Accepted: 28 September 2022

DOI: 10.1111/ejed.12528

ORIGINAL ARTICLE

WILEY

Ceci n'est pas une école: Discourses of artificial intelligence in education through the lens of semiotic analytics

Paulo Blikstein | **Yipu Zheng** | **Karen Zhuqian Zhou**

Teachers College, Columbia University, New York, New York, USA

Correspondence
Paulo Blikstein, Teachers College, Columbia University, 525 West 120th St, New York, NY 10027, USA.
Email: paulob@tc.columbia.edu

Abstract

New ideas and technologies enable new ways of doing as well as new forms of language. The rise of Artificial Intelligence (AI) is no exception. The implications of changing activity and language take on new gravity in certain fields to which AI is applied, such as education (AIEd). Terms like *smart*, *intelligence*, and *learning*, which had certain meanings when describing human cognition, take on new meanings in the context of computational systems, with the potential for *polysemy* when the human and computational meanings meet. This article unpacks what AIEd companies mean when they use these terms. Drawing on findings from a mixed-methods study, we first describe how AIEd companies used these terms on two websites. Then, using Natural Language Processing techniques, we quantitatively analyse a corpus of over 65,000 words scraped from 26 AIEd company websites. Our analyses suggest that commonly promoted narratives around student learning and 21st Century skill-building are not supported by the language on AIEd company websites, which focus instead on mass customization, efficiency, and monitoring—all tasks at which computers excel. Also, notably scarce in the corpus were extensive articulations on ethics. Given these findings we propose that although AIEd companies create powerful new technical possibilities, they must also be evaluated for the powerful ways in which they shape narratives around the use of technology in education and the behaviours and capabilities that constitute education.

1 | INTRODUCTION

The idea of artificial beings interacting with humans can be found in several ancient myths, such as the Golem or Hesiod's narrative about Hephaestus—the Greek god of invention—creating Talos and Pandora. It is an idea that has fascinated—and terrified—humans for millennia. Thus, it is not surprising that when we go through periods in which technology is strongly present in the zeitgeist, Artificial Intelligence (AI) reappears as a core component of the ultimate human utopia. In the late 1950s, with the first digital computers, AI pioneers McCarthy, Simon, Minsky, and Newell envisioned that learning and intelligence *can in principle be so precisely described that a machine can be made to simulate it* (McCarthy et al., 2006). Simon believed then that we were just a couple of decades away from simulating intelligence, but the first AI Winter of the early 1970s and several ensuing AI boom-and-bust cycles proved him wrong.

Whereas technologists have attributed the ebbs and flows of interest in AI to a lack of computing power, inconsistent funding, and other infrastructural factors, philosophers and sociologists have questioned the very validity of the endeavour—why and how are we building artificial beings? These conversations intersect with discussions on the politics of technologies (Joerges, 1999; MacKenzie & Wajcman, 1999; Winner, 1980) and of technologies acting as amplifiers of oppression and inequality—well captured in Benjamin's (2019) analysis of the early images of robots as slave home servants for humans, subserviently catering to all of our needs. These arguments are powerful reminders of how the issue of AI development and adoption goes beyond mere technological obstacles.

Nevertheless, one possibly less explored aspect of how we think about AI might be the language we use to describe its goals, nature, and role in society. At the same time as AI was developing as a field in the second half of the 20th century, semiotics and modern linguistics were also emerging. These disciplines became increasingly concerned with how we create meaning and how language creates, rather than merely represents, reality itself (Barthes, 1964; Benveniste, 1966; Blikstein, 2020). The analytic tools of semiotics and discourse analysis might be useful for examining the discourse on artificial intelligence. As we contend below, half of the work of birthing AI was, in fact, creating language to redescribe what it really is. Imagine, for example, if AI was named instead *statistical training with large datasets* or *rule-based diagnostic systems*. Most likely, its impact on the public sphere and on society's zeitgeist would be radically different. In other words, without creating its own vocabulary and thus changing the very meaning of *intelligence* and *artificiality*, AI would never have achieved the iconic societal status it enjoys today.

Consider, as an example, Grey Walter and Elsie, the simple light-seeking robot he created in the 1950s. Walter famously claimed that because Elsie exhibited unintended behaviours such as finding where to recharge its batteries, it was acting with self-awareness (Holland, 2003). However, Elsie's apparently *smart* behaviour was simply a function of how Walter organised the environment, calibrated the circuits, and how the motors responded to a low-power state: Elsie had no intention to stay alive or recharge its batteries. Fast forward to another example from 2014. RollScout, a crowdfunded product campaign (Kooser, 2014), promised consumers a *smart* toilet paper holder. The product detects, through a sensor, the end of the roll and warns the user wirelessly.

A remarkable feat of discursive reconstruction took place in the almost seven decades that separate a supposedly self-aware and smart Elsie from smart toilet paper holders. The fact that a simple sensor-actuator circuit is unproblematically called and recognised as *smart* is more than good marketing: by resignifying what intelligence, agency, and self-awareness are, the field of AI effectively created a new reality in which being smart has an entirely different meaning than it used to. This discursive move allows technologists to put forward products that, despite being simple or unintelligent, behave in ways that today are recognised as the *new* smart. In the context of AI, the term *smart* came to refer to systems that can autonomously adapt to their environment and learn from experience—for example, a robot that could navigate a new environment without human intervention. The term *intelligent*, at least in the early decades of AI, was devoted to strict specialist systems designed to perform precise tasks, such as playing chess. Finally, *learning* in AI has a very particular meaning, related to how systems reconfigure themselves when they are fed new data.

However, even if some metaphors look similar (e.g., brains reconfiguring themselves in the presence of new stimuli), these meanings differ from their uses in everyday life or the Social and Psychological Sciences. When AI engineers state that they designed a smart system that "learned" to recognise cats, they mean that the system was fed enough data (millions of cat photos) to accurately categorise new photos of the same kind. The so-called learning there is not the one we would see happening in classrooms or museums with children. An *intelligent self-driving car* bears little resemblance to what we would consider carbon-based intelligent thought or decision-making.

This distinction is key in one particular field of application of AI: *education*. Since the first mechanical 'teaching machines' created by Pressey and later refined by Skinner (Watters, 2015, 2021), the idea of a contraption that would perform the duties of a teacher has been a mainstay in the development of educational technologies. The so-called learning that machines perform to become what is referred to as smart, can be easily confounded with the learning that children need to do to accomplish the same—and in that seemingly harmless coincidence lies dangerous territory.

In previous work (Blikstein & Blikstein, 2021), we have discussed the process by which Silicon-Valley-inspired companies validate and elevate their products using a series of discursive moves, such as dialogism (e.g., the creation of an antagonist), polyphony (many discourses intertwined in time and space), intertextuality, and the conative function of language (Bakhtin, 1984; Benveniste, 1966; Jakobson, 1968; Todorov, 1989). This article extends our earlier work with a deep dive into the discourse of Artificial Intelligence in education (AIEd). In particular, we focus on *polysemy* (Ullmann, 1951), a process by which words acquire new meanings depending on historical, cultural, and political contexts. We describe cases in which everyday educational and psychological terms (e.g., intelligence, learning, smart) are first reframed to describe technological accomplishments in AI, and then dangerously pointed back at education itself to reframe the work of students and teachers in terms of the words' newly acquired meanings. Based on their widespread application to technologies and commerce, these reconfigured meanings gain considerable power and credibility at the same time as they are unmoored from their foundations in education theory. To document the nature of polysemy, we first present as examples language from two AIEd company websites, analysing the discursive strategies used to describe the companies' educational products. Then, to assess the wider scope of such discursive strategies, we apply Natural Language Processing techniques to analyse language use on 26 AIEd company websites. We interpret these paired qualitative and quantitative analyses, concluding with reflections and recommendations for the future use of AI in education.

2 | POLYSEMY IN PRACTICE

We begin with a glimpse into how educational technology companies describe their use of AI and depict the *intelligence* of their systems. We seek to understand what is meant by AI and *AI-powered* systems. Consider the following excerpts from the website of Cognii, "*a leading provider of Artificial Intelligence based educational technologies*" (Cognii, 2022).

> Using Cognii's proprietary **Natural Language Processing** algorithms, Cognii Assessment Platform analyzes the syntax, the deeper semantics, and the hierarchical structure in learners' written answers to open ended questions. [...] Cognii VLA is optimised to engage students in a meaningful **formative assessment** based conversational experience focused on ideas. Students get real time feedback on what they have written and make multiple attempts to the point of mastery.
>
> (Cognii, 2022, August 2)

Using an array of technical terms, Cognii lauds the abilities of its Conversational EdTech. Its main distinction from other essay scoring software seems to be the ability to provide a "*conversational experience focused on ideas*" (Cognii, 2022). A diagram of the chat interface (Figure 1) illustrates concretely what that conversation might look like. Even though the chat visually looks like a conversation, it is not. In practice, the text-based chat system provides a prompt, analyses the student's answer—referred to as "*the syntax, the deeper semantics, and the hierarchical structure*" (Cognii, 2022), and offers simple feedback ("*Very close!*"), followed by a request that the student provide additional details. This evaluation and feedback model closely follows the classic Initiation-Response-Evaluation (IRE; Cazden, 1988) format—perhaps a good fit for recall exercises but a stretch for teaching "*any subject area, grade 3 and up*" (Cognii, 2022), as the website claims.

The website claims that students get "*real time feedback* [and] *make multiple attempts to the point of mastery*" (Cognii, 2022). That is a powerful example of polysemy: the real time feedback given by teachers would be fundamentally different from the feedback given by a piece of software along many dimensions (e.g., the physical presence of the teacher, the awareness that a human is providing feedback, the teacher's holistic understanding of their students, the human connection that generates and results from feedback sessions, etc.). Nevertheless, the Cognii website uses the same term, real time feedback, that we would use in a regular educational environment and, in doing so, immediately reframes its meaning to what software can do well: fast, low-cost, standardised automated feedback based on machine learning techniques. One can imagine the next rhetorical step would be to point the critique back at schools and teachers to claim that the feedback students currently receive there is slow, expensive, and unreliable—thus, AI becomes fundamentally better at real time feedback.

Nevertheless, in this polysemic dilemma, we are fundamentally talking about two different kinds of real time feedback with a considerable power imbalance. On one side, we have a modern company offering fast, reliable service, and on the other, "old-fashioned" teachers with inefficient ways. The two offerings are radically different, but once they are made equivalent through this discursive move, Cognii's product becomes unequivocally superior.

In addition to unpacking what this company means when it talks about AI, we also consider the ways in which they establish the authority of their AI system. As their website claims,

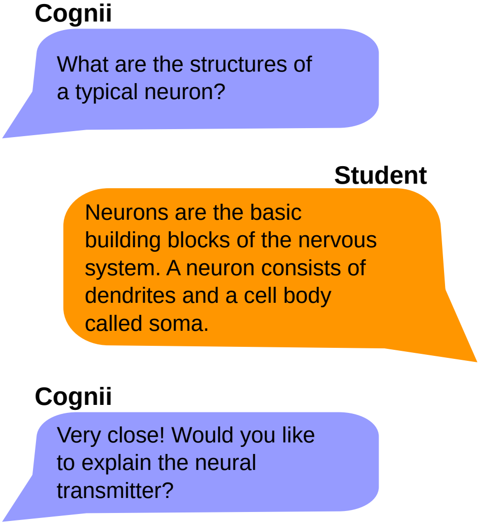

FIGURE 1 Example of Cognii Conversational EdTech conversation. *Source*: Figure constructed by the authors. [Colour figure can be viewed at wileyonlinelibrary.com]

> Cognii's ability to evaluate writing is highly accurate. In a controlled **research study,** Cognii's assessment was found to be 96% as accurate as humans in evaluating short essays. Cognii uses **data mining** and **machine learning** to ensure that the scoring and feedback become more accurate over time.
>
> (Cognii, 2022, August 2)

As is typical for many of the websites we analysed, Cognii employs polyphony: multiple voices validate their product. These technologists call on the authority of controlled research studies while omitting details on the content or methods: the point here is simply to borrow the authority of research studies. In addition, they generally name the technical processes underlying the technology, such as data mining and machine learning, but do not provide enough detail to support their claims. In fact, a closer scrutiny of the product (Figure 2) reveals the simplicity of the interaction between student and software: cursory-level prompts are hidden under the guise of terms like *feedback* and *mastery*.

Similar to Cognii, Mindojo also offers a chat-like learning platform. The website elaborates how its courses are made of

> [...] tiny, interconnected content units, usually just a few sentences long [which its algorithm will then] automatically experiments with different teaching strategies [and] competes between content variations to identify the most effective ones [and] assembles these units into a chat-like learning flow that keeps students engaged, while adapting to each student's level.
>
> (Mindojo, 2022)

The website further explains that the "*non-linear content*" required by the "*conversational teaching style*" needs to be developed by teachers using authoring tools (Mindojo, 2022). The platform then automatically creates different combinations of the sentence-long content units and delivers one combination to the learner based on its historical records. Such a learning experience certainly differs from a traditional lecture, but whether it is more engaging or more effective requires further evaluation. This example illustrates how many

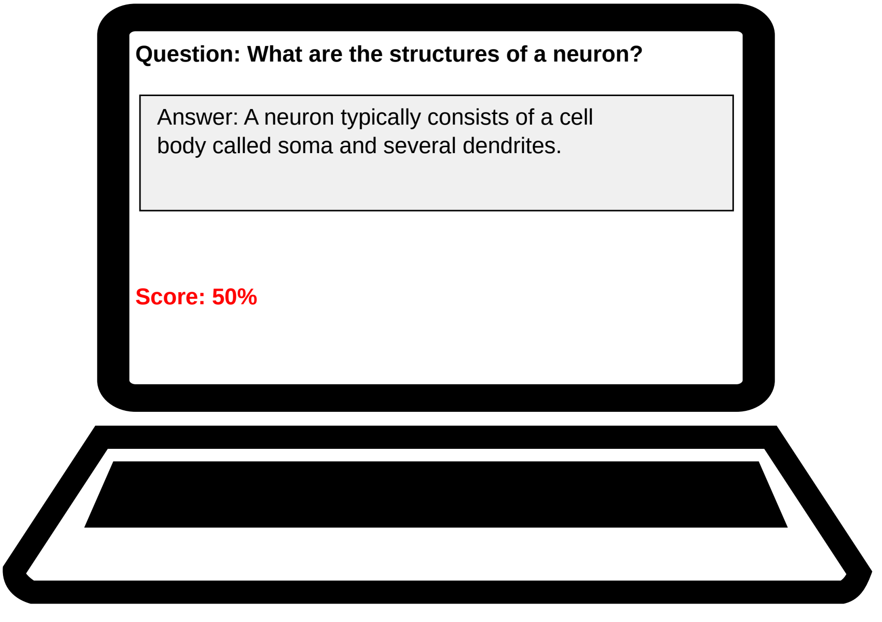

FIGURE 2 Illustration of Cognii's Assessment platform. *Source*: Figure constructed by the authors. [Colour figure can be viewed at wileyonlinelibrary.com]

terms such as *conversational teaching style*, *teaching strategies*, and *engagement* are appropriated, resignified, and then pointed back at schools for an implicit critique. Experimenting with different teaching strategies as conceptualised by teachers in schools would be quite different from what the software claims to do. Here, again, the likely simplified, so-called *automated* teaching experimentation done by the software gains authority. The use of language that already has a positive connotation in the audience's mind is crucial: if the website stated instead that the system *uses computer algorithms to experiment with different sequences of content presentation*, the effect would not be the same.

Building on polyphony, Mindojo builds authority for its personalised learning platform by introducing their board of directors, all high-ranking researchers and business leaders in the fields of Science, Psychology, Education, and Investment. Besides a few sentences sharing the values of the Mindojo enterprise—specifically, *disruptive innovation*, *doing good*, and *moving fast*, and two short paragraphs on how the team is global and multidisciplinary—the website does not otherwise justify the mechanism and the effectiveness of the AI-empowered learning platform. While having access to a group of respected board of directors and diverse teammates does no harm, it is certainly not sufficient for proving the quality of the learning platform. However, this means of establishing authority and building *trust* is commonly used by other AIEd companies as well, as seen in our analysis.

The main purpose of this qualitative analysis is not to merely criticise the existing AIEd companies and their products. Many of them are experimenting with different ways to deliver content and structure learning and are gradually contributing to innovation in education. However, we invite researchers, educators, school administrators, policymakers, and entrepreneurs to think carefully and critically about what we really mean when we use the word *Artificial Intelligence* in the context of learning and teaching: do intelligence and learning mean the same in the contexts of computer science and education? What might be the ramifications of adopting the computer science meanings of these terms in education, especially if done unknowingly?

3 | NATURAL LANGUAGE PROCESSING ANALYSIS OF AIED DISCOURSE

Although the qualitative analysis reported in this article draws on the language from two company websites, we do not wish to single out Cognii or Mindojo as practicing a unique brand of discourse within the AIEd space (Cognii, 2022; Mindojo, 2022). To assess the scope of such discourse within AIEd more broadly, we next turn to a quantitative analysis of the websites of 26 different AIEd companies. This analysis allows us to examine different patterns that emerge from the data corpus in a more representative and comprehensive fashion. The goal of this analysis is to ascertain if we can observe, beyond the superficial layer of discourse and marketing, who these companies are designing for, what the products do, and what educational commitments are expressed between the lines of their messaging. In that task, we keep in mind the tools of semiotics, attempting to decipher not the visible, but the intelligible, in the same way that appraisers distinguish real paintings from forgeries by inspecting insignificant details (Ginzburg, 1980).

3.1 | Methods

To conduct text mining analysis using Natural Language Processing on a larger data set, we first considered the selection of search terms. We selected search terms that were at the same time generic and likely to capture most companies and institutions operating in the space of AI in education: *AI education company*; *artificial intelligence education company*; and *AI education company in Africa, Asia and Pacific Islands, Europe, South America, North America*. We used these terms in the Google search engine and in the CrunchBase website (which lists most education technology companies). The result was a list of 26 well-known AIEd companies across fourteen countries, which became our text mining analysis targets. The entire official website of each company was scraped and the text from each website was stored as an individual corpus. Using the *tm* (Feinerer et al., 2008) package in R and following standard procedures, white spaces and English stop words were removed from the corpus and all words were transformed to lowercase. After the text pre-processing, the text dataset contains 26 corpora and a total of 65,489 words. As the corpus size varies, word frequency in each corpus was calculated by normalising total observations of the word in the corpus by the size of the respective corpus (Silge & Robinson, 2017).

We first did an exploratory analysis on frequently used words in the entire dataset and sentiment analysis among the 26 corpora. Then, we narrowed in on the text descriptions around different stakeholders (i.e., students, parents, teachers, and schools) to understand how the AIEd companies perceived and portrayed different stakeholders in the learning settings with AI. We started by identifying all words referring to four stakeholders of interest in the dataset (see Table 1).

We sampled some segments of the text including the selected words of interest and read for descriptives that would be most indicative of AIEd companies' attitudes and perspectives of these stakeholders. The intuition would be to look for adjectives first (Eirinaki et al., 2012; Feldman, 2013). However, the reality was that stakeholder words are seldom used with adjectives in the dataset, except for occasional phrases referring to, for example, *unique students* or *experienced teachers*. Although adjectives were not as useful as we originally thought, another part of speech attracted our attention—verbs (Karamibekr & Ghorbani, 2012; Sokolova & Lapalme, 2008). As the words of interest represented different stakeholders, they always served in a sentence as *a subject* to initiate some action or *a direct object* to be acted upon. In other words, they were always used in conjunction with a verb in a sentence. Different choices of verbs, therefore, reflected what roles different stakeholders are able and/or supposed to play in the perspective of the AIEd companies.

To analyse combinations of *subject and verb*, or *verb and direct object*, phrases systematically, we parsed each corpus into bigrams and selected all bigrams containing words representing stakeholders in Table 1. Then, words in all selected bigrams were tagged with their part of speech using the *qdap* package in R (Goodrich et al., 2018). Bigrams without verbs were removed. Eventually, 388 bigrams were retained for analysis. The 388 selected bigrams were then divided into two groups: (1) verb-stakeholder bigrams and (2) stakeholder-verb bigrams. The former group indicated how different stakeholders were acted upon (i.e., the stakeholder as the direct object of the verb), while the latter indicated what actions different stakeholders might take in the context of learning with AI, as portrayed by the AIEd companies.

To triangulate the qualitative findings, we also conducted a frequency analysis of keywords to identify common narratives about the role of Artificial Intelligence in education. Finding some discrepancy, we then delved into the particular stakeholder roles described within the website corpora as well as their mentions of ethics and related issues. These quantitative findings suggest different narratives on the role of AI in education, which we elaborate on further in our discussion.

TABLE 1 List of words representing different stakeholders

Stakeholders	Words for analysis
Student	Child, kid, learner, student
Teacher	Educator, instructor, mentor, teacher, tutor
School	College, school
Parent	Caregiver, dad, father, guardian, mom, mother, parent

Source: Authors.

3.2 | Findings

3.2.1 | Stakeholder roles and behaviours

The role of AIEd with regard to all stakeholders was analysed by aggregating verb-stakeholder and stakeholder-verb bigrams. According to the verb-stakeholder bigrams, we categorised three major roles that the AIEd product take: (1) assist, (2) lead, and (3) monitor or analyse. Almost half of all verb-stakeholder bigrams involved the stakeholder receiving assistance of some form (49%). The remaining half of verb-stakeholder bigrams were split equally between leading the stakeholder and monitoring or analysing the stakeholder (26% and 25%, respectively).

Here, we focus on *students* as key stakeholders and their relationship to AI through student-verb bigrams. As de-picted in Table 2, the most commonly mentioned aspects for students were *cognition* (33%; e.g., understand, read, ask) and *achievement* (22%; e.g., succeed, master, complete, exceed). Collaboration, autonomy, behaviour, and student intention were somewhat commonly mentioned for students but at a much lower rate (11%, 11%, 9%, and 8%, respectively). Student emotion accounted for only 1% of student-verb bigrams.

3.2.2 | Consideration of ethics-related content

Our text mining analysis also revealed that equity or ethics-related topics are seldom mentioned on AIEd companies' websites. To examine the prevalence of such topics, we used the Fairness, Accountability, Transparency, Ethics, and Safety & Security (FATES) framework (Wing, 2018) to systematically search for ethics-related keywords in the corpus. Only one company included all five FATES components. Over half the companies had two or fewer dimensions, includes three companies that had none.

Of the five dimensions, ethics was the most commonly mentioned, appearing in 77% of the companies (Table 3). Notably, the most common sub-dimension for ethics was *privacy*, most typically used in phrases referring to *privacy policy*. Fairness was the next most common dimension, mentioned by half the companies. The remaining three dimensions were mentioned in 35% or fewer of the company corpora, with *transparency* being the least mentioned.

We also note a range in quality when it comes to the specificity with which each company addressed each FATES dimension. For example, while some companies talk concretely about how their practices support a given FATES dimension (e.g., ProctorU follows the thirteen Australian Privacy Principles and other requirements of the Privacy Act to ensure transparency with respect to its processing of Australian user information; ProctorU, 2022)

TABLE 2 Stakeholder-verb bigram frequency by stakeholder

Stakeholder	Descriptor category	% of stakeholder descriptors
Student	Cognition	33%
	Achievement	22%
	Collaboration	11%
	Autonomy	11%
	Behaviour	9%
	Intention	8%
	Emotion	1%
	Other	5%

Source: Authors.

TABLE 3 Occurrence of terms associated with FATES dimensions across company websites

FATES Dimension	% Companies Mentioning	# Mentions by Sub-dimension			
Fairness	50%	Diversity	Inclusion	Accessibility	Equity
		46	23	7	7
Accountability	35%	Reliability	Responsibility	Accountability	Trustworthiness
		12	3	1	1
Transparency	15%	Transparent	Integrity		
		9	4		
Ethics	77%	Privacy	Ethics	Justice	
		176	3	1	
Safety & Security	35%	Safety	Security	Cybersecurity	
		45	38	1	

Source: Authors.

most remain vaguer (e.g., quoting efforts to work as a transparent and adaptive team to achieve excellence. See Table 4 for further examples).

In general, although education technology (EdTech) companies talk about FATES dimensions, there are typically limited specifications or concrete descriptions of their approaches to ensure alignment. This finding is particularly worth noting given the overwhelming exposure such topics have had in popular media and academia (e.g., Zuboff, 2015). This finding might indicate that AIEd companies see themselves as more technical and less engaged in ethics issues, but we see this stance as problematic given the public discourse around AI in the larger society and especially in education (Taddeo & Floridi, 2018).

3.2.3 | Four narratives of AIEd

Our last emergent exploration into the corpus focused on narratives about AIEd. The data revealed four main narratives: (1) AI for adaptive and personalised learning, (2) AI for increasing efficiency, (3) AI for monitoring and predicting learning, and (4) AI for 21st century skills. As shown in Table 5, AI for adaptive and personalised learning is the most prevalent narrative found on the companies' official websites, while AI for 21st-century skills has less than one-fifth of the weight compared to the first three categories. In addition, concrete alternative possibilities of incorporating AI in learning that go beyond the idea of individualised or adaptive learning are missing from the conversation. Such possibilities include the 'orchestration', or coordination, of learning activities among multiple people and resources; augmenting learners' cognitive apparatus; broadening the learning competencies that can be reliably measured; and revealing learning outcomes or connections that are hard to visualise in traditional assessments, as pointed out by Roschelle and Hodkowski (2020).

4 | DISCUSSION AND CONCLUSION

In this article, we argued that certain educational technologies cannot be simply analysed by their technical possibilities because they operate only partially at the level of their potential concrete benefits for education. The other part of their operation is the creation of a powerful discourse to command much larger narratives. AIEd is, thus, half technical and half a narrative: as configured in the corporate world today, it cannot survive without these two

TABLE 4 Examples of FATES language in company corpora

Dimension	Rating	Examples
Fairness	Concrete	• Siyavula Education: "[...] *Siyavula has produced book titles spanning Mathematics and Science subjects from Grades 4–12. These are high-quality, curriculum-aligned Open Educational Resources. Releasing them under a Creative Commons license lowers the legal barrier to sharing them, while making them available in multiple formats lowers technical barriers to accessing them.*"
	Vague	• ApplyBoard: "*Our 1000+ team members (and growing) are as diverse as the students that we support.*" • ProctorU: "*We are committed to accessibility. We want our platform to be accessible to everyone.*"
Accountability	Concrete	• Edmentum: "*This 15-minute formative assessment reliably measures grades 6–12 students' strengths and needs in domains reflective of CASEL competencies and school engagement.*"
	Vague	• Renaissance Learning: "*Trust the validity and reliability of Star data, backed by research, validity studies, and millions of data points.*" • Kinedu: "*Find trustworthy answers from developmental experts and eliminate the guesswork.*"
Transparency	Concrete	• ProctorU: "*ProctorU follows the 13 Australian Privacy Principles and the other requirements of the Privacy Act to ensure transparency with respect to its processing of Australian user information.*"
	Vague	• ALEKS: "[...] *our unwavering commitment to transparency and integrity in all we do.*" • Edmentum: "*Working as one team, transparent and adaptive, to achieve excellence.*"
Ethics	Concrete	• ALEKS: "*We maintain a Code of Business Ethics (COBE) on which all employees receive training each year. Each employee is required to acknowledge and agree to abide by the COBE annually as a condition of employment.*"
	Vague	• Sense: "*Yes, learner privacy is very important to us, and we comply with both US and EU laws related to the protection of personal information.*" • Mindojo: "*Doing good. We're driven by a desire to make the world a better place and we'll take ethics over profits any day of the week.*"
Safety	Concrete	• Renaissance Learning: "*Safe. Authentic reporting by professional journalists and a careful review by a child psychologist help ensure every article is unbiased and appropriate for children.*"
	Vague	• ProctorU: "*Students should expect that their remote academic work is secure and that their privacy and security are maintained.*" • BabySpark: "*Toy Safety for Toddlers: Choosing and Using Safe Toys*"

Source: Table constructed by authors, excerpts retrieved from ApplyBoard (2021); BabySparks (2022); edmentum (2021); Kinedu (2022); McGraw Hill (2022); Mindojo (2022); ProctorU (2022); Renaissance Learning (2022); Sense (2022); and Siyavula Education (2022).

components. The first is the *transcendental buy-in* (Blikstein & Blikstein, 2021); it is not enough for AIEd companies to attract school systems based on proven, but perhaps modest, results. The buy-in needed to attract capital and press exposure must be transcendental: it must feel like schools and policymakers are joining a revolution in the making. Our data mining efforts to review 26 major websites show that there is, indeed, hyperbole about the possible results, but a discrepancy with regard to the actual implementation. As illustrated in our analysis, what EdTech companies referred to as fluent conversation was really just a simple content question—as in Skinner's

TABLE 5 Four narratives of AI and their normalised frequencies

Four narratives	Example target words	Frequency across the corpus
AI for adaptive/personalised learning	Adapt, customise, personalise	0.223
AI for increasing efficiency	Accelerate, efficiency, fast, quick, speed	0.126
AI for monitoring/predicting learning	Control, monitor, predict, forecast, assess, evaluate	0.163
AI for learner agency/self-regulated learning/21st century skills	Agency, self-aware, self-care, self-confidence, self-conscious, self-control, self-direct, self-esteem, self-pace, self-regulate, self-reliance, self-select, self-service, self-study, critical, problem solving, create, innovate, communicate, collaborate, cooperate, initiative, productivity, accountability, leadership	0.099

Source: Authors.

teaching machine. Terms such as 21st century skills, problem-solving, and critical thinking appear on webpages describing AIEd products, but our analyses show that in the bulk of the webpages, the narratives of control, monitoring, and compliance are the backbone of AIEd technologies.

The second component is the polysemic effort of redefining crucial educational language in AI's image. If *intelligence*, as we know it, cannot be accomplished *in-silico*, these companies' answer is to redefine it based on the capabilities of current technology and then recolonise schools with this new definition. A new 'smart' student becomes the one that can excel in the smart AI system. The new 'learning' becomes mimicking the ways algorithms and computers learn. Our analysis showed that the action verbs relating to students are mostly in categories related to achievement, cognition, and behaviour, with almost no language describing attention to students' intentionality, emotions, culture, or autonomy.

Another puzzle piece is the cursory appearance of ethics and privacy issues in the sample data. The growth of AI technologies in education has been considerably propelled by the global COVID-19 pandemic and remote learning. With the increased use of AI in education came greater responsibility for companies to examine its weaknesses and risks, especially within the realm of ethics, data privacy, and unhealthy public-private partnerships. As more education technology companies claim that they are approaching the implementation of AI systems at a large scale, they are required to not only think of how to design effective systems from a technical perspective but also to shed light on potential social, ethical, cultural, or political issues that might come with the AI 'hype' (Berendt et al., 2020). Our data shows that, instead, those issues are mostly dealt with in vague, cursory, and dubious ways.

It is not news that some technologies are more compatible with certain social relations than others, even if it is incorrect to see technology as always requiring specific social relations (MacKenzie & Wajcman, 1999). Consequently, the decades-old controversy about technological artefacts' politics comes to life again. Even though Winner's assertion that *artefacts have politics* has been contested and complexified, his concluding remarks sound especially fitting here, *"people are often willing to make drastic changes in the way they live to accord with technological innovation* [...] *at the same time they would resist similar kinds of changes justified on political grounds"* (Winner, 1980, p. 135). Winner might be amused to know that school systems that have resisted progressive policies for decades are now quick to embrace all kinds of technological innovations, AIEd in particular. The power of these technologies—and their proprietors—cannot be understated. AIEd systems, for their power, are in a position to reach millions of children in public schools. In spite of this, our findings showed that ethical and data privacy issues are generally ignored or barely addressed. Students' actions are often described in terminology that places them in position to be monitored and controlled. The overall hyperbolic mission of companies in statements proclaiming to *bring students into the 21st century* differs from their actual products, which are mostly concerned with surveillance, assessment, metrification, and mechanisation. This is only made worse by the fact that the use of computer-science-inspired metaphors and definitions may also change the very meaning of learning, as those systems colonise schools. In the words of Lewis Carroll's Humpty Dumpty, "*When I make a word do a lot of work like that, I always pay it extra*". It seems like words such as intelligence and personalisation are doing a lot of work for AIEd companies—except that our children might be the ones paying extra.

ACKNOWLEDGEMENTS

Very special thanks to Leah Rosenbaum for her insightful ideas, fantastic edits, and invaluable help on this article. And another special thanks to Izidoro Blikstein, my father, for his ideas, references, books, and all the São Paulo late night conversations on Semiotics: they inspired not just this paper, but a way to see, think, and feel the world.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are derived from resources available in the public domain and listed in the References section of this paper.

REFERENCES

ApplyBoard. (2021, November 2). About. *ApplyBoard*. https://www.applyboard.com/about

BabySparks. (2022). *Toy safety for toddlers: Choosing and using safe toys*. https://babysparks.com/2020/02/07/toy-safety-for-toddlers-choosing-and-using-safe-toys/

Bakhtin, M. M. (1984). *Esthétique de la création verbale*. Gallimard.

Barthes, R. (1964). Éléments de sémiologie. *Communications*, *4*(1), 91–135.

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the New Jim Code*. John Wiley & Sons.

Benveniste, E. (1966). *Problèmes de linguistique générale*. Gallimard.

Berendt, B., Littlejohn, A., & Blakemore, M. (2020). AI in education: Learner choice and fundamental rights. *Learning, Media and Technology*, *45*(3), 312–324.

Blikstein, I. (2020). *Semiótica e totalitarismo*. Editora Contexto.

Blikstein, P., & Blikstein, I. (2021). Do educational technologies have politics? A semiotic analysis of the discourse of educational technologies and artificial intelligence in education. In *Algorithmic rights and protections for children*. MIT Press. https://doi.org/10.1162/ba67f642.646d0673

Cazden, C. B. (1988). *Classroom discourse: The language of teaching and learning*. ERIC.

Cognii. (2022). *Cognii*. https://cognii.com

edmentum. (2021, May 10). *BASE education*. https://www.edmentum.com/products/base-education

Eirinaki, M., Pisal, S., & Singh, J. (2012). Feature-based opinion mining and ranking. *Journal of Computer and System Sciences*, *78*(4), 1175–1184.

Feinerer, I., Hornik, K., & Meyer, D. (2008). Text mining infrastructure in R. *Journal of Statistical Software*, *25*(1), 1–54.

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM*, *56*(4), 82–89.

Ginzburg, C. (1980). Morelli, Freud and Sherlock Holmes: Clues and scientific method. *History Workshop Journal*, *9*(1), 5–36. https://doi.org/10.1093/hwj/9.1.5

Goodrich, B., Kurkiewicz, D., & Rinker, T. (2018). *Package 'qdap.'* Tech. Rep., 2018. Online manual. https://cran.rproject.org

Holland, O. (2003). Exploration and high adventure: The legacy of Grey Walter. *Philosophical Transactions of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, *361*(1811), 2085–2121.

Jakobson, R. (1968). *Lingüística e comunicação*. Cultrix.

Joerges, B. (1999). Do politics have artefacts? *Social Studies of Science*, *29*(3), 411–431.

Karamibekr, M., & Ghorbani, A. A. (2012). Verb oriented sentiment classification, *1*(1), 327–331.

Kinedu. (2022). *Kinedu Blog—Baby development*. Kinedu Blog https://blog.kinedu.com/

Kooser, A. (2014). *Smart toilet paper holder won't be ignored when roll runs out*. CNET.Blogtext. https://www.cnet.com/culture/smart-toilet-paper-holder-wont-be-ignored-when-it-runs-out/

MacKenzie, D., & Wajcman, J. (1999). *The social shaping of technology*. Open University Press.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12–14.
McGraw Hill. (2022). *Social responsibility and sustainability*. McGraw Hill https://www.mheducation.com/about/social-responsibility-sustainability.html
Mindojo. (2022). *Artificial intelligence learning platform*. Mindojo https://www.mindojo.com/platform.html
ProctorU. (2022). *Accessibility, accommodations, and process exceptions*. ProctorU https://support.proctoru.com/hc/en-us/articles/5465054178701-Accessibility-Accommodations-and-Process-Exceptions
Renaissance Learning. (2022). *Star assessments—Overview | Renaissance*. https://www.renaissance.com/products/star-assessments/
Roschelle, J., & Hodkowski, N. M. (2020). *Using research on homework to improve remote and hybrid learning*. White Paper. Digital Promise.
Sense. (2022). *Sense*. https://www.sense.education/
Silge, J., & Robinson, D. (2017). *Text mining with R: A tidy approach*. O'Reilly Media, Inc.
Siyavula Education. (2022). *Technology*. https://www.siyavulaeducation.com/technology-approach.html
Sokolova, M., & Lapalme, G. (2008, May). Verbs speak loud: Verb categories in learning polarity and strength of opinions. In *Proceedings of the Conference of the Canadian Society for Computational Studies of Intelligence* (pp. 320–331). Springer Berlin, Heidelberg.
Taddeo, M., & Floridi, L. (2018). How AI can be a force for good. *Science*, *361*(6404), 751–752.
Todorov, T. (1989). *Nous et les autres. La réflexion française sur la diversité humaine*. Éditions du Seuil.
Ullmann, S. (1951). *The principles of semantics*. Jackson.
Watters, A. (2015). *The history of the future of education*. Hack Education.
Watters, A. (2021). *Teaching machines: The history of personalized learning*. MIT Press.
Wing, J. M. (2018, August). Data for Good. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. (p. 4). ACM, London.
Winner, L. (1980). Do artifacts have politics? *Daedalus*, *109*(1), 121–136.
Zuboff, S. (2015). Big other: Surveillance capitalism and the prospects of an information civilization. *Journal of Information Technology*, *30*(1), 75–89.

How to cite this article: Blikstein, P., Zheng, Y., & Zhou, K. Z. (2022). Ceci n'est pas une école: Discourses of artificial intelligence in education through the lens of semiotic analytics. *European Journal of Education*, *57*, 571–583. https://doi.org/10.1111/ejed.12528