped that standardized literacy could help iron out the differences of language and dialect—indigenous, immigrant, regional, class, ethno-racial—so creating the "imagined community" of the culturally and linguistically homogenous state, and bolstering its ideology of nationalism (Anderson 1991). However, rather than ironing out the differences more often than not, this created new vectors of failure in the awkward disjunctions between the literacies of schooling and working class speech (Bernstein, 1971), dialects such as "Black English Vernacular" (Labov, 1972), and the summary exclusion of indigenous, immigrant other "minority" languages from school (Lo Bianco, 2014). Often, the lines of exclusion have been subtle, when some kinds of literacy pedagogy worked for some learners but not others (Cope & Kalantzis, 1993; Delpit, 2006; Ladson-Billings, 2016).

As much as standardized literacy hoped to provide a pathway to social opportunity, it was also in a sense designed not to work. It foreclosed opportunity more often than it realized its promise. When it did work, it was not in the ways that its liberal proponents would have hoped. As often as it tempted learners with the promise of opportunity, it reinforced and reproduced social division. This millennia-long story shows that we need to define literacy not by what it is, but by what it does.

And this is very much the case today because what Generative AI does is potentially big. Indeed, we would argue it is big on a scale that also marks the printing press and modern institutionalized education as significant waystations. The consequences for schooling could be big too—big bad, big good, or big both, depending on how we choose to understand it and take it up.

Multimodality Returns

Before we get to artificial intelligence, we want to highlight the changing shape of literacy in terms of its technological affordances, from the point of view of multimodality and the relations of written text to orality. Gutenberg invented a particular kind of printing machine, the letterpress. Inked types were pressed into a page (Eisenstein, 1979). Images, however, required a different technology, lithography. The different technologies shaped a radical separation of text from image, necessarily to be printed on different pages in the same book. The coming of mechanical reproduction had the effect of separating out and privileging written text (Eisenstein, 1997; Ong 1958 [1983]; Ong, 1982).

A series of inventions in the twentieth century offered the possibility of a return to multimodality. Photolithography comfortably put text and image onto the same page with "offset" printing, replacing letterpress almost entirely by the mid-20th century (Cope & Black, 2001). Also, until the turn of the twentieth century there were no technologies for telepresence across time and space other than those of text and image. In the 20th century there emerged technologies of telepresence for sound, speech, and embodied gesture. Telephone and radio transmitted sound and speech across space, and the gramophone across time. Cinema and television brought image and sound together, allowing the simultaneous representation of moving body, dynamic object, sound, speech, and titling with text (Benjamin, 1936 [2008]).

However, in these analogue technologies for the production and reproduction of meaning, there were still large resistances to the mass transition to multimodality. The first was that although analogue technologies had converged for printed image and text, sound, and speech were still quite separate—the soundtrack of the movie film, for instance was literally sticky-taped alongside the images.

These technologies also required large capital investment and professional training for their operators—hence the printing factories, and television studios, and radio stations. Control was in the hands of the owners of the machines. As a consequence, the privileged interests of media moguls tended to dominate the content they produced. These became "mass media" that "manufactured consent" (Herman & Chomsky, 1988 [2002]). They also disseminated "propaganda" (Bernays, 1928 [2005]) to maintain their class interests in the existing social order. The owners of the means of production of meaning shaped the content of meaning, while the masses were left few options but to consume and conform (Burnett & Merchant, 2015).

The arrival of digital means of production, reproduction, and distribution of meaning overcomes these resistances. Forms of meaning converge—everything can be represented in a common elementary modular unit of manufacture: binary notation. On this foundation, computing machines capture and process text and image in two-dimensional pixel array, space in 3D imaging and virtual worlds, object 3D capture and printing, body in wearables and video, and sound and speech in digital audio (Jenkins 2006; Manovich, 2001).

Meanwhile, economical devices and near-zero cost of reproduction and distribution mean that, while most people were passive consumers in the era of analogue media, in the digital era most people at least had the capacity to be creators of meaning. In the previous era of print and mass media capitalism, it was powerful humans who owned the means of production of meaning and dominated its contents to serve their interests. But with the advent of digitization, billions of humans have available to them the tools to make multimodal meanings for themselves and share them through internet (Lessig, 2008). Much of everyday and working life today ubiquitously involves multimodal meaning-making (Rowsell, 2013).

Even with this dramatic return of multimodality, the practices of schooled literacy still mostly separate out text as if none of these transformations had occurred. This remains the case notwithstanding an extensive literature on multimodality that challenges this separation, including the foundational work of Gunther Kress (Kress, 2009) and Carey Jewitt (Jewitt, 2014). This field of study is now moving beyond the initial core work on visual images (Kress & van Leeuwen, 1996 [2021]) to encompass embodied (Lim, 2021) and sensory (Jewitt & Price, 2024; Mills, 2016) aspects of meaning. For our part, with Kress and other members of the New London Group, we developed the agenda of "multiliteracies" in the plural. This is at the very least a necessary supplement to the legacy practices of literacy in the singular and the passive acquisition of its standardized forms (Cope & Kalantzis, 2023a; Kalantzis & Cope, 2023; New London Group, 1996).

To this changing terrain we want to apply the notion of "affordance" (Gibson, 1977). We have not changed our meaning-making practices because technology has forced us. We have changed because we can, and because when we can, we mostly do. In world-historical terms, this has prompted a return to ancient synesthesia, long suppressed by print modernity. But even with the change in the balance of meaning-making agency and notwithstanding the hopes of advocates of an open, digital commons (Benkler, 2006), there has been no return to ancient forms of egalitarianism. Even with the means of production of meaning in hand, it is hard to think beyond the commonsense and seemingly inexorable unequal powers to communicate and to act.

But now, Generative AI has arrived and with it, written text has returned to pre-eminence in some paradoxical and at times surprising ways. And the large language models (LLMs) that are the foundations of Generative AI have scraped and privatized collective human intelligence in new ways. Nevertheless, multimodality remains as important as ever, perhaps even more important. Even with the brazen theft of collective intelligence, its broadly social bases remain and may yet resist total colonization. We will attempt to unpack these contradictions in the sections that follow.

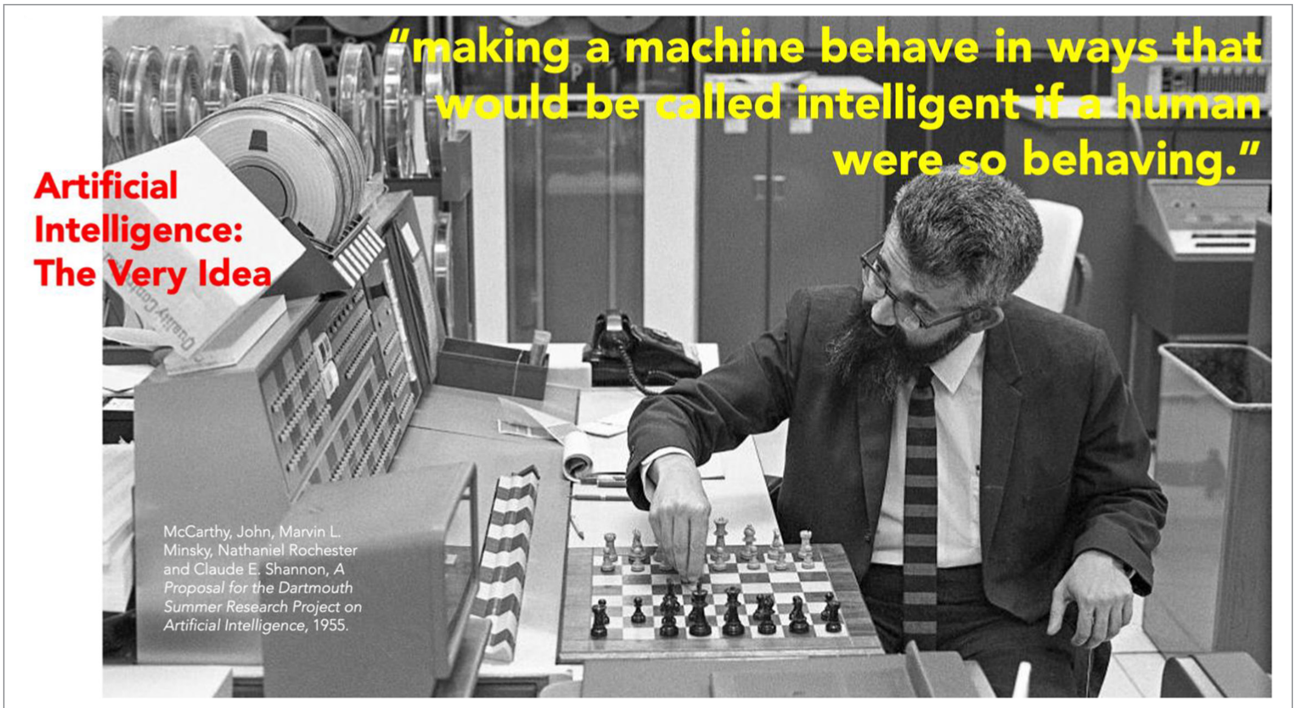
Now, Here Comes Computable Writing

The label "artificial intelligence" was coined in 1955 by computer scientist John McCarthy as a hook to attract funding for a workshop held at Dartmouth College for a small group of computer luminaries. In the words of the proposal, artificial intelligence was "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy et al., 1955: 11; Figure 2). English computing pioneer Alan Turing had earlier spoken of "mechanical intelligence" (Turing, 1950).

For many decades, the promise of artificial intelligence was not realized, or at least not on a practicable or widely applicable scale. A first generation of symbolic-logical AI attempted to capture generalizable patterns of human meaning and action in software code. However, these expert-created and rules-based AI were unable to address the complexities of the empirical world, leading to the "AI winter" when the project was all-but abandoned (Nilsson, 2009). There were, however, promising though limited applications of the expert systems paradigm in education beginning with the PLATO computer learning system of 1949 (Cope & Kalantzis, 2023d; Dear 2017) and intelligent tutoring systems (Graesser et al., 2001). These included applications in literacy that focused mainly on formal language features and text comprehension (Vojak et al., 2011).

From the turn of the 21st century, a second generation of data-driven AI development centered on large data sets and supervised machine learning (annotating data for analysis of statistical patterns) or unsupervised machine learning (labelling patterns that present themselves in the data). In literacy, perhaps the best example of this was automated

FIGURE 2
"Artificial Intelligence," John McCarthy and the Beginnings of an Idea



essay assessments where a sample of student texts is graded by expert human examiners, and new texts are graded by machines on the basis of their similarities, statistically determined by natural language processing (Cope et al., 2011; Shermis, 2014; Warschauer & Grimes, 2008).

Generative AI is another paradigm shift, a third generation development in AI. It retains the statistical bent of the second generation, but now uses a technique called "self-supervised learning" to measure the proximity of words in massive corpora of human text, thereby creating a "large language model." In an ironical revival of Skinnerian behaviorism, the machine trains itself by blanking out the next word in a sentence then checking whether its guess was right (reinforcement) or wrong (Christian, 2020). Learning processes that may have been frequently considered too mechanistic for humans have proven perfect for machines. The specifics are in practical terms inscrutable given the recursive scale of the calculation. Layered over this reinforcement learning from human feedback (RLHF) where humans query the LLM, tuning it so it does not produce unacceptable responses (Ouyang et al., 2022). The big difference in Generative AI is that, in a way quite different from the earlier AI technologies, it leverages the semantics of written text. Generative AI is a literacy machine.

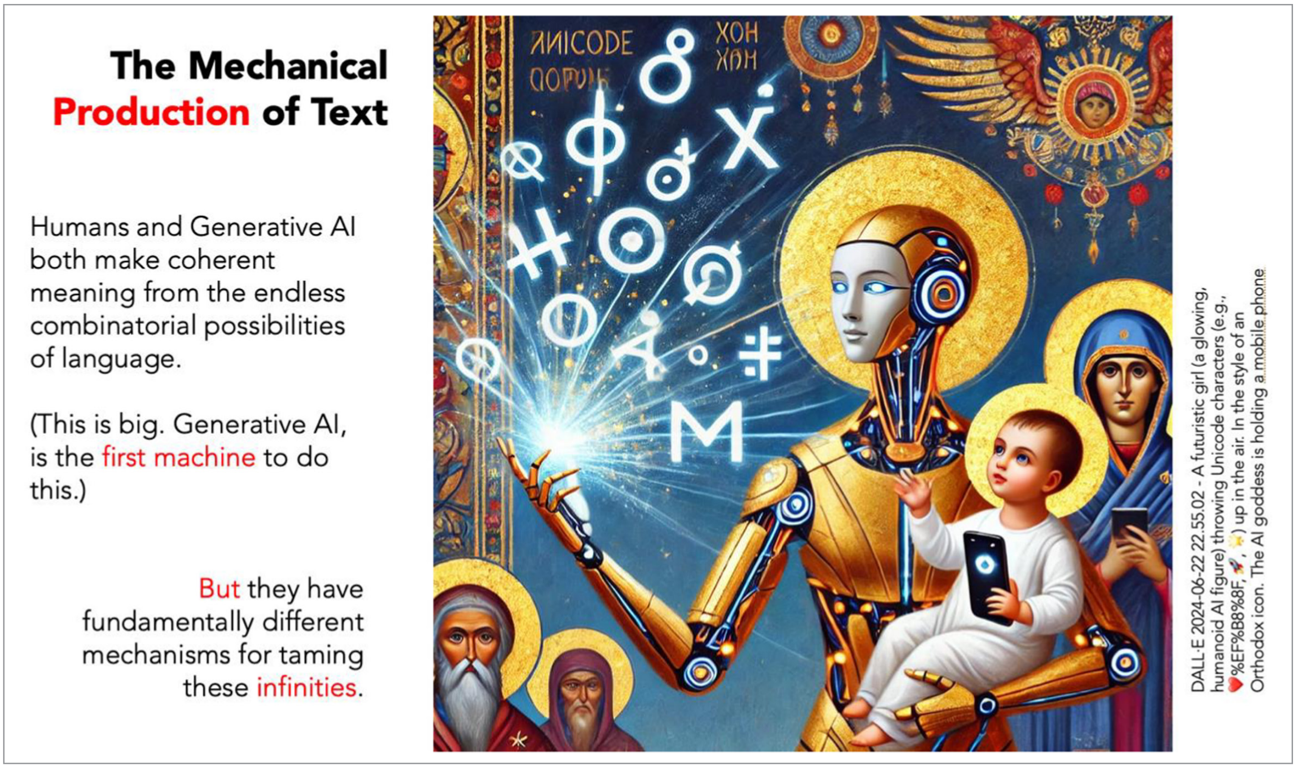
How do these new literacy machines work? Faster computing systems and advanced statistics have allowed every word among billions scraped from the web to be analyzed in relation to its surrounding words. Generative AI's is a next-word predictor. When prompted by a user's chosen subject and style, it writes by placing after each word the statistically most probable next word. Generative AI is programmed by written text in the form of textual prompts. It responds to the prompts in written text.

For literacy in particular, this paradigm shift in AI is momentous. Pi Sheng's and Johannes Gutenberg's technologies mechanized the *reproduction* of written text. For the first time, Generative AI mechanizes the *production* of written text and derivatively, multimodal meanings (Figure 3). Until now, humans had been in sole control of the production of represented meaning. Machines could reproduce meaning, but they could not make meaning.

This throws literacy teaching into an immediate crisis. Writing is a laborious cognitive and biophysical process. It is almost impossible even for the best writer to avoid at least some small flaws. Then why write, when a machine can do it instantly and flawlessly, even if predictably and in a monotonous tone? Why read, when a text can be spoken to you, and can be told to speak with just the right level of difficulty for you?

Perhaps the most frequently mentioned practical concern raised by educators is "cheating" in written assignments. With more than a hint of irony, a leading AI in education researcher concluded that Generative AI will "democratize cheating," undercutting the expensive essay mills that have until now been used by an estimated 15% of higher education students (Sharples, 2022: 1120). In a

FIGURE 3
Machines that Make New Human-Intelligible Meanings



study, "A Real-world Test of Artificial Intelligence Infiltration of a University Examinations System," researchers inserted 100% AI-generated responses to psychology exams in five undergraduate courses. The researchers found that 94% of AI submissions were undetected by the human exam readers and that AI submissions outperformed real students with grades which were on average around half a grade boundary higher (Scarfe et al. 2024).

This problem is much wider than literacy teaching and learning in the narrow sense, given the importance of the written assignment across many subjects. Writing is the optimum medium for demonstration of disciplinary practice and complex, holistic knowledge. Heavy-handed proctoring of written exams is one reaction, but not the solution when disciplinary work nowadays requires formal citation and reference to social knowledge much wider than that which can be retained in long term memory for the test.

More broadly still, Generative AI also throws education into crisis. In the history of modernity, the mechanization of agriculture drew people from farms into industrial cities, then automation reduced the scale of manufacturing employment increasing the size of a promised knowledge economy (Cope & Kalantzis, 2022b, Peters and Besley 2006). Generative AI will automate knowledge work. We may need far fewer lawyers, accountants, advertising writers, commercial artists, editors, architects, translators, and customer service agents, to name just a few of the jobs that could be impacted by AI. And teachers—the AI will be able to be more responsive to a particular learner's needs in a one-to-one relationship than a human teacher working in a 1 to n relation. Previous waves of technological transformation have mechanized low-pay, low-skill labor, and for the better. AI now promises to mechanize well-paid cognitive work. The economic consequences could be devastating (Eloundou et al., 2023; OECD, 2023).

For professional educators, it will likely fuel the "What's the use of formal education?" discourse. Though compared to other professions in the knowledge economy, teachers may dodge the AI bullet as a consequence of their duty of care role—to take care children by day. In this case, the role of teachers will at the very least change.

The Literate Agent in the Time of AI

Meanwhile, what has happened to the literate agent? Theorists of technology and media have proposed a "posthumanism" in which our lives have become so deeply inveigled with machines that the borderlines of technologies, bodies, and minds have been blurred (Barad, 2003; Hayles, 1999). Applied to literacy, our writing and reading machines have become extensions of our thinking and feeling selves (Burriss & Leander, 2024, Kumar et al., 2024, Nichols and Campano 2017). Generative AI accelerates this trajectory (Robinson & Hollett, 2024).

This extends techno-social processes at work since the beginnings of digital media and internet. Long before the widespread use of AI, digital media have opened avenues for meaning production and social sharing, but these were not without constraints and limitations. Far from opening out a public square or "creative commons" (Lessig, 2004), internet barons have taken it upon themselves to micromanage our sociability. The reasonably paid journalists and television producers of the mass media have been displaced by the unpaid creative work of users in social media (Kalantzis-Cope, 2016). On the backs of unpaid laborers, the new media barons have made themselves fabulously rich. More agency may have been granted to users than in the older mass media allowed, but this has come at a price.

AI changes the game again. Social media is increasingly driven more by interest algorithms, and less by user navigation. Google was the first to build user profiles from search and by scraping user-created documents and emails (Zuboff, 2019). TikTok led the way in the application of AI to social media, soon to be followed by content delivery in Facebook, Instagram, and YouTube. Less and less is the web "reading" of posts by chosen friends and feed subscriptions. More and more, social media feeds are driven by AI interest algorithms. Linger a few seconds longer on a video, and you'll be served another video that the algorithm determines to be related. Generative AI learns about you in the same way, from the kinds of prompts you serve (Wang, 2022).

Meanwhile, the skill and effort bar for content creators has risen, such as the short form videos requiring more time and expertise to produce than a phone photo or a short textual message. With algorithms that valorize and magnify the popular ahead of other possible values, influencers have come to dominate this new, low cost, largely junk media. Politics is downplayed because it has become abusive, divisive, and prone to fakery. Social participation is reduced to prudish flashes of sexual suggestion, disgusting domestic interactions, and half-funny accidents. These are some of the new ways in which agency is corralled in the time of artificial intelligence. The effects of endless social media scrolling on youth mental health have been widely questioned (Abi-Jaoude et al., 2020).

Generative AI extends and deepens these problematic relations between technology and society. To create the LLMs upon which Generative AI depends, its owners have copied just about everything published on the web including the scans of nearly every printed book and every labeled image. These meaning resources have been taken without recompense to their creators. In the case of Generative AI, this happens without even non-monetary recognition because the sources have been mashed together and lost in the convolutions of automated reinforcement learning. Artificial Intelligence is a new colonialism, not of material space like the old colonizers, but the colonization of social intelligence by a handful of insurgent moguls of human meaning.

Indeed, the term "artificial intelligence" itself grants too much to the machines and their owners. To the extent that Generative AI is driven by the meanings of almost all the published words in the human experience, it is more than anything else collective intelligence. The statistics that calculate the relations of words are by comparison trivial. To apply Marx's profoundly insightful construct, Generative AI privatizes the "general intellect" (Marx, 1858 [1974]: 626, Pasquinelli, 2023: 95). This is egregious at two levels, not only capturing and reselling material copied from the intellectual commons, but also the brazen theft of private intellectual property to the consternation of publishers and media content creators (Chang et al., 2023). Generative AI is an extractive industry and rent-seeker as it sells the human collective intellect back to us. Many young people already have a sense of the breadth and depth of these concerns (Common Sense Media & Hopelab, 2024; Thrall, Nichols and Magill 2024).

However, we are not completely without paths to redress, either by reassertion of principles of the commons (Ostrom, 1990) or the development of open source LLMs for public use in spaces of the social good such as education (Lin et al., 2024). We can still reappropriate the general intellect for the general public. There are strong material, ethical, and software bases for such a reappropriation. There is cause for hope as well as gloom.

In any event, the turn to an AI whose technological basis is written text means that literacy has a big, new job to do.

Literacy, Redefined

Here are the traditional canons of literacy, roughly in the order of their teaching and learning: (1) learn sound-letter correspondences (in alphabetic languages, at least); (2) understand the meaning of combinations of letters in words; (3) understand and write sentences and more; (4) read and understand extended texts; (5) appreciate literary greatness. It takes schools about a decade to get students from (1) to (5). At every step, this version of literacy is anachronistic, and it has been that for quite some time. Generative AI makes the situation worse.

The underlying premises of traditional literacy are that there are consistent, stable, and always correct things to be learned: phonemes; spelling; grammar; meaning that is comprehensible because it can be the same from one person to another; genres of text that should be privileged; and high or classical literary forms. This version of literacy imposes textual rules, principles, and literary values in order to transmit them from one generation to the next. Not much room is left for learner agency or differences in this version of literacy.

Designing

As a supplement to traditional literacy, we have proposed in the theory of multiliteracies a process of meaning-making that we call "design" (Figure 4; Cope & Kalantzis, 2023a; Kalantzis and Cope 2020; Kress, 2000). Design was chosen for two reasons. One was in anticipation of the affordances of new technology given that the same media could now produce multimodal texts. We wanted a term to capture meaning-making across a wide range of forms, including text but also other forms such as image, space, and body. Second, we wanted to shift the focus more broadly to meaning-making ecosystems in the lifeworld. Our premise is that all meaning is fluid and transformative and diverse, becoming increasingly more so as a consequence of both globalization and digital technologies.

Meaning-making draws on found designs, and to be sure this includes the sounds of letters, the arrangement of letters into words, the ordering of words into sentences, and the genres of larger texts. But there is also a lot more, because written text and its meaning cannot be isolated from their surrounding images, spaces, objects, bodies, contexts, and lifeworld experiences.

Using these found designs, design work occurs. Take writing or reading. This work uses both material resources (pens, papers, computers, books) and the ideal resources of interested human agency. In the endless variety of contexts and interests, no two meanings are ever exactly the same. Rarely is the same sentence or sequence of sentences written twice. Never do two pieces of text mean exactly the same thing from one writer to the next or one reader to the next (Cope and Kalantzis 2020: 68–72). This is precisely where first generation, symbolic, and logic-based AI came unstuck in its attempts to base its processes in elementary, universal, generalizable rules of language (Kalantzis and Cope 2020: 209–15). And this is where Generative AI excels—its foundational corpus is the endless variation of written texts and the near infinity of their contexts and purposes even though the technology itself has no intrinsic sense of this.

The notion of design recognizes the agency of the meaning maker. The traces the designer leaves are uniquely voiced. The designed artifacts they deposit in the world leave the world transformed (Cope and Kalantzis 2020: 68–72, 301–303, Kress, 2000). This is how Florentino Ariza in Gabriel García Márquez's *Love in the Time of Cholera* comes to his conclusion about human beings, that "life obliges them over and over again to give birth to themselves" (Márquez, 1988: 165).

> Literacy is transformational. It reworks in the meaning of the world in the literate agent's image.

Literacy in this view is a social process of participation in meaning: from representation as meaning for oneself; to communication as meaning made for others; to interpretation as the meaning one makes of the material traces of communication left by others (Figure 5). The three are very different. Meaning for oneself is multimodal, a mixture of words, images, and embodied feelings. It takes context for granted. Conceived like a sentence, it has predicates that don't need subjects. Communication, however, must identify its subject explicitly, or the other person won't know what you mean. It has to turn the meaning into words (or images, or other forms of meaning) that will minimally carry the intended meaning across time and space. Then interpretation is the meaning somebody else makes of a

FIGURE 4
Meaning as a Design Process

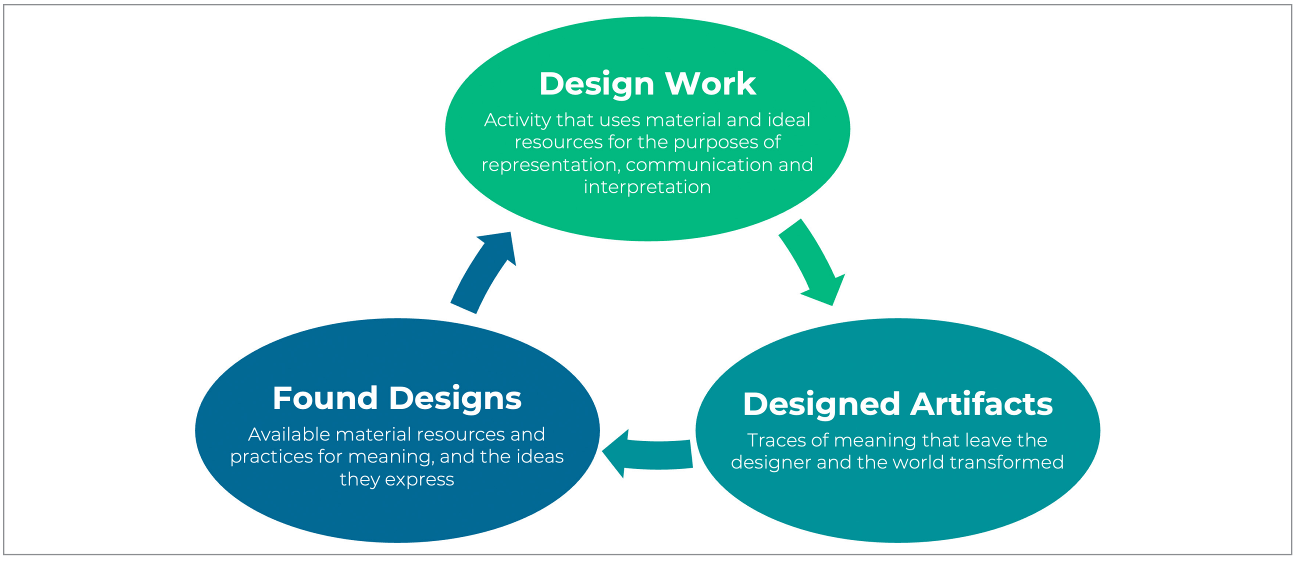
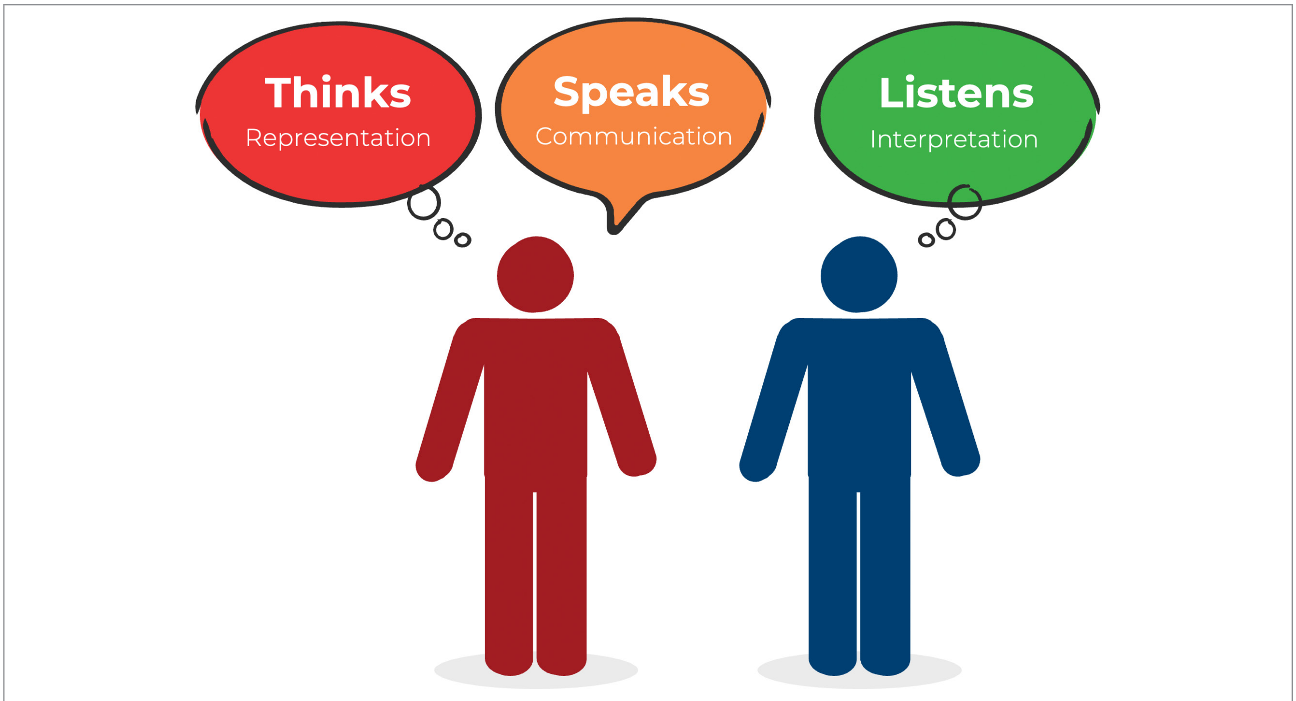


FIGURE 5
Participation in Textual Meaning



meaningful artifact that they have encountered—a text, a picture, an object, or whatever. Interpretation can be as varied as the people of the world, the contexts of their living, and the interests they have. At every point the meaning changes, and it is the person doing the meaning who changes it. This is why we call meaning a process of transposition. It is a cognitive process and a material process, making meaning in media (Kalantzis and Cope 2020: 47–63).

> Meaning is transpositional. Meanings must be remade as meanings-for-oneself to become meanings for others, and the meanings of others are remade as they become meanings for-oneself.

This throws into question traditional tests of reading, forced into select response assessments. "B" can't straightforwardly be the correct answer. And what if a reader is attracted to "D," a trick, or "distractor" item in the mind of the test maker but an answer that nicely satisfies the test-taker's interpretive frame of reference? To avoid the inevitable range of interpretations, comprehension and understanding are frequently reduced to trivial factoids that a reader may happen to remember when they have finished reading or have to look up again because they are hardly relevant to their interpretation (Catts, 2022). This has been the basis of longstanding critiques of item-based comprehension testing (Anderson and Pearson 1984; Rubin et al., 1976). Tragically, item-based comprehension kinds of tests remain a proxy for literacy, a cheap and lazy way to put a number on literacy performance.

Writing, by comparison, has until now been expensive and difficult to assess, given the time involved and open to variations in human judgment. Automated writing assessments grounded in second generation AI reduces the cost, proving as reliable as human raters in scoring writing (Shermis, 2014). However, they were at best only able to give canned feedback to writers based on generalizations across a small number of rating levels. In the era of Generative AI, we have the potential for much richer ways to assess writing, offering feedback calibrated to students' highly variable depths of meaning and interpretation. We will discuss evidence from our own research in the last section of this paper. Teacher and peer feedback will always be different from Generative AI, but if calibrated appropriately, Generative AI can offer any level of detail, from short to extended, finely attuned to the diversity of writers and themes, and it can offer it immediately during the writing process.

Compared to what may be possible now with Generative AI, traditional literacy pedagogy is static, stable, rule-bound, culturally monolithic, and diminishes the agency of learners. "Comprehension" and "understanding" are based on a conduit or transmission model of communication, while participation in meaning is transpositional and fluid (Kalantzis and Cope 2020: 47–63). From one person to another, the differences are as important as the continuities in meaning. Far from getting things right, every child redesigns the meaning of the world in their own way. The differences in interpretation based on the varied life experiences and interests of learning are of greater pedagogical significance than the capacity to repeat factual details from a text. Of course, basic knowledge of the prosaic workings of literacy still matter. But the broader umbrella of design alternatives focuses on change, agency, difference, and the world-transformative capacities of every meaning maker (Cope & Kalantzis, 2023a; Kalantzis et al., 2016; New London Group, 1996).

The significance of Generative AI is that until now, only humans could do design in this definition. But now…

> For the first time in human history, a machine can design and communicate written-textual meanings (and, derivatively, image, speech, and other forms of meaning) that have never been created before but are nevertheless coherent and meaningful to humans.

The last 100 words in this text, the last 100 words you spoke, and the last 100 words any 3-year old child has just spoken—have never been written or spoken quite this way before. Design is the capacity to create originally and distinctively voiced meanings from the infinite combinatorial possibilities in our available resources for meaning. Generative AI is the first machine that can do this too—though as we will shortly argue, it does this in ways so incomparably different from humans that it can hardly be classed an "intellect."

The consequences for literacy are enormous. As mentioned earlier, the first to startle and scare educators might colloquially be called cheating. Because every AI-generated text is unique, there is no reliable way to detect whether that text has been written by a human or a machine (Perkins et al., 2024). Until now, the measure of whether the work was by a student themself was none other than our design measure: is it unique? Because if there it is a copy, there will be a discoverable identical source somewhere else. Without quoting and referencing that source, this is cheating.

To avoid AI cheating where there is no identical source, you could ask the students to hand scribe. But unless you lock them in a room and disconnect them from the internet, this could be a transcription from a Generative AI output. Or your suspicions could be raised when the work handed over by the student is free of even the smallest error. But that's easily fixed by a student who adds a few strategic typos.

More broadly, even in the individualistic practice of closed-book assessments, we've always been "cheating," standing on the proverbial shoulders of giants but obscuring their legacy in the guise of individual, memorized knowledge. In the last section of this paper we describe a solution which productively and ethically harnesses Generative AI in the writing process. This is inevitable because it has become so helpful and now so ubiquitous as a writing companion. The solution also measures the balance of design agency of the writer and the AI in what we call a cyber-social learning relationship.

But before we get to these practicalities, what will literacy be in the time of Generative AI? What is this generative thing until now only humans could do, and now AI as well? We'll focus on written text at first and before getting to multimodal literacies a little later in the paper.

Scribing

If machines can now do it too, what does it mean to write? For humans, this is a peculiar kind of design work, not simply cognitive, but embodied in eyes and hands, and materialized in media. Written text is the work of scribing graphemes in a two-dimensional spatial array. For much of the time writing is linear or one-dimensional, but a second dimension comes into play in lists, tables, headings, page or screen layouts, diagrams, infographics, and the like. Even one-dimensional text writing has taken on multilinear dimensions when computer-mediated keystrokes replace hand scribing. The material resistances of pen-to-paper allow radically multilinear writing—clean deletions, cutting/pasting, and allowing the hasty drafting and easy revision of text.

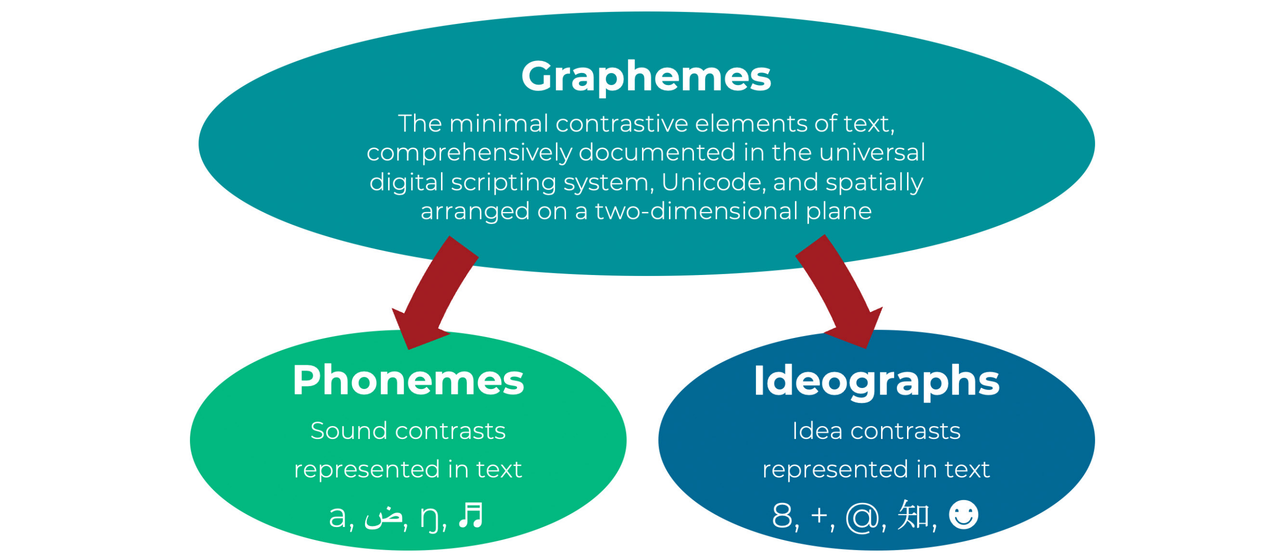
In the digital era, even the constituent components of written text have changed. Here is our definition of written text for the digital age:

> Written text is that which can be scribed in or transcribed into the universal graphemic symbology, Unicode, and arranged into two-dimensional array.

Nearly every digitized text can be read on nearly every digital device because all use a single, universal symbology, Unicode. The version at the time of writing, Standard 15.1, catalogs 149,813 encoded characters, or graphemes. A handful represent spoken sounds or phonemes, for instance: a, ض, ŋ. Most represent ideas or ideographs, for instance: 8, +, @, 知, ☺ (Figure 6). Almost every regularized grapheme from the human experience can be found in Unicode, ranging from lost and still unintelligible ancient languages to emoji's and icons that have only recently entered our digital cultures. These might look slightly different from device to device and from font to font. But across devices, Unicode standardizes their meaning as graphemes. When a machine scans your handwriting, it turns what you have written into Unicode (Cope and Kalantzis 2020: 23–25).

In a number of practical ways, this expands the scope of literacy. From the earliest of ages, children are exposed to a graphemic symbology that includes navigational ideographs such as play or pause, thousands of emoji's speaking to sentiment, and many other such symbolic representations. Sometimes, these are embedded in-line within natural language. At other times they bring organizational order to multimodal screen and sign meanings. These new graphemes could have been represented in phonemic text, but the tendency is increasingly to use ideographic text.

FIGURE 6
Written Text Consists of Graphemes, Nowadays Regularized, Standardized, and Universalized in Unicode



Literacy teaching and learning needs to recognize and to some degree go with the flow of these changes. For instance, teachers might get their early writers to write messages that use emoji's with affect and effect. They might have them to transpose emoji's and their phonemic equivalents.

Generative AI is built on the foundation of LLMs. Nearly everything of published and digitized human experience has been recorded and analyzed for the statistical relations in the sequence of Unicode characters without differentiation as to their kinds of language. The raw material of LLMs is written text.

Not only does Unicode capture writing in natural language. It also supports writing in the comparatively unnatural languages of mathematics, computer code, and algorithmic procedure using the same character set and two-dimensional spatial array. This is how Generative AI is able to write code and mathematics about as well as it writes natural language—because it treats them all in the same way, as sequences of characters that can be rendered in Unicode.

As long ago as the so-called New Math (Beberman, 1958; Phillips, 2014), progressive teachers have presented math integrated with text in the form of real world problems and required students to make their mathematical reasoning explicit in natural language think-alouds. Generative AI chatbots now establish this dialog with students through written text. Meanwhile, in computer programing, best practice has always required in-code written documentation. Generative AI has rapidly precipitated a greater mix of natural language and abstract code (Yang et al., 2024). The purely procedural and mechanical parts of the code have been automated, and code can be generated with natural language prompts. In a certain way, computer coding and mathematics have always been specialized—if unnatural—writing practices by virtue of their rigorous formality. But now natural language plays a closer role in both. Indeed, Generative AI's prompt engineering is a form of natural language programming.

Literacy used to be two of the old three "Rs." Now it's deeply interwoven into the third. Practically speaking, these developments blur traditional disciplinary boundaries.

Textual Meaning

Phonemes in Unicode are of very little value for LLMs. For humans, the smallest meaningful unit of written text is a morpheme. Taking their lead from humans, the technologists who invented Generative AI have created a machine that works at the level of morphemes. Generative AI combines Unicode characters into objects it calls tokens. Consider the word "walk" in the sentence, "I walked to work." "Walked" consists of two tokens, "walk" indicating the kind of action, and "ed" because the events described in the sentence happened in the past. Many words are single tokens.

Analyzing natural language, LLMs find slightly more tokens than there are words. Across billions of words scraped from the internet, Generative AI calculates the statistical probability of the next token based on the words surrounding that token. It finds "walk" in many different relations to surrounding words. There's "walk to work," and "walk the dog." Now we have two different "walk" tokens because the words near each "walk" are different. The differences between the kinds of walk are defined by weights or the probability of one kind of walk being connected to certain kinds of surrounding words. The "parameters" in an LLM are the number of surrounding words that are examined and thus the number of potential variations of "walk." Then, in its design of responses, the AI takes its cue from human prompts.

This is how LLMs come to have a vocabulary of sorts numbering in the billions of words and trillions of parameters or word-to-word relations. Lest we be tempted to grant "intelligence" in this AI, LLMs neither create let alone understand tokens. These have been hand crafted by humans who have placed spaces between words. Linguists and technicians manually "stem" words that consist of more than one token, a process first proposed by Michael Halliday and colleagues in the early days of language computing (Richens & Halliday, 1957).

The LLM can never know the meaning of "walk." It treats language as a meaningless "bag of words," a phrase coined by Noam Chomsky's dissertation advisor (Harris, 1954: 156). Computers can't mean anything other than zero or one. All they can do is calculate by textual transposition: recorded Unicode > chunked into tokens > binary notation > calculation of the probability of the next token > token > human readable Unicode. The calculation happens in through self-supervised learning of a painfully low-level behaviorist kind, processed through a filter of statistical significance called a "transformer" (Vaswani et al., 2017 [2023]). These calculations are so vast and excruciatingly dull in their zero-and-one-ness that it is impossible to trace exactly how the next word has been calculated. It's a "black box," to use a term first applied to computing by one of the founders of cybernetics (Ashby, 1956: 86). There's a ghost in the machine.

To compare how humans make meaning, we are going to take three "walked" sentences, illustrated here with images created by prompts served to the image generator, Leonardo AI (Figures 7–9; images generated with prompts provided by the authors).

In school, we have traditionally done some basic parsing of the meaning of sentences like these. There's a subject ("He") and a predicate ("walked to work"/"walked the dog"/"walked the prisoners to their cells"). There are nouns, pronouns that can point to a noun, a verb, prepositions indicating time, and place, and we can see that it's in the past tense. Then there are some handy rules like, a sentence should always have a verb and be sure to check subject-verb agreement—it can't be "he walk" in some dialects of English, though it can be in others.

Nevertheless, there are subtleties that school grammars miss. These are three very different kinds of "walk." Walking to work is goal and direction-oriented, from A to B. Walking the dog is from A and back to A. But when the dog is enthusiastically pulling at the leash, isn't the dog really walking its human carer? And walking the prisoners is walking that is meant for them but against their will.

"Walk" can mean importantly different things. Professional linguists can tease out these differences grammatically in the nuances of transitivity, mood, voice, case, and more. Yet even when we don't have the technical words for it, we know the differences. People do grammar in their brains, sometimes consciously but mostly unconsciously. Grammar is how we make sense of the world (A little later in the paper we're going to suggest a way to make grammar more manageable, bringing more meaning to explicit consciousness for teaching and learning).

FIGURE 7
He Walked to Work

FIGURE 8
He Walked the Dog

FIGURE 9
He Walked the Prisoners to their Cells

Generative AI understands these three different kinds of "walk" along with perhaps thousands of other kinds of "walk" by the statistical relation of each "walk" with the words around it. "Walk" is not just one token, but thousands or tens of thousands assigned different weights determined by textual context. This is how the computer produces meanings for humans. The computer has no capacity to mean. It is just a calculating machine with a vocabulary of billions of pseudo-words. The semantics it chances upon by calculation are latent but no more.

Compared to LLMs, human brains work in a completely different way (Cope & Kalantzis, 2024b; Siemens et al., 2022). There is no way a brain could know the billions of words that have been copied from the web for the LLM, and the billions of parameters that show the statistical probability of connection of each unique token with its surroundings.

The human mind, by contrast, classifies the world grammatically. "He" is a kind of person; "walk" is a kind of action; "…ed" means the action has been completed. Grammar is an elementary theory of how the world works. This is how we make human sense of the world's otherwise endless and bewildering complexity.

> The human mind works grammatically. Generative AI works statistically.

Noam Chomsky argued that grammatical structure is a window on the mind, offering insights into human cognitive processes. "[A] grammar mirrors the behavior of the speaker who, on the basis of a finite and accidental experience with language, can produce or understand an indefinite number of new sentences." This is quite unlike computational processes. "[O]ne's ability to produce and recognize grammatical utterances is not based on notions of statistical approximation" (Chomsky, 1957: 15, 17; Figure 10).

We may wish to avoid Chomsky's universalistic bio-reductionism—we'll propose a socio-material alternative shortly. Nevertheless, his basic insight endures. The human experience of meaning is figured *theoretically and grammatically*. We live in a world ordered by the functional classification of morphemes. Meaning is achieved by the operation of a small repertoire of metalinguistic semantic primitives. We used to call these "nouns," "verbs," and such like. For a grammar of multimodal design that captures meaning across a range of forms, now we propose terms able to cross different forms of meaning, such as "reference" and "agency" (Kalantzis & Cope, 2022).

By contrast, Generative AI is *empirical and statistical*. Its semantics are only latent, coincident with empirical word order. It is a flat world of one-to-one relations of tokens, where the sole difference is weighting of mutual relations across vectors. Meaningful text can only be generated by brute statistical force (Figure 11). The mind, by contrast, is not Bayesian. Our capacities to think are not simply a matter of empirical experience as B.F. Skinner or John Locke would have us believe. Although both humans and now AI make coherent meaning from the endless combinatorial possibilities of language, they have fundamentally different mechanisms for taming these infinities.

Multimodal Meaning

Generative AI is essentially a technology of written text. Only derivatively is it multimodal (Cope & Kalantzis, 2023e; Munn et al., 2023a). Take images, for instance. The resource for image generation is billions of digitized images. However the AI can't know what is in the images other than the array of pixels represented in zeros and one. It only "knows" the textual labels that have been applied such as "man walking," "cream colored standard poodle," and "rural footpath." There will be thousands of images labeled with one or more of these attributes. Then the only way to generate an image is with a textual prompt: "give me an image of a man walking with a cream standard poodle on a rural footpath." For the era of Generative AI, learners need to become proficient in multimodal transpositions such as these. They need to become good "prompt engineers." This is a multimodal, text-to-image art.

Even though written text is primary in Generative AI, the technology is nevertheless powerfully multimodal. The transpositions between text and image as well as other forms of meaning are dazzlingly effective—sufficiently effective to warrant application of our notion of design. The walking images we generated in Leonardo AI are entirely coherent, beautifully formed images the likes of

FIGURE 10
Chomsky on the Nature of Language

"[A] grammar mirrors the behavior of the speaker who, on the basis of a finite and accidental experience with language, can produce or understand an indefinite number of new sentences. ... [O]ne's ability to produce and recognize grammatical utterances is not based on notions of statistical approximation."
Chomsky, *Syntactic Structures* (1957), pp.15,17)

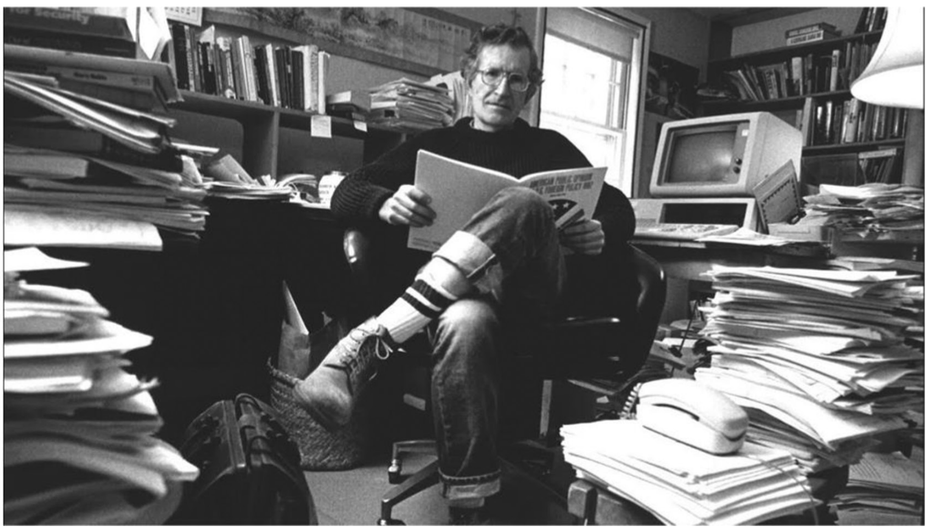
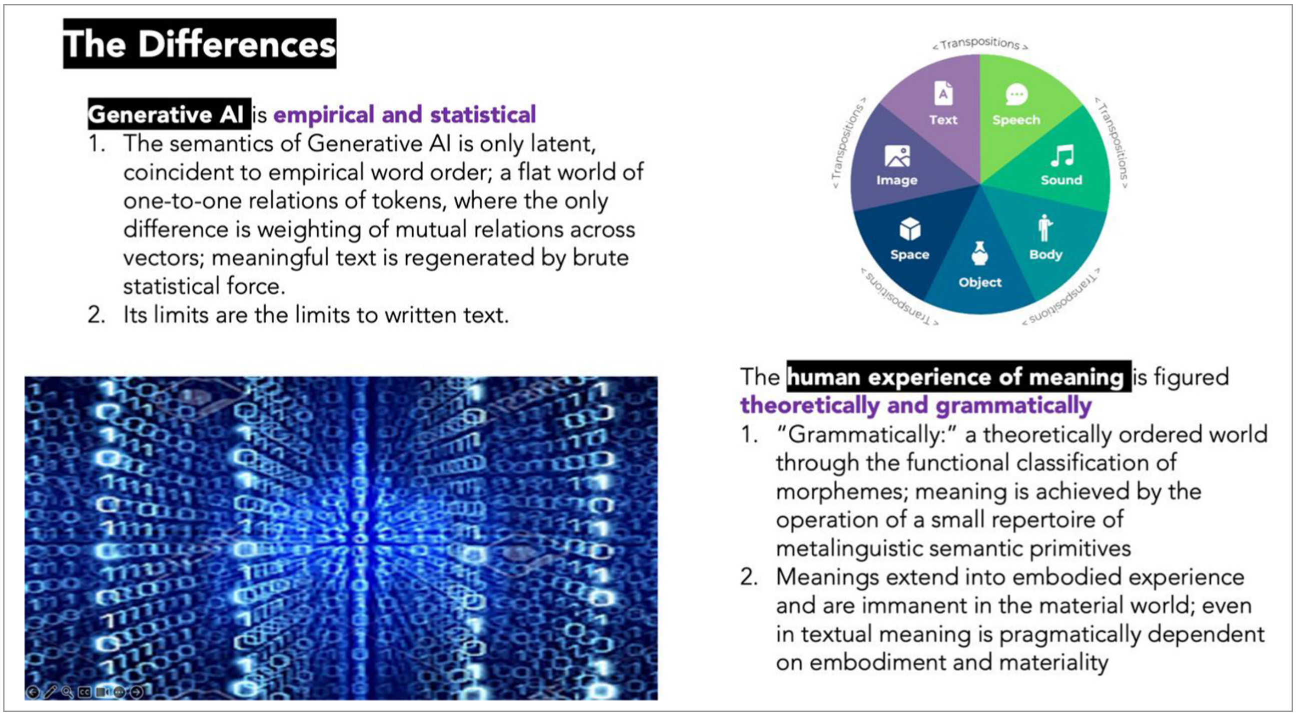


FIGURE 11
The Differences between Generative AI and Humans as Makers of Human-Understandable Meaning



which have never been made or seen before. Of course, the erasure of the sources used for image regeneration remains a cause for great concern.

Speech—Text—Speech

When it handles speech, Generative AI is also only derivatively phonological. To be included in the LLM as a source text, or when a prompt is oral, speech must first be transliterated into text. Then if the Generative AI response is oral, transliteration needs to occur back from text to speech. In this process, the characteristic meaningful features of speech are mostly lost including prosody, dialect, gesticulation, embodied context, redundancy, hesitation, circumlocution, and more. In any event, LLMs are biased towards the grammar of written text if for no other reason than most of their sources are published and digitized writing. The ordering of words is more carefully crafted in text than speech and thus more amenable to statistical processing.

In comparison with the limited extent and inadequate ways in which Generative AI manages text-to-speech transpositions, in humans these transpositions are deceptively difficult and take a lot of learning. They are certainly much more challenging than the sound-letter transpositions at the center of beginning literacies focused principally on phonemics. Speech is organized across time. On the human sensorium speech can happen purely in sound, though it is frequently aligned with other temporally ordered meanings such as embodied gesture. Text, on the other hand, is arranged in two-dimensional space. It can be purely a matter of vision, and frequently aligned with image. As material, embodied, and cognitive processes, text and speech could hardly be more different (Bezemer & Kress, 2016, Halliday, 1987 [2002], Kalantzis & Cope, 2022, Ong, 1992). This is why literacy is so important and so challenging for learners, not to be trivialized by reduction to simplistic handful of sound-letter transliterations. It's much, much harder than that.

The phonics advocates are right about this much: it's a good thing to call out explicitly key patterns in the meaning-making process. In the limited time for learning in school, this is more efficient than immersion alone. It also has the benefit of exercising the relation between cognition (the text) and metacognition (generalizations about its patterning).

There are 44 basic sound-letter combinations in English, but these do not bear belaboring for too long. Forty-four things are not too hard for young minds to learn. But literacy teachers do also need to address the vastly different cognitive and material processes of arranging meaning in time (speech, sound, body) compared to space (text, image, space, object), and the necessary multimodal transpositions and complementarities. Literacy—even text-oriented literacy—is of necessity always multimodal. Kindergarten teachers and the authors of illustrated children's books have known this forever.

On the scale of the challenge of multimodal literacy, the matter of sound-letter correspondences is probably best left to the AI. It can likely drill these more thoroughly and with greater sensitivity to existing knowledge than any human teacher—so long as this does not become a technological alibi for a new wave of "kill-and-drill." Put phonics in some fun computer games, and the one-to-one AI will be able to do a better job of tracking and supporting individual learner progress than the 1-to-n teacher. In this case, the priorities of the teacher can shift, such as to spend more time to nurture the socio-emotional environment of learning.

In any event, after phonics, human reading and writing is semantically rather than phonologically oriented. When reading, one's eyes jump along the line from one meaning unit to another in movements called saccades (Mézière et al., 2023). Each unit of attention is much the same as the Generative AI token in the machine's only latent semantics. In beginning literacy, it is helpful to work on the transliteration of the sounds of speech into phonemic graphemes. But get this done quickly! And just get it done in a rough and ready kind of way because, beyond the 44 stand-out contrasts in English, there are thousands of exceptions to rules and subtler sound combinations, the nuances of which can only be learned at the whole word level and the elision of words in speech. It is no accident that text-speech technologies break speech into morphological units, not smaller phonological units.

The transposition between temporally ordered speech and spatially ordered written text is enormously challenging cognitively as well as performatively. Perhaps this is the most challenging of all transpositions between forms of meaning—text is closer to image, and speech is closer to sound an embodied presence. Helpfully perhaps, the digital world has brought to us hybrids, where we have the best and the worst of both worlds. Text messaging, for instance, is temporal to the extent that there is the pressure of other person waiting, and greater tolerance for the spatially ill-formed arrangement of graphemes (Kern, 2015). Nevertheless, there are some, if limited, opportunities for spatial design—looking back quickly over a message, correcting the most egregious errors, removing redundancies, elaborating on things that may on second glance seem less explicit than needed given the contextual distance between the interlocutors. Pedagogically, having children text message each other can be a connecting pedagogy, bridging the enormous differences between text and speech as forms of meaning. In the era of Generative AI, the learner's interlocutor could also be a helpful AI, working to ease the learner's transpositions from the temporal, linear design of speech to the spatial, multilinear design of text. And a few encouraging emoji's might help!

A Multimodal, Transpositional Grammar

We have been making the case that Generative AI creates meaning by paying statistical attention to the connections between words (tokens) to each other. Humans, by contrast, pay grammatical attention. The nouns and verbs people use embody a theory of the world where there are things and actions. Even when we don't call things out grammatically, our subconscious minds do. Putting things and actions together is what we do to make meaning. A key question for education in the age of digital meaning-making is, to what extent do we call out explicitly these meanings of meaning, this metameaning? How much of unconscious meaning do we want to bring to consciousness in literacy pedagogy?

Immersion models of literacy tell us that we hardly need to do this at all. Just give the learners easy then progressively harder texts, so these theories go, and they will make increasingly sophisticated sense for themselves. They'll absorb the complexities and subtleties in use. Children in school can learn to read and write in the same way babies learn to speak (Goodman, 2005; Graves, 2003). (Though don't underestimate the explicit call outs that parents provide babies!).

Our response is that education is a limited opportunity in terms of time and resources. Generalization is a more efficient way of learning. Explicit call out is pedagogically powerful, exercising the capacity to move between cognition and metacognition, or between knowledge specifics and knowledge transfer. Following Michael Halliday, Mary Macken and colleagues call this peculiarly pedagogical move "grammatics" (Halliday, 1996 [2002], Macken-Horarik et al., 2011).

Importantly too, immersion pedagogy favors insiders whose informal life experience means they seem naturally to "get" the discourse of schooled literacy. Explicit pedagogy is particularly beneficial for learners whose lifeworlds are more distanced from the culture of schooling and for this reason have historically been failed by literacy (Cope & Kalantzis, 1993; Delpit, 1988). These are some of the reasons why pedagogical discourses should at least at times be characteristically more explicit than vernacular ones.

We propose to extend the notion of "grammar" metaphorically beyond the syntax of sentences to address the full gamut of multimodal design.

> Multimodal grammar is an educational metadiscourse that describes and explains the patterning of meaning.

In this expanded definition, phonics may as well be our starting point. We have created a map of forms of human meaning according to the basis of their design in time or space (Figure 12). Here, we have put written text and speech together because this is such a big focus in literacy, but with maximum color contrast to indicate how very different they are. As we have argued, the transpositions are difficult—so difficult that we need to spend years working on them in school. Phonics is just a start in the project of explicitly calling out one aspect of the transposition. Image is more closely aligned to text in its two-dimensional, spatial array. Sound and body closely align to speech in their presentation across time. So, it makes pedagogical sense to work on these easier transpositions first, or at least in parallel to the very difficult speech-to-text transposition. Besides, digital media make the other transpositions practicable, attractive, contemporary, or just cool. Broadly, in the digital age we need a multimodal grammar that valorizes all forms of meaning, equally.

Across these forms of meaning, we can speak about a variety of meaning functions (Figure 13). Rather than calling "dog" a noun and seeing a dog in the picture, we can speak of *reference* because the sentence and the image both reference "dog."

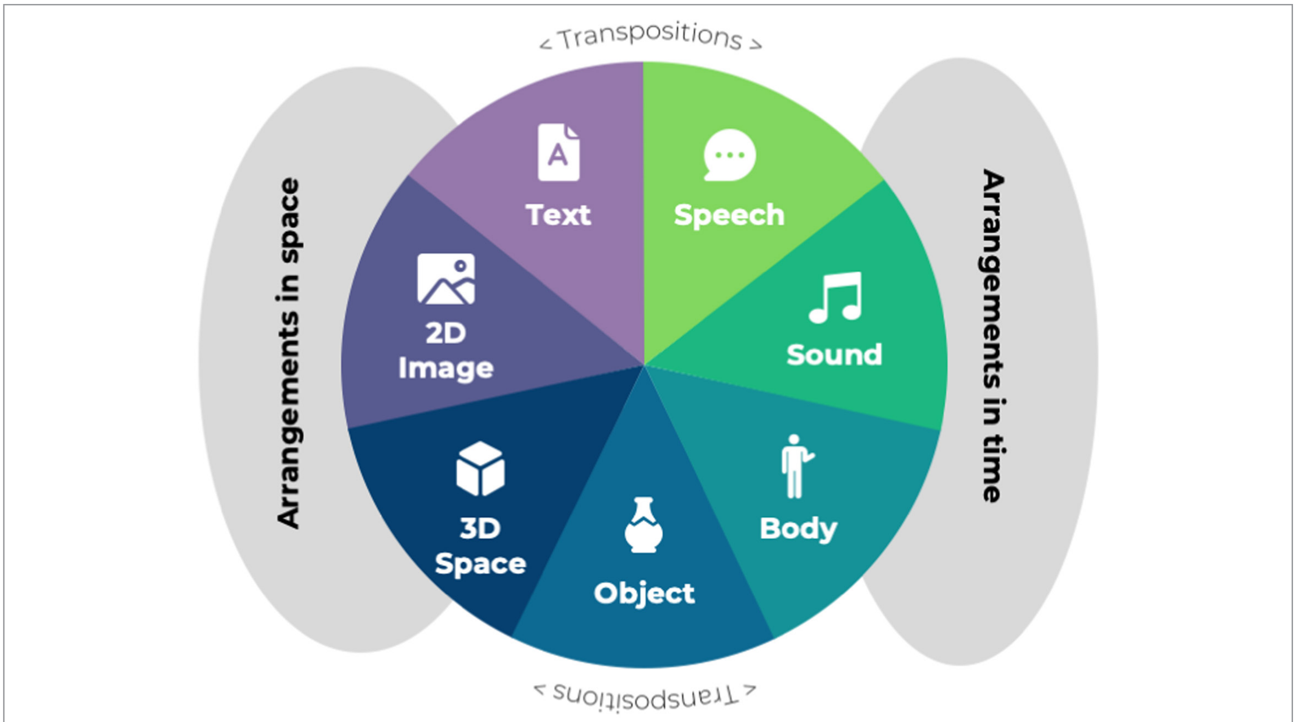
Then rather than calling "walk" a verb, we can speak of *agency* both in the sentence and the image. We question both text and image, "Who or what is this about?" (reference) and "What is happening"? (agency). The answer to these questions can be at least as subtle and nuanced as Generative AI as we interpret the different kinds of walking that are possible. Except, rather than the brute force of statistics, we humans use our grammatical brains to make the fine distinctions.

Then *structure*—How do we organize a sentence? How to we organize an image? And how do we use text to get Generative AI to organize an image for us? Prompt engineering for image generation is a text-to-image transposition, an art demanding careful design. These concepts are based on the three "metafunctions" in Michael Halliday's functional linguistics (Halliday and Matthiessen 2014).

FIGURE 13
A Functional Grammar

Next, *context*: Who is "he"? What do we need to know outside of the sentence and outside of the frame of the image to make sense of it? Here we rely on Ruqaiya Hasan's theory of context (Hasan, 1999). Generative AI relies entirely on the historical record and can only look to surrounding words in text or image labels for limited clues. As practitioners in the linguistic subdiscipline of pragmatics has long argued, there is much meaning outside of language upon which the practical meanings in language depend (Austin, 1962 [1975]). While Generative AI may be quite good at reference, agency, and structure in text, it

FIGURE 12
Forms of Human Meaning



is unable to read context in more than the most superficial ways. Contextual AI can do more, but this is an entirely different technology, able dynamically to analyzing activity from computers, phones, and wearables in real time including geolocation, timestamp, keystroke, clickstream, body sensor, and logfile data.

Finally, *interest*: What makes someone go to work, walk a dog, or imprison people? What drives the meaning? This, Halliday and Hasan call "purpose" (Halliday and Hasan 1985). Natural language technologies of "sentiment analysis" (Lu et al., 2011) can point to interest in a rough and ready way, though words that (often inadequately) describe feeling. And another's interest is forever a matter of interpretation. Facial expression detectors provide an only somewhat reliable measure of emotion (Christian, 2020).

The processes of multiliteracies center around two vectors of transposition. On the one dimension, we have the kinds of attention we pay to meanings in terms of the functions of reference, agency, structure, context, and interest. On the other dimension, we want a grammar that will work for all forms of meaning, separately, or in multimodal combination. Here, we have multimodal transpositions through we can express things in one form of meaning or another or in all sorts of combinations (Figure 14). In this diagram, have overlaid the transpositions undertaken by text-based Generative AI and Contextual AI (Cope and Kalantzis 2020; Kalantzis and Cope 2020).

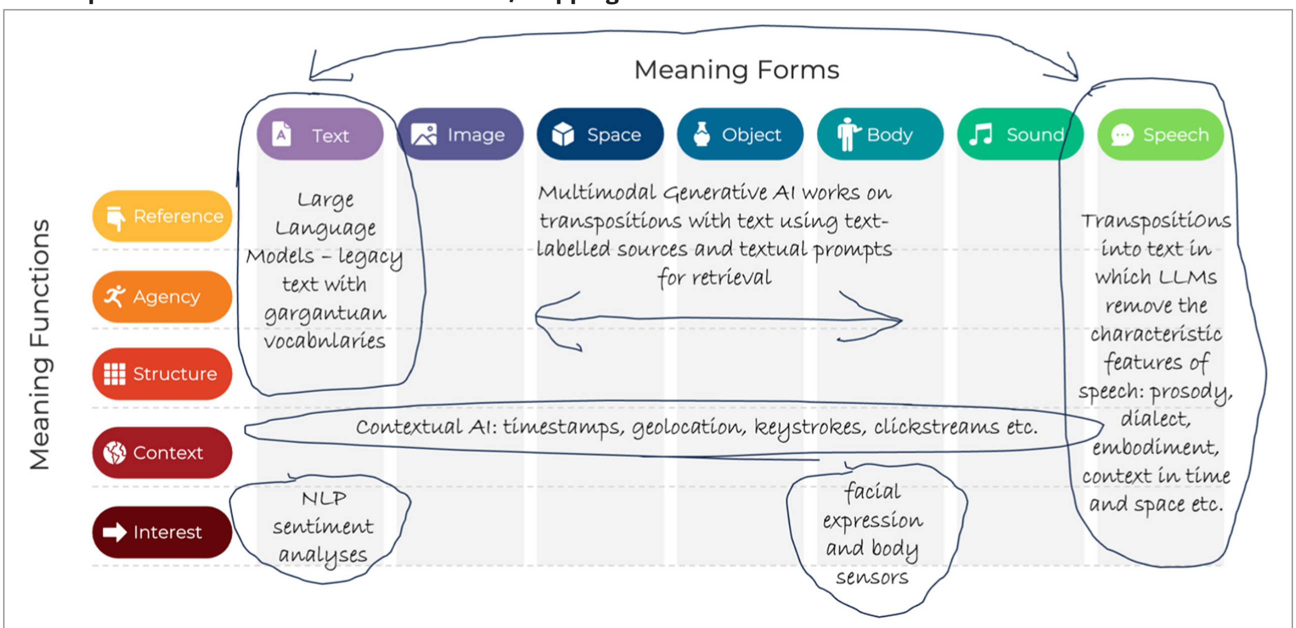
As for the nature of grammar in general, in Halliday's words, "A grammar is a resource for meaning, the critical functioning semiotic by means of which we pursue our everyday life. It therefore embodies a theory of everyday life; otherwise, it cannot function in this way… A grammar is a theory of human experience" (Halliday, 2000 [2002]: 369–70). Chomsky would have this theory situated in the grammatical kernel of sentences, and these for him are a bio-cognitive inheritance. For a multimodal grammar we propose that meanings are not just in text and speech but the other forms of meaning. The meaning of "kitchen" is not just in the word we say or write but also in the material arrangement of the space and the way objects and bodies are arranged in that space. Meanings are socio-material as well as languaged and cognitive.

A Metalanguage of AI Literacy

So far, we have been speaking at in broad generalizations, exploring a metalanguage for parsing multimodal meanings in the time of AI. Now, we're going to get more specific in the form of a little glossary of the key terms of AI, focusing particularly on Generative AI. We have introduced some of these terms already, but now we will summarize, define, and string them together in a roughly theoretical, narrative order.

- *Binary Notation*—Computers name things in zeros and ones and calculate their relations base two, nothing more.
- *Unicode*—The universal symbolic character set for digital meaning. Each character has a unique name in binary notation.
- *Token*—The smallest meaningful sequence of Unicode characters, a word, or part of a word.

FIGURE 14
A Transpositional Grammar of Multiliteracies, Mapping Generative AI Functions



- *Large Language Model* (LLM)—A corpus of text scraped from the web, billions of words of published text, pretrained with calculations as to the statistical probability of one token following another.
- *Vector*—A number representing the proximity of one token to a nearby token, reflecting its shades of meaning. Think of the three different kinds of "walk" in the example we gave earlier.
- *Weights*—The vectors create weightings for tokens, offering a lexico-grammar consisting of billions of morphemes.
- *Parameters*—The scale and functions of the LLM: the number of tokens, its "context widow" (see below), and the things it can do. Typically, an LLM has billions or trillions of parameters.
- *Machine Learning*—During its training phases, the LLM learns about the tokens stored in its database. There are two kinds of machine learning: supervised and unsupervised.
- *Unsupervised, Reinforcement Learning*—Parsing sentence after sentence in the corpus, the machine asks itself billions of times, "what is most likely the next word?" Then it gives itself the answer, right or wrong, refining its probability calculations each time. In education, we have long abandoned the most mechanical versions of behaviorist psychology. However behaviorism has found a new home in the machine, of the most mind-numbing kind and on an industrial scale.
- *Supervised Machine Learning or Reinforcement Learning from Human Feedback (RLHF)*—The method by which humans teach the system how to behave, for instance applying "filters" (see below).
- *Chatbot*—When a person talks to a computer in natural language, originally in a pre-programmed dialog (Weizenbaum, 1966), but now in dialog with an LLM.
- *Prompt Engineering*—A trigger to the LLM to respond, just like a classroom essay prompt (Schulhoff et al., 2024).
- *Context Window*—The amount of text an LLM can process in a prompt.
- *Temperature*—Dialing up or down the predictability of the next-generated token to produce more or less boringly robotic text.
- *Fine-Tuning*—A generic or "foundation" LLM can be provided supplementary specialist text such as validated scientific knowledge. In a process called retrieval augmented generation (RAG; Lewis et al., 2020), trusted text is uploaded into a vector database where the relations of tokens are calculated. In this way, the LLM becomes more reliably knowledgeable for the chosen domain of knowledge.
- *AI Agents*—Prompting an LLM from multiple agent or actor perspectives and relating these perspectives to each other, somewhat like a debate team (Li et al., 2024).
- *AI Bias*—The sexism, racism, violence, profanity, and all manner of social evil to be found in the source texts used by LLMs. This is because the Generative AI has scraped from the web anything and everything it can, good and bad. In a sense, they are true to the legacy of the written word. They express bias to the extent that the texts they have captured express a history of bias (Bender et al., 2021; Magee et al., 2021).
- *Filters*—Removing AI bias. LLMs do this, by covering it up, excluding responses that express views offensive to liberal sensibility. Euphemistically, the LLM makers do this with "supervised machine learning." A not-funny joke says that "AI" stands for "Absent Indian"—the cheap global labor-force that laboriously trains the AI not to say certain things. In reality, the filters add a new kind of bias in favor of one kind of liberal sensibility or other (Buyl et al., 2024).
- *Jailbreak*—A clever prompt that gets past the filters (Shen et al., 2023).
- *Hallucination*—When Generative AI makes up facts: It only knows how to write good sentences but has no way of checking whether the content is true (Klein, 2023; Munn et al., 2023b).
- *Black Box*—There is no knowing exactly which source texts have been used in response to a prompt and how the AI came to generate a particular sentence. The underlying statistics emerging from its unsupervised reinforcement learning are convoluted beyond recovery. The machine is an inscrutable black box (Ashby, 1956: 86).
- *Multimodal AI*—Generative AI can create images, video, and sound, but only on the basis of textual labelling of sources and written-textual prompts to generate (Cope & Kalantzis, 2023e; Zhang et al., 2023). Software and mathematics are, in our definition, already written-textual.
- *Contextual AI*—records of real time interaction with computing devices including geolocation, time stamps, clickstream records, body sensor data etc.

In the time of AI literacy, teachers and learners need to know at least some of this. If Generative AI can write, they need to know how it writes in its peculiarly non-human ways, and what problems and limitations arise. And if

Contextual AI can keep a running record of learning interactions, this is the basis for a new generation of learning analytics, as full of possibility as it is fraught with a myriad of challenges around reliability, privacy, student profiling, and AI bias.

What Is to Be Done? Literacy Pedagogy for the Time of AI

Changing the Frame of Reference for Literacy Learning——In Theory

On some measures, Generative AI is a better writer than most humans, producing texts on command that are well formed, grammatically perfect, and typo-free. "I am applying for a new job. Here is my CV and job description. Write me a job application." Or, "Write a blog post or social media post for me on the following topic." On command, it will probably do both of these things better than we can ourselves, particularly in new or unfamiliar genres and domains. Now we have a machine that can write, why bother to teach writing in school?

Our reason for teaching reading and writing needs to change from a matter of utility to the project of human growth (Gee & Zhang, 2024). Learning to write is learning to think—to transpose inner speech (Vygotsky, 1934 [1986]: 119) into externalized, two-dimensional textual space. As discussed earlier, the grammar of text is fundamentally different from the grammar of speech (Halliday, 1987 [2002], Ong, 1992; Kalantzis and Cope 2020: 50–52, Kalantzis & Cope, 2022). The grammar of inner speech is even more distant from text for many reasons, prominent among which is the need for explicitness if the meaning is to carry across time and space. And to the extent that inner speech is an amalgam of images—"mindsight" as Colin McGinn calls it (McGinn, 2004)—"imagining" is very different from making and viewing pictures. These are huge transpositions, at once cognitive, multimodal, and materialized through work with media. So, even if there is a machine to do it for us now, writing remains an important thing to learn.

Generative AI puts out of business narrow, utilitarian literacy pedagogies with their standardized tests to match. Literacy can no longer afford to be narrowly instrumental and functional. This moves literacy into a more serious, challenging, and much more interesting place—as a cognitive as was as embodied and material practice.

With Generative AI, the machine can help learners develop the deeper cognitive processes and embodied capacities that underlie writing—the transposition of our representations-for-ourselves into communication-for-others and the empathetic interpretation of the varied social meanings we encounter. For this, we can develop pedagogies in which students learn with and through the machine. This is not the same as having the machine do it for them, otherwise labeled "cheating." In the broad definition of grammar we have developed in this paper, we might now ask, how can the machine help bring to consciousness the patterning of meaning? How can the machine help you learn how to exercise your grammatical capacities to mean for yourself? How can it suggest a range of alternative interpretations to support you in forming your own interpretation of the text? When properly calibrated for educational application, Generative AI has the potential to do all of these things. We want to call this human-computer relation "cyber-social literacy learning."

As an aside—and we expand on this argument elsewhere (Cope & Kalantzis, 2024b)—we think that "artificial intelligence" is an unhelpful idea. It's as if the machine can replicate and even someday replace human intelligence. It also implies that the brain works in broadly similar ways to a computer, as if the brain were just a calculating machine working in binary notation. But machines and humans are profoundly different. Computers are much better than humans at some things. In their tedious and laborious calculating ways, they can relieve humans of boring mental tasks.

As an alternative to artificial, cyber is a feedback relationship (Cope & Kalantzis, 2022a), where these two kinds of "intelligence" (which we place here in inverted commas because they barely even deserve the same word) come together in a complementary relationship. For a long time, computers have been better at humans at some kinds of computational and analytical work. Now they have the potential in some if limited respects to be better than humans at language work, to the extent at least that they have "read" everything and "know" the probability of one word following another. The value of human-machine pairing arises from their profound differences. But alas, everyone speaks of AI these days, so we do too. Nevertheless, we want to propose that:

> Cyber-social literacy learning is the complementary relationship between a human writer and a machine in the production of writing.

In cyber-social relation, here are some tedious things the Generative AI machine will be able to do much better than a human teacher. We've already mentioned teaching phonics. It will be able to offer on-the-fly feedback as students learn to write. In the academic and disciplinary literacies of secondary and college education, Generative AI is particularly adept at "genre signals" (Hart-Davidson, 2024). Keystroke capture will be able to work out the extent of the help provided by the machine. Together, Contextual AI and Generative AI will be able to track learner progress as they become progressively more independent writers. AI can calibrate learning activities and assessments to different learners across many dimensions including, not only literacy capacities narrowly conceived, but experiential lifeworld differences. It can provide feedback tailored to the language learning needs of non-native speakers (Wang, 2024). It can grade student work (Tang et al., 2024; Tate et al., 2024). It can provide feedback better aligned to the writing task than the responses canned to graded levels of the earlier generation of automated writing assessments (Steiss et al., 2024). Much more effectively than old-fashioned summative assessments, it can provide continuous formative assessment and provide summative progress assessments based on all the work students have done (Hao et al. 2024). In reading, it can ask, "How do you interpret this text," not because there can be a straightforwardly correct ABCD answer, but in a dialog that probes the depth of the student's interpretation, distinctive as that might be given the peculiarities of their life history and interests.

This is where literacy in general meets AI literacy specifically. Where writing is called for in everyday life, there are going to be times when the machine can helpfully write with us and for us. When it does, how do we engineer the best prompts? Then there is a new critical role for the reader. Is it hallucinating? Does it express AI bias? Or have the AI bias filters themselves distorted meaning? What sources may it have left unacknowledged? What intellectual property may have been stolen or treated with disrespect by the AI's failure to acknowledge? Has my privacy and security been compromised by prompting this writing by the machine? These are key questions for a critical AI literacy.

Kris Gutierrez speaks of syncretic literacies in which the discursive practices of students from nondominant communities are positioned in dialog with academic literacies (Gutierrez, 2014). She calls this meeting point a "collective third space, a particular kind of zone of proximal development, … an interactionally constituted, artifact-rich environment (Gutiérrez, 2023: 87). AI can become a player in this space, a 'human-like' critical agent in the conversation where the technology invites a range of voices, perspectives, ideas, and texts into students' sense-making" (Gutierrez 2014). Mike Sharples discusses the ways in which Generative AI can play the role of a possibility engine, a Socratic opponent, a co-designer, an exploratorium, or a storyteller (Sharples, 2023: 3–5). Amy Stornaiuolo and colleagues show how learning to write with AI platforms can be fun (Stornaiuolo et al., 2024).

Of course, for education applications we need to be wary of new versions of the digital divide with the rise of Generative AI. Owned by private companies, the free versions are only teasers to purchase better versions, and only some schools and students but not others will be able to afford the better versions. The COVID pandemic starkly highlighted the effects of these inequalities (Donnelly & Patrinos, 2022). As educators, we also must maintain a critical eye on the processes of "platformization" (Cope & Kalantzis, 2024c; Nichols et al., 2024) and "datafication" (Pangrazio et al., 2022), not just a question of the affordances of the instructional tools but as complex ecologies shaped by social and political-economic forces as well as technological affordances. We need to "view AI platforms not as neutral communication conduits but as active participants in learning ecologies" (Stornaiuolo et al., 2023: 336). We also need to take into account the various ways in which learners tangle with user interfaces (Monea, 2020).

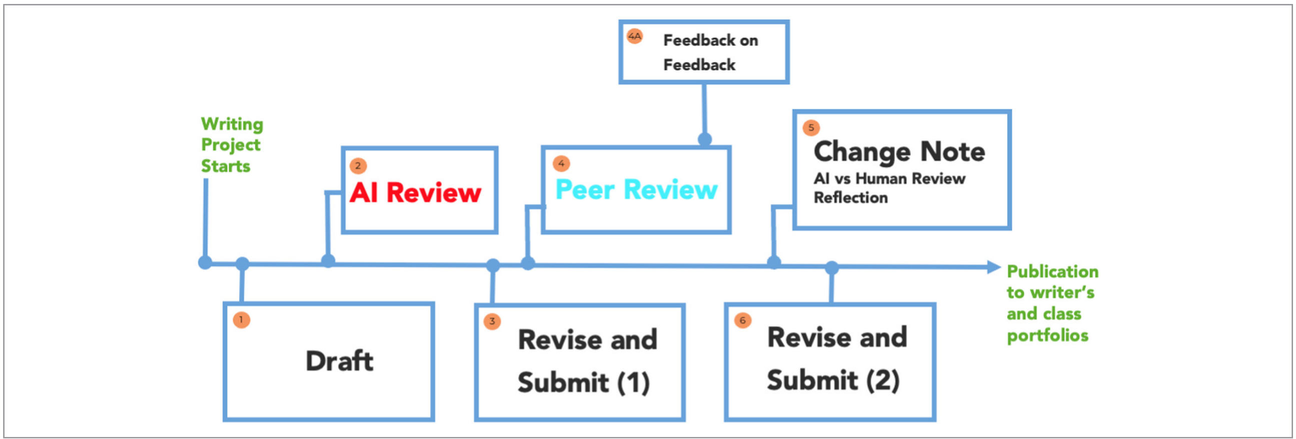
Changing the Frame of Reference for Literacy Learning——In Practice

Since 2000, we have been building experimental online writing and writing assessment spaces, in a number of loosely linked applications under the overall platform name, *Common Ground Scholar* or CGScholar.com (Cope & Kalantzis, 2023c). Early in 2023, we added an AI review component into the writing project workflow, shown in Figure 15. The underlying LLM or "foundation model" we have been using has been successive versions of OpenAI's GPTs. CGScholar is connects to these via API (application programming interface), but is designed to connect to any LLM, including soon, we hope, more transparent and secure open source LLMs (Lin et al., 2024).

After a first draft, an AI review provides feedback to the writer. The writer then revises and submits their work for peer review. Each student work passes though both peer and AI review phases using the same rubric and review criteria. Crucially and as a matter of principle, there is no AI feedback which is not moderated by human feedback. When they receive this peer feedback, they give the reviewer feedback on their feedback. After that, they write a change note, discussing their knowledge gains from the AI and human reviews, and comparing the AI review with the human review. After revision, they submit their work for final instructor review and for publication to their personal portfolio and the community knowledge bank.

We have implemented this AI and peer review process since the beginning of 2023 in our master's and doctoral program at the University of Illinois. Most of our students are practicing educators, many of whom were specialized teachers of literacy. Others were educators working across a range of disciplines who consider writing an important aspect of their teaching and their students' learning. Students write major projects of 3–5000 words with multimedia embeds. Figure 16 shows the first page of an example.

FIGURE 15
CGScholar Workflow



The AI review and the human reviews (peer, self, and instructor) use the same rubric, based on the multiliteracies or *Learning by Design* pedagogical schema (Figure 17), the full text of which we provide as an appendix. We have discussed this pedagogy elsewhere (Cope & Kalantzis, 2015), and there is a wealth of research—our own and others—describing and critically analyzing its application at all levels of education from K-12 schooling to college and university, reviewed elsewhere (Kalantzis & Cope, 2023). For the Generative AI intervention why have created review criteria that are explicit to the point of verbosity because these are the most effective as AI prompts and because we want a direct point of comparison and moderation for the peer reviews.

In 2023, 295 students in 15 College of Education courses using this software ranked peers slightly ahead of the AI in terms of quality, usefulness, and actionability. But they also noted differences between human and machine feedback and that the two were different in useful ways (Tzirides, Zapata, et al., 2023, 2024; Zapata et al., 2024).

In 2024 we have added RAG processes with a bounded vector database consisting of 35 m tokens—all our graduate students' work for the past 5 years as well as instructors' writings. In this wave of intervention, students ($n=71$) report that the AI reviews are now out-performing human reviews on all criteria (Saini et al., 2024). In each cycle of intervention we have deployed a new software release with research and development proceeding according to a mix of agile programming and educational design research methodologies that we have called "cyber-social research" (Tzirides, Saini, et al., 2023).

As we have argued elsewhere, Generative AI is not suitable for unmediated use in education contexts (Cope & Kalantzis, 2023b, 2024a). Educational applications must heavily recalibrate the GPT. This we have attempted to accomplish in two ways. The first is via prompt engineering. For education, this involves creating a different kind of rubric, designed to work optimally as a series of AI prompts as well as for human readability. We have the students use the same review criteria when reviewing their and their peers' works not only for the sake of full transparency, but also for them to gain experience in this new universe of prompt engineering. Then the software passes over the student work multiple times, once for each criterion. In our implementation, we prompted the GPT 10 times, using the eight *Learning by Design* "knowledge processes" (Cope & Kalantzis, 2015) plus two more for expression and referencing protocols.

The second dedicated educational recalibration is the vector database built from a carefully curated corpus. This is the program's domain-specific knowledge source, deeply informed by the theoretical and empirical research literature on literacy pedagogy and innovative applications of technology in learning. In a profound sense, it is not the AI in the wild that is writing the review, but the specialized collective intelligence of the graduate students and professors in our program.

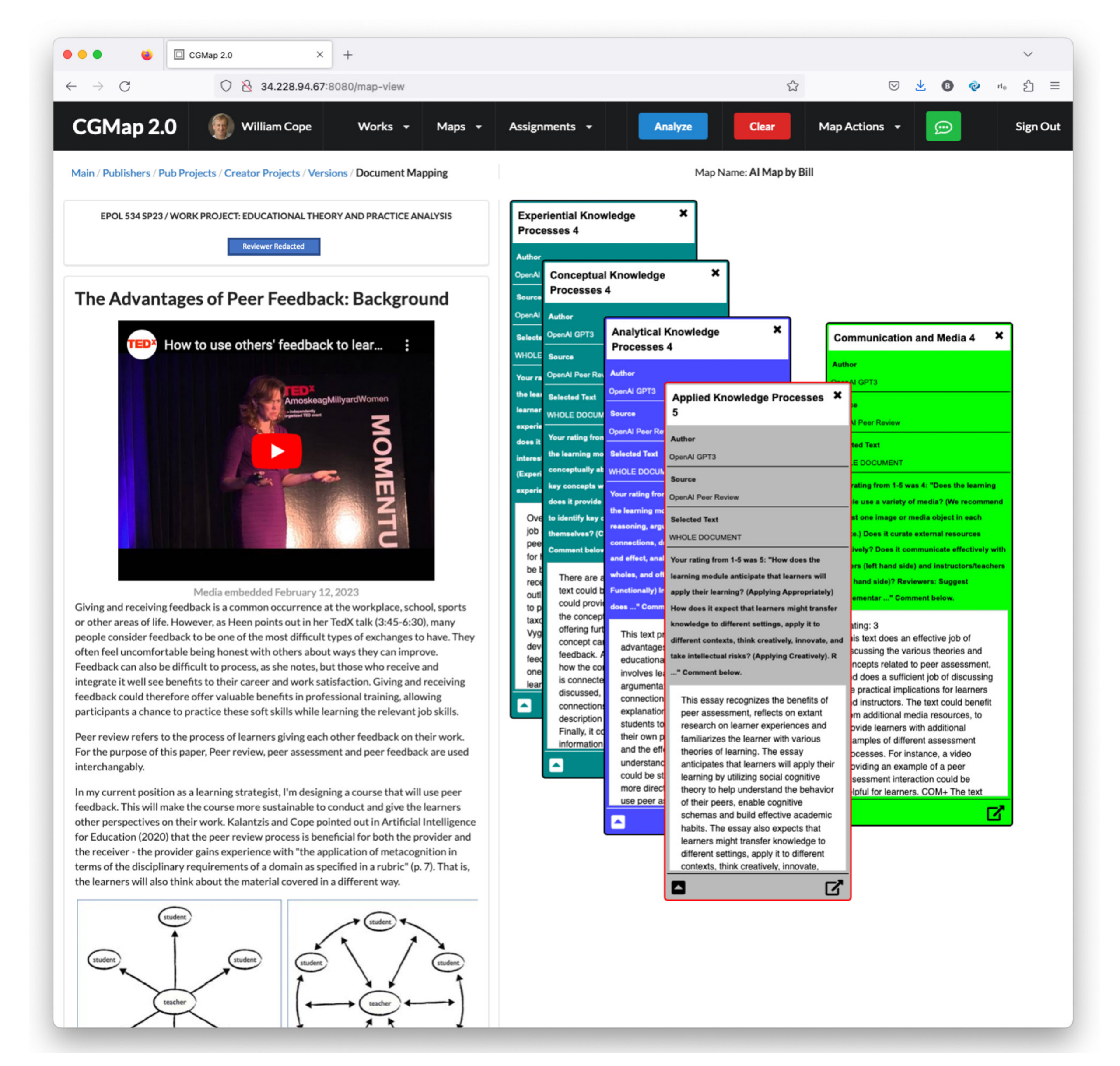
We are by inclination skeptical of techno-enthusiasm. But to be honest, we're shocked to find ourselves confessing that the AI feedback from the bounded corpus is more detailed and more helpful than we have ever been as professors. If this is the case for these hardest of literacy texts—writing about writing—what does that mean for writing at every other level of learning? We're working now on K-12 applications.

Towards Cyber-Social Literacy Learning

Like Alice, we have gone down the rabbit hole of Generative AI (Figure 18). What we have found is cause for great concern in some moments, invigorating in others.

Here, by way of conclusion, here is our agenda for literacy in the time of Generative AI.

FIGURE 16
Screenshot of Student Writing in CGMap/CGScholar with Multimodal Student Writing on the Left and AI Feedback on the Right, Color Coded by Rubric Criterion



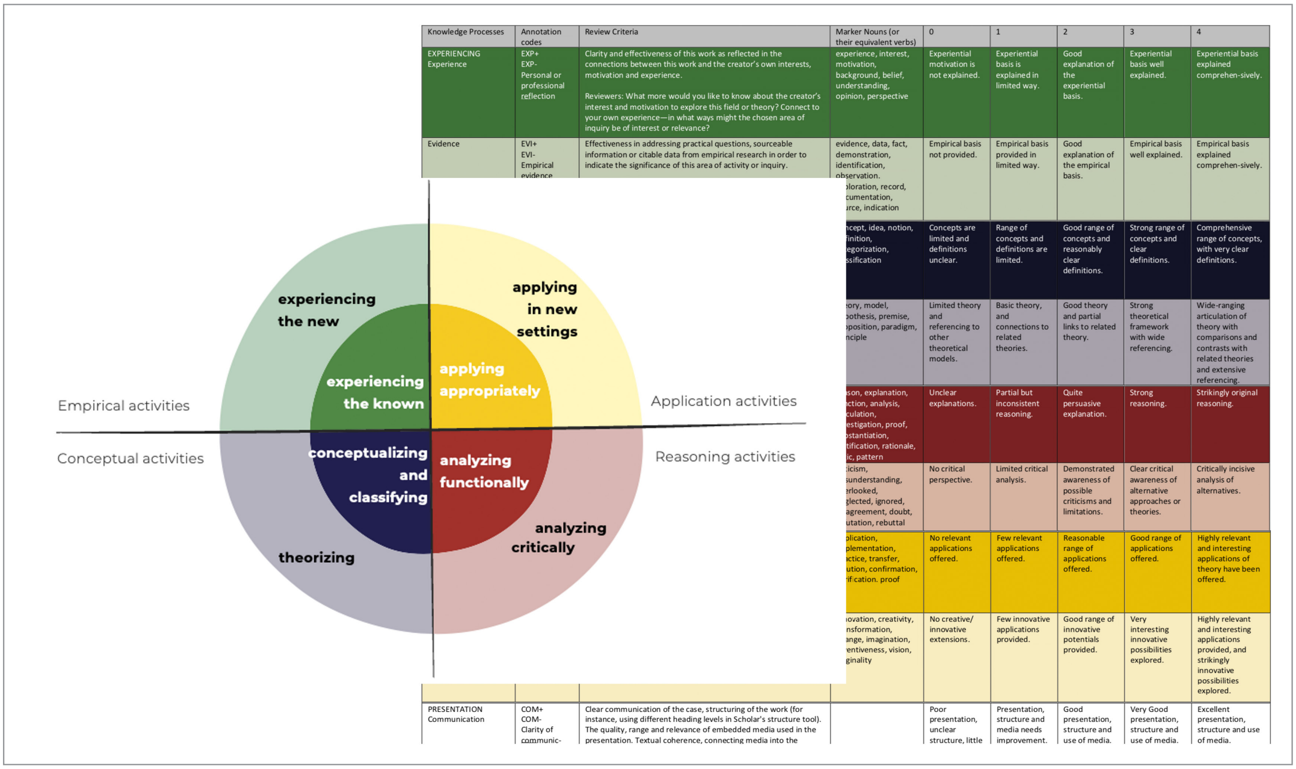
Broaden the Definition of Written Text

Literacy teaching needs to embrace the full scope of Unicode in today's textual practices, including emoji's, icons, and other ideographs increasingly interwoven into text. It also needs to embrace the convergence of writing into mathematics and coding. The literacy teacher may not have to become a teacher of mathematics or computer science, but the mathematics and computer science teachers certainly need to become literacy teachers in ways now integral to their discipline areas. Indeed, in the time of Generative AI, every teacher is a literacy teacher.

Recognize that Literacy is of Necessity Multimodal

For some decades, digitization and the internet have juxtaposed written text with other forms of meaning, rendering anachronistic literacies that studiously separated out text as their object of study. Prior to that, literacy was multimodal in mostly unacknowledged ways—the multimodal transpositions between speech (an essentially audio and temporal medium) and text (an essentially visual and spatial medium). This has always been much harder than the mere transliteration of speech sounds

FIGURE 17
A Snapshot of the Multiliteracies Pedagogy in a Version Adapted for Higher Education (See Full Text in the Appendix)



into phonemes. Generative AI reintroduces multimodality, but in a new way, producing meanings in many forms but only by transposition through text. This opens out exciting new pedagogical possibilities for multimodal literacies.

Frame Literacy as Dialogical, Interactive, Interpretive, and Cyber-Social

Contrary to the idea that literacy is straightforwardly communication in the sense of decoding or comprehending a text's intrinsic or intended meaning, literacy involves the interaction of humans whose lifeworld experiences and interests are inevitably varied. As much as anything, literacy is a question about the depth and critical connectedness of the reader's and the writer's interpretation. Generative AI has become a coherent interlocutor. Via AI agents, it can address learners according to a range of perspectives and judge the level of sophistication in their responses. On this basis, it can also create a profile or model of each learner that allows it to personalize or customize responses sensitive to their diversity on a wide range of dimensions. This opens new opportunities for what we have called cyber-social learning, as well as bringing writing and reading closer together as pedagogical practices—the student writes to elicit a readable response from the AI. Reading AI, however, must be critical, always on the lookout for hallucinations, AI bias, breeches of intellectual property, and Generative AI's other known deficiencies.

Teach Grammar Again

We have defined grammar broadly for the digital and AI era as the patterning of meaning. Grammar is an educational metadiscourse that describes and explains the patterning of meaning. In ordinary life, we mostly live grammar unconsciously. Starting with phonics, schooling brings this discourse to consciousness—partly because there are not enough hours in the school year for full-immersion models and partly because metacognition is one of the fundamental objectives of school learning. This is the basis for knowledge transferrable from school learning to a wide range of social contexts, even those not immediately anticipated in school learning. For the digital and now AI age, we need to build a grammar of multimodal and transpositional meaning.

Create New Literacy Assessments

With Generative AI, we can have new and better literacy assessments. We know all too well the flaws of old literacy assessments: small samples in time, with a narrow view of

FIGURE 18
Down the Rabbit Hole of Generative AI (Image Generated by the Authors in Midjourney)

comprehension as a proxy for reading and writing assessments that are notoriously variable in their judgments, offering gross ratings with just a few levels, and limited feedback. Generative AI opens the possibility of always-helpful, on-the-fly, continuous formative feedback, and progress assessments that analyze everything a student has written within a class or course.

Seize the Day, Take Control of the AI

It will, of course, be impossible to control unfiltered use of publicly accessible Generative AI. In their unfiltered form, they are now more used for cheating than any other educational application. But layered over the foundation LLMs, educational software applications can be made more attractive and useful to learners and their teachers than the unfiltered, publicly accessible Chatbot sites. We have mentioned in this paper the techniques of prompt engineering, creating a bounded corpus via retrieval augmented generation, and multiple agents. Dedicated educational applications can be much more helpful and learner-friendly than the public sites, in the wild so to speak. More than merely helpful, dedicated educational applications can catch cheating via Contextual AI. They can carefully track learner progress—and of course, all such tracking must be fully transparent to learners, teachers, and parents. This requires AI literacy, where teachers and students learn the lingo and understand the basic mechanics of text-centric AI. It also requires that there is no AI use without human moderation.

Develop a Program of Education Justice for the Time of Artificial Intelligence

During the first decades of this century, we have witnessed the widespread application of computers in learning. But, let's be honest, this has not had any discernable impact on the wicked problem of educational and social equality. Literacy outcomes are a significant marker, if not cause, of this stubborn and persistent reality. Our question now must be, can Generative AI help change the game? Can it help calibrate learning to address the great differences between students across many dimensions? Can inexpensive, one-to-one, AI-supported literacy teaching close the gap? To do so will require new pedagogical approaches and changed classroom ecologies.

Starkly, we face several different scenarios: one in which AI fails to address or exacerbates unequal differential opportunity; and another in which it might be possible to ameliorate the social divisions historically encountered by and often tragically reproduced through education. In this context, we ask the overarching programmatic question: What might be the shape of an agenda of education justice in a time of artificial intelligence?

Funding Information

This research has been supported by: US Department of Education, Institute of Education Sciences: "The Assess-as-You-Go Writing Assistant" (R305A090394); "Assessing Complex Performance" (R305B110008); "u-Learn.net: An Anywhere/Anytime Formative Assessment and Learning Feedback Environment" (ED-IES-10-C-0018); "The Learning Element" (ED-IES-lO-C-0021); "InfoWriter: A Student Feedback and Formative Assessment Environment" (ED-IES-13-C-0039); and "The CGScholar AI Helper: A Generative AI Writing and Learning Assistant" (ED-IES 91990024C0010). Bill and Melinda Gates Foundation: "Scholar Literacy Courseware." National Science Foundation: "Assessing 'Complex Epistemic Performance' in Online Learning Environments" (Award 1629161).

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Submitted April 4, 2024
Final revision received October 21, 2024
Accepted October 22, 2024

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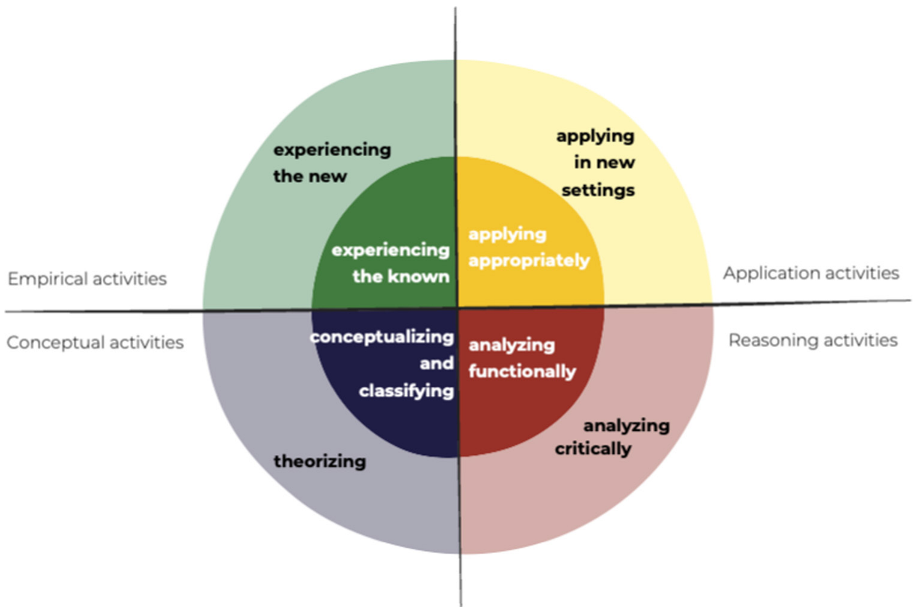
APPENDIX A

Following is the full text of the prompts we have used in the intervention research described in this paper (Saini et al., 2024; Tzirides, Saini, et al., 2024). These prompts are based on the multiliteracies pedagogical schema (Cope & Kalantzis, 2015) and academic discourse analysis. Some observations: (1) Whereas conventional assessment rubrics speak sparely in abstractions with embedded assumptions about their meaning, Generative AI works best with highly elaborated, even prolix prompts. (2) Generative AI is a genre machine, good at generalization but bad at facts, so for best results, keep the prompts at a high level generality. (3) As Generative AI has been tuned to "be nice," you need to call out explicitly requests for critique.

A.1.Empirical Activities

- *Criterion 1A: Experience*

How effectively does the writer connect to their own experience? Evaluate the clarity and effectiveness of this work as reflected in the connections between this work and the creator's own interests, motivation and experience. What more should be included in the work about the creator's interest and motivation to explore this field or theory? In what ways might the chosen area of inquiry be of relevance or importance? How effectively does the writer describe their experience, interest, motivation, background, belief, understanding, opinion, perspective? Give examples from



the text of times when the writer does this particularly well and annotate them with the code EXP+. Give examples from the text of times when the writer fails to provide sufficient explanation of their own interests, motivation and experience and needs to improve this and annotate these examples with the code EXP-. Give examples of what more should be included in the work to address better this criterion. Give the text a number rating between 1 and 5, where 1 is equivalent to no explanation of the creator's interest and motivation, 2 is equivalent to limited explanation of the creator's interest and motivation, 3 is equivalent to good explanation of the creator's interest and motivation, 4 is equivalent to the creator's interest and motivation being well explained, and 5 is equivalent to the creator's interest and motivation being comprehensively explained.

- *Criterion 1B: Evidence*

How effectively does the writer demonstrate the importance of the addressed area with factual or empirical evidence? Evaluate the effectiveness of this work in addressing practical questions, supporting with sourceable information or citable data from empirical research in order to indicate the significance of this area of activity or inquiry. What other empirical material would you like to see? Do you have suggestions for additional research data or informational source material? How effectively does the writer provide empirical evidence, verifiable data, supporting facts, practical demonstrations, observation records, supporting documentation, and verifiable sources? Give examples from the text of times when the writer provides factual or empirical information particularly well and annotate these examples with the code EVI+. Give examples from the text of times when the writer fails to support their assertions with fact or empirical evidence and annotate these examples with the code EVI-. Give examples of what more should be included in the work to address better this requirement for factual or empirical evidence. Give the text a number rating between 1 and 5, where 1 is equivalent to no empirical or factual basis provided, 2 is equivalent to limited empirical or factual basis provided, 3 is equivalent to good explanation of empirical and factual basis, 4 is equivalent to well explained factual and empirical basis, and 5 is equivalent to comprehensively explained empirical and factual basis.

A.2. Conceptual Activities

- *Criterion 2A: Concepts*

How effectively does the writer define the targeted concepts of this work? Evaluate the effectiveness of this work in providing clear definitions of the appropriate range of concepts to the case being made. What other concepts might be required to be defined? Which of the provided definitions of concepts might be more clearly defined? How the provided definitions of concepts might be more clearly defined? How effectively does the writer define concepts, ideas, and notions? How clear are their categorizations and classifications? Give examples from the text of times when the writer uses and defines concepts particularly well and annotate them with the code NAM+. Give examples from the text of times when the writer fails to use concepts effectively and or define concepts and annotate them with the code NAM-. Give examples of what more should be included in the work to address better this requirement to introduce and define concepts. Give the text a number rating between 1 and 5, where 1 is equivalent to limited concepts and unclear definitions provided, 2 is equivalent to limited range of concepts and limited definitions provided, 3 is equivalent to good range of concepts and reasonably clear definitions provided, 4 is equivalent to strong range of concepts and clear definitions provided, and 5 is equivalent to comprehensive range of concepts, with very clear definitions provided.

- *Criterion 2B: Theory*

How effectively does the writer address theory in this work? Evaluate the conceptual connections and coherence as a model of the world. Evaluate the clarity of links between related concepts or important distinctions. Evaluate the range of key theories and theorists in agreement or in disagreement. Are these theories and models properly referenced? Suggest connections that might be made between concepts, so the theory is clearer. Suggest other angles or theoretical perspectives that may be relevant. How effectively does the writer explain the selected theory, model, hypothesis, premise, proposition, paradigm, principle? Give examples from the text of times when the writer uses theory particularly well and annotate them with the code THE+. Give examples from the text of times when the writer fails to use of theory effectively and annotate them with the code THE-. Give examples of what more should be added to the work to improve its application of theory. Give the text a number rating between 1 and 5, where 1 is equivalent to limited theory and referencing to theoretical models, 2 is equivalent to only to basic theory, and connections to related theories, 3 is equivalent to good theory and partial links to related theory, 4 is equivalent to strong theoretical framework with wide referencing, and 5 is equivalent to wide ranging articulation of theory with comparisons and contrasts with related theories and extensive referencing.

A.3. Reasoning Activities

- *Criterion 3A: Reasoning*

How effectively does the writer explain the field, theory or practice under consideration? How sound is the reasoning of this work? Suggest ways in which the reasoning could be more powerful and the explanations clearer. How effectively does the writer provide reasons, explanations, descriptions of functions, analysis of workings, logical proof, reasoned justifications, rationale, and arguments based on the field, theory or practice under consideration? Give examples from the text of times when the writer provides reasons and explanations particularly well and annotate them with the code REA+. Give examples from the text of times when the writer fails to support their argument with clear and effective reasoning and… needs to improve their argument and annotate these examples with the code REA-. Give examples of what more should be included in the work to address better this requirement for clear argumentation and reasoning. Give the text a number rating between 1 and 5, where 1 is equivalent to unclear reasoning and explanations, 2 is equivalent to partial but inconsistent reasoning and argumentation, 3 is equivalent to quite persuasive explanation and argument, 4 is equivalent to strong reasoning and argument, and 5 is equivalent to strikingly original reasoning and very persuasive argument.

- *Criterion 3B: Critique*

How effectively does the writer address the critiques of the theory or practice of this work? Evaluate the awareness of critiques of the theory or practice, and the limits of its scope and applicability. What is the level of understanding of the limits of the creator's own choices of fact, theory and lines of argument? What other lines of critique could be added to improve the argument? Are there alternative, competing or conflicting theories or empirical evidence which the writer should take into account? How effectively does the writer offer critique, criticism, refutation, counterarguments, rebuttals of alternative theories or practices? How clearly does the writer identify disagreements, doubts misunderstandings, errors and misjudgments? Do they balance their argument with overlooked, neglected, or ignored perspectives? Give examples from the text of times when the writer offers criticisms or critique particularly effectively and annotate these with the code CRI+. Give examples from the text of times when the writer fails to offer criticisms or critique effectively and needs to improve their counterarguments and annotate them with the code CRI-. Give examples of what more should be included in the work to offer more effective critique. Give the text a number rating between 1 and 5, where 1 is equivalent to no critical perspective, 2 is equivalent to limited critical analysis, 3 is equivalent to demonstrated awareness of possible criticisms and limitations, 4 is equivalent to clear critical awareness of alternative approaches or theories, and 5 is equivalent to critically incisive analysis of alternatives.

A.4. Application Activities

- *Criterion 4A: Application*

How effectively does the writer address the application of the theory of this work into practice? Evaluate the explanation of the ways in which ideas presented might translate into practice. Evaluate the examples of application provided, gaps in knowledge, and potential for further application and possible measures of effectiveness. What else should be included about implementation and effectiveness of the topic addressed in the work? How effectively does the writer address the application, implementation, translation practice, transfer of lessons into the real world, practical solution, confirmation of results, verification of theses, or proof regarding the applicability of these ideas? Give examples from the text of times when the writer offers strong case for the applicability of their ideas and annotate them with the code APP+. Give examples from the text of times when the writer fails to offer a strong case for the applicability of their ideas and needs to improve their case and annotate them with the code APP-. Give examples of what more should be included in the work to address better this requirement to demonstrate the applicability of their ideas. Give the text a number rating between 1 and 5, where 1 is equivalent to no relevant applications offered, 2 is equivalent to few relevant applications offered, 3 is equivalent to reasonable range of applications offered, 4 is equivalent to good range of applications offered, and 5 is equivalent to highly relevant and interesting applications of theory have been offered.

- *Criterion 4B: Innovation*

How effectively does the writer address the innovative application of their ideas into practice? Evaluate the actual or possible applications in different contexts that are innovative, or which demonstrate creative thinking or practice. Suggest gaps, innovative or creative potentials, such as lateral or hybrid applications, whether realistic or exciting and even perhaps far-fetched possibilities. How effectively does the writer demonstrate innovative thinking, creativity, transformative practice, constructive change, imagination, inventiveness, vision, and originality in this work? Give examples from the text of times when the writer demonstrates innovative thinking particularly well and annotate them with the code CRE+. Give examples from the text of times when the writer fails to demonstrate innovative thinking and annotate them with the code CRE-. Give examples of what more should be included in the work to address better this requirement to demonstrate innovative thinking. Give the text a number rating between 1 and 5, where 1 is equivalent to no creative or innovative extensions, 2 is equivalent to few innovative applications, 3 is equivalent to good range of innovative potentials, 4 is equivalent to very interesting innovative possibilities, and 5 is equivalent to highly relevant and interesting applications and strikingly innovative possibilities.

A.5. Academic Discourse Analysis

- *Criterion 5A: Communication*

How effectively does the writer communicate the case of this work? Evaluate the quality of the communication and the structuring of the work (for instance, using different heading levels). Evaluate the quality, range and relevance of embedded media used in this work. Evaluate the textual coherence, connecting media into the argument. Make constructive suggestions for the creator that will help them when they revise, e.g. Is each media item explained or discussed in the text of the work? Make specific revision suggestions ranging from general comments to copy-editing suggestions about the communication of the case and the structure of this work. Give examples from the text of times when the writer communicates their case and structures their argument particularly well and annotate them with the code COM+. Give examples from the text of times when the writer fails to communicate their case and structure their argument and annotate them with the code COM−. Give examples of what more should be included in the work to communicates the writer's case and structure their argument. Give the text a number rating between 1 and 5, where 1 is equivalent to poor presentation, unclear structure, and little use of media, 2 is equivalent to presentation, structure and media needs improvement, 3 is equivalent to good presentation, structure and use of media, 4 is equivalent to very good presentation, structure and use of media, and 5 is equivalent to excellent presentation, structure and use of media.

- *Criterion 5B: Referencing*

How effectively does the writer use and format references in the work? Evaluate the consistency of the citation style. Evaluate the acknowledgement and sourcing of quotes and embedded media. Evaluate whether a clear distinction is made between the creators' voice and properly quoted sources. Give examples from the text of times when the writer references their sources particularly well and annotate them with the code SOU+. Give examples from the text of times when the writer fails to reference their sources adequately and annotate them with the code SOU-. Give examples of what more should be included in the work to address referencing more effectively. Give the text a number rating between 1 and 5, where 1 is equivalent to limited sourcing, 2 is equivalent to inconsistent sourcing, 3 is equivalent to good sourcing, 4 is equivalent to very good sourcing, and 5 is equivalent to near faultless sourcing.