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Teacher alchemy? The potential for combining digital and social methodologies in supporting learners in the humanities and social sciences

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ABSTRACT

Debates surrounding the use of data science in educational AI are frequently rather entrenched, revolving around commercial models and talk of teacher replacement. This article explores the potential for digital textual analysis within humanities and social science education, advocating for a sociologically-driven approach that complements, rather than replaces, the professional skills of teachers. It outlines existing methods for analysing learner writing using socio-cultural theories, including Halliday's Systemic Functional Linguistics, and Maton's Legitimation Code Theory. While the quality of linguistic output only forms one learner progress indicator, it is central to the process of schooling, and therefore deserves scrutiny. Digital Textual Analysis methods can be developed through natural language processing techniques to harness both formal and informal learner texts to map conceptual development and language use, informing classroom practice and assessment. The article emphasises the ethical considerations of such data use, advocating for socially inclusive analysis techniques that ensure fairness, transparency, and inclusivity. By leveraging machine learning and statistical techniques, we suggest that digital textual analysis can significantly enhance teachers' ability to monitor and support learner progress. We present a vision for redefining teacher professionalism in the digital age, proposing a balanced integration of technology that enhances rather than undermines the teacher's role, ensuring a learner-centred, ethical approach.

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Introduction

Considering the role of data science in education often involves engaging in a somewhat entrenched debate around the problem of whether (some) teachers can usefully be replaced by digital systems, and whether doing so represents a reductive model of education or imposes a dominant curriculum model (Kucirkova & Leaton Gray, 2023). This article examines the broader scope for using digital textual analysis in teaching and learning, potentially infused with socio-cultural approaches, considering its role as complementary to the professional skills of a teacher. Humanities and social sciences have been chosen here as they are the most text-based of all the subject domains commonly encountered in school.

The article locates digital textual analysis within the context of contemporary challenges arising from teacher recruitment and workload pressures which can lead to problems with continuity of staffing in schools, a phenomenon that is well documented over the last decade but exacerbated by the Covid-19 pandemic (Allen et al., 2022; Menzies, 2023). This in turn can lead to difficulties in consistently monitoring pupil progress over time, whilst also recognising and accommodating the uniqueness of each individual (Atteberry et al., 2017; Carver-Thomas & Darling-Hammond, 2017; Gibbons et al, 2018). In the face of such challenges, existing education platforms and technology-led assessment mechanisms may fall short in capturing the full range of pupil development, particularly in educational phases and situations that lack externally moderated summative evaluations.

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To that end, the article explores the potential of using particular forms of what can be described as 'digital trace data' (Hakimi et al., 2021; Menchen-Trevino, 2013) combined with the analysis of longer form writing such as coursework and homework, using socio-cultural analytical mechanisms, combining them as a transformative tool for teachers seeking a broader and longer view of learner progress. Here we focus on a particular type of digital trace data that relates to intentionally contributed pieces of writing such as posts onto educational platforms, messages and emails to and from teachers, and general online communication carried out in the context of school, using approved platforms such as Google Classroom, Moodle, etc. While there are significant ethical issues surrounding the use of such data (Williamson et al., 2020), and risks of bias in terms of the applicability to native and non-native speakers or a language, there is also potential for teachers to enhance their capacity to engage in assessment for learning, beyond the development of a language primarily aimed at formal assessment (Basterra et al., 2010; Rakovic et al., 2022). This is particularly the case in relation to language use and development, but also in terms of the ability to create a conceptual schema for learning, something which is vital for effective pupil progress. When combined with the digital textual analysis of more formal writing such as classwork and homework tasks, if the right approach is used, this can help reconceptualise what it means to be a teaching professional in school, beyond the reductive technicist model promoted implicitly (or explicitly) by many software platforms.

The sociology of education has something vital to add here. Developing innovative data analytics models based on the principles of sociology can provide a socially inclusive basis for the use of machine learning and statistical techniques. This is especially the case if they are designed sensitively to accommodate theoretical frameworks such as Halliday's Systemic Functional Linguistics (Halliday, 1985, 2003: Halliday & Hasan, 1989; Halliday & Matthiessen, 1999) and Maton's Legitimation Code Theory (Maton, 2014a; Maton, et al., 2016; Maton & Chen 2016, 2019). This contrasts with seeing data collection or analysis processes as an algorithmic end in themselves, enabling the identification of trends and indicators within language usage. It can indicate progress (or difficulty) that may elude routine human observation, whilst being sensitive to the social situation of particular pupils or groups of pupils. The scalability of these techniques to large datasets further enhances any potential, making them valuable tools for longitudinal assessment at a collective level as well.

Using language tracking in this way is not new, for example Saint et al. (2020) use a similar framing in their study of engineering students, in which they use data mining techniques to identify different types of self-regulation habits in learning, and Plunas (2018) uses sociolinguistics in framing aspects of mathematics education. Kerz et al model children's first language writing development across different grades in England and Germany using what they term 'complexity contours' (Kerz et al., 2020), and Wood, et al. (2020) successfully use lexical diversity to track written language growth amongst school-aged children. Language tracking is also not limited to individual learners. As exemplified by Suraworachet, et al. (2024), it can also be used to track groups' language discourse to detect their challenges and social regulation.

The central argument of this methodological article has three key dimensions. Firstly, it argues that tracking language is invaluable, as linguistic nuances can be intrinsically linked to developmental, cultural, educational, and also potentially health- and disability-related factors that can be recognised and remediated if brought into the daylight throughout the learning process. Subtle exploration of linguistic features in this way becomes key to unlocking the potential for improvements in subject knowledge and understanding during the learning process, whilst also accommodating inherent variability in language usage across individual learners (in other words, resisting the temptation to narrow language in order to make it easy to assess). The article suggests a number of suitable techniques and metrics that can be used and combined in order to achieve this. Secondly, the article explores how incorporating information about linguistic ability and usage over time, in informal (trace data) and formal (coursework and homework) written contexts can contribute to mapping progress holistically, as well as aiding in the ongoing identification of learners requiring additional support. It argues that a sociological framing is essential to ensure that any approach is ethically grounded to a sufficient degree. Finally, the article considers that these mechanisms and practices potentially allow for a redefinition of teacher professionalism in schooling and a clarification of how technology can act as a teacher adjunct. Such a redefinition incorporates data-driven enquiry whilst at the same time maintaining important characteristics of teacher professionalism that promote the holistic understanding of learners as individuals.

By exploring the potential of digital textual data analysis for education, the article then seeks to address the broader question of how learning and assessment processes can be redesigned to include an element of automation, ensuring fairness, transparency, explainability, reliability, accountability, privacy, inclusivity and ethical use across diverse social groups, linguistic backgrounds, regions, and educational levels, which can be a challenging enterprise (Sanderson et al., 2023). The proposed sociological perspectives offer a novel way of aligning contemporary educational challenges with these important affordances of data science, suggesting new ways of optimising learning experiences and support structures with particular relevance for the humanities and social sciences, but also across the wider educational domain.

Reframing teacher professionalism

It is well-recognised that digital transformations, such as the one proposed here by the integration of digital textual data analysis for education, can pose significant risks to the teaching profession and can lead to cognitive atrophy (Cukurova, 2024). Unless they are infused with sociological perspectives, such data-driven processes may run the risk of reducing teaching and learning processes to calculations. They may also pose challenges to teachers' professional status through the inappropriate automation of tasks as a means of replacing human teachers. They do this by reducing semantic analysis of textual data to what digital data analysis techniques can process, model, and deliver. Without careful consideration of the socio-technical nature of the issues, unjustified enthusiasm can exacerbate the existing international crisis in teacher recruitment and retention. This can happen as a result of disproportionate spending on digital transformation for textual data analysis in education systems, repurposed from overall budgets for employing and developing teachers.

We propose an alternative sociological perspective, that allows for better alignment of digital textual data analysis with existing real-world educational problems. There are numerous challenges with existing AI solutions that lead them to be unfit for adoption in real-world classes. These include AI's inflexibility in relation to the ever-changing dynamic contexts of everyday classrooms, as well as a lack of human-centred design considerations. In addition to technological factors such as the reliability and credibility of the AI tools, Cukurova et al. (2023) have identified three other crucial aspects: the pedagogical aspect (the extent to which AI empowers teachers in their pedagogical practices while reducing workload); the governance aspect (reflecting the organisational vision of AI in practice) and the teacher empowerment and interaction aspect (emphasising the importance of a supportive community for AI use in schools). The proposed sociological perspectives in this article have the potential to help address some of these concerns to a great extent.

Implementation needs careful consideration, as there is a risk of creating additional work for teachers without a sufficiently positive outcome for learners. Therefore, we see this approach being carried out by individual classroom teachers after adequate personalised training along the lines of that suggested by Palacios-Rodriguez et al. (2025), using carefully designed platforms that emphasise the formative nature of such an assessment without creating a new administrative or assessment burden for education professionals. Teachers' AI competency development is highlighted frequently both among scholars (Nazaretsky et al., 2022), and international organisations like UNESCO (Miao, & Cukurova, 2024) as a necessary but not sufficient condition for AI to make any positive real-world impact in education. In this context, this methodology can be seen as a form of new digital competence for teachers that supports their wider role as educators.

Potential methodologies for digital textual analysis

Language plays a crucial role in learning, but the specifics of how language is tied to cognitive processes, and what this might mean for learning, has been a topic of debate for two centuries. Explaining the debate fully is clearly well beyond the scope of this article, although it is useful to trace the intellectual thread very briefly here, prior to considering the relationship between the development of language and thought in the context of digital learning.

In the early 19th century Humboldt (1999, 2nd edition) categorised language and culture as a mental power, emerging from human necessity, and serving both communicative and cognitive functions. Later, Sapir explored whether the structure of language influences the way speakers perceive and categorise their experiences, laying the groundwork for the Sapir-Whorf hypothesis (Sapir, 1929). Whorf, a student of Sapir, suggested that language structure shapes cognition, demonstrating some degree of variation in mental concepts (Whorf, 1956). As Penn (1972) reminds us, much of this linguistics research was designed to identify whether language had such a thing as a 'universal', or fundamental component (indeed Chomsky, 2006, argues that children have an innate linguistic capability, which he termed a 'language-acquisition device', to this end). Where this becomes more relevant to education is through the work of Vygotsky, who argued that rather than language being in some way universal and innate, social interaction was key to the development of mental abilities such as speech and reasoning in children, as it was a socially mediated process (Vygotsky, 1980). It may not be possible to identify precisely which specific cognitive mechanisms are at play within Vygotsky's sociocultural theory of language development, and his theory has been criticised for this reason. However his theory does pave the way for tracking language development over time on digital platforms, as learners engage with subject knowledge as well with others, also using it as a proxy for measuring learning p,rogress. This can be achieved via passive monitoring systems that work in the background while spontaneous and/or scheduled writing tasks are completed, such as emails, messages, contributions to class forums, classroom assignments or homework, using metrics that will be described in detail later in the article.

Surprisingly there is little empirical research on the development of academic language skills in children's first or native language (Kerz et al., 2020), suggesting this is a neglected area. Vygostky's theories indicate that when developing any kind of holistic analytical framework for education, it is important to incorporate different ways of understanding a pupil's latent receptive and expressive language function, as well as understanding how that links to the social and cultural context of the learner. It is here where additionally drawing on the work of authors such as Halliday and Maton can be particularly useful, although there are two key considerations to be taken into account before we do so.

Firstly, we need to bear in mind that language function can of course change over time for reasons unrelated to what is happening in the classroom or overall developmental trajectory. In other words, development is uneven and there could be several reasons for this. For example, there are several common linguistic and memory-related problems experienced by people of all ages at different stages throughout their lives, for example when tired, when busy, distracted or preoccupied, rushing, or when on certain kinds of medication or unwell. This may create a temporary dip in linguistic ability, and children and young people are certainly no exception.

Secondly, the difficulty with identifying most of these linguistic artefacts is that they are relatively 'high-level' and not easily identified digitally; for example, relating ideas or events in order. It is here where the professional skill and expertise of the teacher are in most demand. However, as an adjunct to human review, it is possible to analyse lower-level linguistic features digitally: for example, tracking the frequency and variety of particular words, technical terms, or semantic categories in speech. Here, software tools incorporating known and novel techniques can usefully be developed for language analysis, drawing upon existing software tested against multiple datasets such as the Linguistic Inquiry and Word Count (LIWC) developed by Pennebaker et al. (2001, 2007). Five main types of analysis are of particular interest here: Type-Token Ratio for linguistic variety (TTR), analysis of low-frequency words, mean length of utterance, incidence of regular versus irregular grammar, and (to a lesser extent) a collation of many of these via Large Language Models (LLM) The article now describes the advantages of each in turn, along with any potential disadvantages or mitigations that need to be made. (It should be noted that mapping these metrics is only the first stage in tracking learner development; providing adequate sociocultural context is discussed in the subsequent section).

Type-token ratio (TTR) for linguistic variety

This is a key metric in linguistic analysis that provides insights into the lexical diversity of a given text or speech sample in both clinical and non-clinical settings (Yang et al., 2022). As Thomas (2005) reminds us, it has been used in educational research since at least the 1980s, for example, Mizon's study of native versus non-native speakers teaching in England and India, as well as Kleifgen's study of English as a Second Language talk in early years settings.

This ratio is calculated by dividing the number of different words (types) by the total number of words (tokens) in the sample. Essentially, TTR quantifies the variety of distinct words relative to the overall word count, offering a numerical representation of the richness or repetitiveness of vocabulary within a linguistic expression, meaning we would expect a university professor to achieve a much more favourable score than, for example, a young person studying history for the first time.[1] There is significant utility in tracking TTR in terms of pupils' progress, examples are given below.

Vocabulary diversity

TTR serves as a reliable indicator of the diversity of vocabulary used by learners. As they progress, an increase in TTR may signify a growing command of subject-specific terms and a broader engagement with varied linguistic expressions. This may be particularly relevant in humanities and social sciences subjects where a rich and nuanced vocabulary is often associated with deeper understanding and critical thinking.

Subject-specific language proficiency

In disciplines like literature, philosophy, or history, learners are expected to acquire and deploy subject-specific terminology. Monitoring changes in TTR over time can offer teachers insights into learners' proficiency in using technical or specialised language associated with their humanities and social sciences studies. A rising TTR may suggest a maturation in linguistic skills and a deeper integration of subject-related concepts.

Identification of learning challenges

Conversely, a stagnant or declining TTR could be indicative of linguistic challenges or difficulties in grasping subject-specific content, or increasing health or wellbeing issues. Analysing TTR longitudinally potentially enables teachers to pinpoint areas of struggle or potential learning gaps, guiding targeted interventions to support learners in their linguistic and conceptual development, or indicating where onward referral might be appropriate.

Differentiating learning phases

TTR analysis proves valuable in distinguishing linguistic patterns across various educational phases, such as the transition from lower to upper secondary school. Understanding how TTR evolves in different contexts allows for tailored pedagogical approaches, or between home and school, ensuring continuity and coherence in linguistic development. This potentially impacts all school subject areas and contributes to offsetting 'learning loss' attributable to change and disruption (whether planned, such as primary to secondary school transition, or unplanned, such as pandemic lockdowns).

Comparative analysis

By benchmarking TTR against individual, group, and wider learning population norms, teachers gain a comparative lens of progress. This facilitates the identification of outliers and allows for a more nuanced understanding of individual learner progress within broader educational contexts, contributing to improvements in teacher professional development.

TTR emerges as a potent tool for monitoring learner progress by quantifying the inherent lexical diversity in learners' linguistic expressions in a number of complementary ways. These metrics not only capture the evolution of vocabulary richness, which is obviously important in learning but also equip teachers with the possibility of a practical feedback loop to refine their teaching strategies and enhance the overall teaching and learning experience.

In fact, TTR played a crucial role in creating effective machine learning models in early Natural Language Processing (NLP) models, a key aspect of AI. These metrics help train language models, enhancing their grasp of intricate language nuances and improving language generation and understanding. TTR metrics, in this scenario, therefore serve a dual purpose by analysing learner progress and identifying areas for improvement at both individual and group levels.

However as identified by Yang et al. (2022), TTR does face some limitations, particularly in contexts involving younger age groups as well as the use of technical or subject-related language which contains less narrative. Therefore, developing a suitable way of analysing digital texts requires exploring parallel, complementary approaches, accessing algorithms for improved accuracy. Two notable tools, the 'Codes for the Human Analysis of Transcripts' (CHAT) format and the Child Language Analysis (CLAN) software package, are not only technical aids but also sociological instruments shaping the study of language within social contexts. Combined with Parameter D, which tracks vocabulary diversity, they can be used as standardised tools to create greater reliability when tracking learning in the humanities and social sciences.

Codes for the human analysis of transcripts (CHAT)

Rooted in the Child Language Data Exchange System (CHILDES) project (MacWhinney, 2000, 2015), the CHAT format provides more than a structured foundation for linguistic analysis; it is embedded within a comprehensive database devoted to the study of conversational interactions. Sociologically, this integration places linguistic analysis within a broader context of social exchange. CHAT's standardised approach to Type-Token Ratio (TTR) usage facilitates seamless comparisons, not just across linguistic samples, but across the diverse social contexts in which these interactions unfold. This sociolinguistic lens recognises language as a dynamic element within the intricate fabric of social life.

Child language analysis (CLAN) and vocd extension

CLAN, as a software suite designed for language data analysis within the CHILDES framework, gains sociological significance by placing linguistic patterns within the socio-cultural milieu. When coupled with McKee's vocabulary dispersion (vocd) software extension (McKee, 2000; Malvern et al, 2004), CLAN becomes a potent sociolinguistic tool for TTR analysis. This combination enables researchers to explore nuanced vocabulary diversity trends, acknowledging that language use is inherently tied to social dynamics. By identifying optimal fits between empirical and theoretical curves, researchers gain insights into how language evolves within specific social groups and contexts.

Parameter D for vocabulary diversity

The introduction of parameter D addresses the sociological nuances of linguistic diversity by allowing for the researcher to define a broader range of terms than might otherwise be possible (McGhee, 2000:324). This validated parameter therefore recognises the impact of social factors on language use, transcending traditional TTR calculations that might overlook variations in social contexts. With Parameter D values reflecting a spectrum from severely language-delayed infants (who might score 5) to highly technical written texts (which might score 100), this sociolinguistic metric provides teachers with a standardised tool to explore and compare vocabulary diversity across diverse social landscapes. It acknowledges that language, as a social construct, varies in its richness and complexity within different societal settings.

Analysis of low-frequency words

This is also a valuable approach in linguistic analysis, showing the intricacies of the way learners engage with language. This method involves investigating the probability of occurrence of words with lower frequency. This has particular utility in informal writing, or where they are grouped as low-frequency collocations, adjectives and verbs, indicating subjectivity (Wiebe et al., 2004). There are four potential aspects of interest here.

Identification of linguistic progress

Tracking the frequency of words used by learners in their humanities and social sciences work provides a dynamic measure of linguistic progress. A shift in the usage patterns of lower-frequency words may signify an evolving sophistication in language skills and a deeper engagement with complex concepts within the humanities and social sciences curriculum.

Distinguishing linguistic patterns

This analysis allows for the differentiation of linguistic patterns across various stages of learning. By understanding how the usage of lower-frequency words in phrases and sentences evolves, teachers can tailor instructional strategies to meet the changing linguistic demands of learners as they progress.

Potential early detection of cognitive changes

In a broader context, the analysis of low-frequency words could potentially contribute to the early detection of cognitive changes or challenges. Deviations from established patterns may prompt further investigation into learners' cognitive well-being and inform appropriate support mechanisms.

Comparative analysis across groups

Comparative analysis of the frequency of lower-frequency words can provide valuable insights when benchmarked against norms for different groups or educational levels. This comparative lens allows teachers to understand how linguistic patterns vary, adapting teaching approaches accordingly.

Mean length of utterance (MLU)

This is a valuable linguistic metric that serves as a stable developmental measure. It is particularly linked to the early stages of language acquisition in younger children, including those with speech impairments (Rice et al., 2010), but has potential for use further up the age range including adults as well, as it is not necessarily age specific (Borovsky, & et al., 2012). It provides insight into how learners structure their spoken expressions by examining the average length of their utterances, expressed in terms of the number of morphemes or words. As language skills progress, MLU tends to increase, reflecting a growing ability to construct more elaborate and syntactically complex sentences. Research suggests that MLU can offer insights into language development at later stages, providing teachers and researchers with valuable information about a learner's linguistic competence. In the context of academic progress, monitoring changes in MLU over time can help identify developmental milestones and potential challenges that may impact language-related academic skills.

This information can guide instructional strategies tailored to support learners in enhancing their language skills within the context of humanities and social sciences subjects. MLU can be compared against developmental benchmarks, allowing teachers to gauge whether learners are progressing in line with age- or stage-appropriate language development norms. Deviations in MLU may indicate areas where learners may benefit from additional language support or targeted interventions to bolster their academic progress. MLU should also be considered alongside other linguistic metrics for a comprehensive understanding of learners' language proficiency, encompassing vocabulary richness, syntactic complexity, and discourse coherence.

In terms of predictive analytics underpinning the development of AI-based tools, the utility of Mean Length of Utterance (MLU) stands out due to its consistent developmental measure. MLU smoothly fits into AI applications, contributing to the development of language proficiency models. Using data science techniques, predictive models based on a reasonably sized learning population can use historical MLU patterns to predict future language proficiency, helping identify potential language challenges early on. Beyond assessments, MLU also has the potential to become a central part of the technical setup of AI-driven educational support systems in the humanities and social sciences. These systems can adjust to individual language learning paths, providing personalised interventions that optimise the learning experience by encouraging the development of longer and more complex expressions over time.

Incidence of regular vs irregular grammar

This is also a valuable linguistic analysis exercise, and is particularly relevant in assessing the later phases of language learning. This metric involves scrutinising the patterns of grammatical structures employed by individuals, shedding light on their command over language rules and conventions. Regular grammar follows predictable rules, while irregular grammar involves exceptions and non-standard patterns. Therefore, analysing the incidence of these grammatical structures provides insights into the complexity and depth of a person's language proficiency.

This has relevance in two respects. The first, and most obvious, is for foreign language learners, where grammar is likely to be explicitly taught. Here it can demonstrate the success of a particular pedagogical approach, although it is unlikely to add insights that would not otherwise be common amongst trained language teachers. However, in a digital sense, it is likely to have more relevance in relation to the use of a learner's primary native language. The incidence of regular versus irregular grammar here can serve as a potential marker for language delay or impairment. Deviations from expected patterns may indicate challenges in mastering the intricacies of language rules. This metric then becomes instrumental in identifying individuals who may require specific types of educational support tailored to address language-related difficulties.

In terms of developing AI-related tools, the detailed analysis of regular versus irregular grammar once again aligns well with the goals of Natural Language Processing. Existing machine learning algorithms already exist that recognise and refine patterns in grammar usage, resulting in advanced grammar checkers and language correction tools. Applied to humanities and social sciences education, this technical foundation can transform learning experiences, addressing individual language quirks, and enhancing overall language proficiency. Importantly, this process can happen alongside tracking and assessing learners' progress over time.

Generative AI and large language models

Significant amounts of current interest in AI stems from the recent advancements in Large Language Models (LLM). Although these approaches are indeed impressive with their performance in natural language processing, their value for textual data analysis for educational purposes might be limited due to their technical features. Most of state-of-the-art language models are based on a transformer architecture. During pre-training, a large-scale dataset of sentences is used as input to the transformer architecture. The inputs, for example masked-out words or paired sentences, are processed automatically and the neural network model is optimised to reconstruct the original text. First, an input is fed into the neural network, and it passes through the network's layers to produce an output. This process is known as the forward pass, where each layer's output is the input for the next layer, culminating in a final output from the network and it provides some predictions on masked words, next sentences, and so on. Since the actual masked words and next sentences in the original text are known, based on the differences between actual and model predicted labels, a loss function is calculated. This function measures how far the network's prediction is from the actual result and backpropagation is used to minimize the loss by adjusting the weights of the network. This process of forward pass, loss calculation, backpropagation, and weight update are repeated over many iterations (or epochs) across the entire training dataset leading to the final pre-trained large language model. After the pre-training stage, LLMs are commonly fine-tuned to improve their performance. This is the subsequent process of refining the model on a smaller, more specific dataset to adapt it to a particular domain or task (e.g through reinforcement learning with human feedback). They are also further prompt-tuned which involves optimizing the input prompts to guide the pre-trained model's behaviour on specific tasks without actually changing the model's parameters.

This approach leads to current best performing NLP models. However, due to their non-transparent nature described above, their value for digital text data tracking might be limited. They lack clear measures of success as described in earlier more transparent traditional natural language processing approaches, which makes it difficult for feedback opportunities for learners. However, they can still be valuable for diagnosis purposes (e.g. predicting particular language issues with a relatively high accuracy to support teachers in their prioritisation of interventions for their learners).

A sociological framing for digital textual analysis

Any effective system for tracking learning via language metrics needs to go beyond the purely statistical, if it is to achieve its potential in optimising learning, rather than simply classifying and categorising learners in new ways along the lines of labelling theory (Hargreaves, & et al., 1975). It is here where Maton's Legitimation Code Theory (LCT) and Halliday's Systemic Functional Linguistics (SFL) can be most useful in the development of a robust methodology. This is because framing any development process in this way means that the pedagogical praxis is appropriately underpinned by ethical considerations.

These frameworks are particularly relevant because they provide a comprehensive understanding of language, knowledge construction, and social practices within educational contexts. Embracing these theories ensures that linguistic analysis goes beyond technical details, fostering inclusivity and transparency—key elements for any effective AI-based pedagogical intervention or tool. Addressing ethical issues and data privacy, especially in light of regulations like the 2018 General Data Protection Regulation (GDPR), or similar pieces of legislation in different countries (e.g. EU AI Act), is crucial. For instance, teachers carrying out analysis must be vigilant about how student data is collected, stored, and used, ensuring that personally identifiable information (PII) is anonymised if the data are to be shared beyond immediate relevance for classroom purposes.

Proper respect for data privacy and ethical practice is important for various philosophical and pragmatic reasons, but also theoretical considerations like Legitimation Code Theory (LCT) which emphasises fair and equitable knowledge dissemination, aligning with ethical principles of educational access and the protection of learner data. Meanwhile, Systemic Functional Linguistics (SFL) focuses on the functional aspects of language, allowing for nuanced analyses that respect the diverse communicative functions of language. Appropriate caution leads to an inclusive model that remains developmental while considering ethical implications related to data privacy and the potential misuse of personal information. The next section discusses the technical aspects of both models in more detail.

Legitimation code theory (LCT)

In the context of textual analysis in humanities and social sciences education, Maton's Legitimation Code Theory (LCT) (Maton, 2014a; Maton & Chen 2016, 2019; Maton, et al., 2016) is potentially a powerful tool, particularly in relation to its concepts of semantic gravity (degree of complexity of a thing, knowledge or practice), semantic density (the degree of abstraction or distance from context) and specialisation codes (the basis of achievement underlying practices, dispositions and concepts, demonstrating, for example, the relationship between knowledge and knower, which can illuminate wider relationships of power). These ideas become tangible when applied to specific subject areas, for example as demonstrated by Vernon (2021) who examines the way knowledge in Geography is recontextualised by an examination board in favour of an ideal 'knower'.

Consider also, for example, an analysis of learner writing relating to an historical text using LCT-informed tools. The Type-Token Ratio (TTR), quantifies the diversity of historical terms. Analysing it for semantic gravity and semantic density in addition to this reveals the abstractness and richness of the vocabulary associated with developing an understanding of a particular historical period by looking at specialised language. Similarly, applying Mean Length of Utterance (MLU) to, say, philosophical discourse demonstrates the intricacy of specialisation codes relating to different constructs. Longer and more complex sentences may signify a depth of specialisation and a nuanced engagement with intricate ideas (at least when they make sense), although admittedly this is more likely in spoken language than written language.

By integrating LCT concepts with these tools, teachers are able to gain a granular understanding of how language functions within the unique domains of history or philosophy, for example, unravelling the levels of abstraction, specialisation, and complexity inherent in subject-specific texts. LCT can also be used alongside Generative AI or LLMs to assess and challenge the legitimation of knowledge presented.

In this way, incorporating LCT within any textual analysis model contributes to an understanding of the social practices of teaching and learning, extending teacher assessment beyond a simple two-dimensional metric.

Systemic functional linguistics *(SFL)*

Systemic Functional Linguistics (SFL) (Halliday, 1985, 2003; Halliday & Hasan, 1989; Halliday & Matthiessen, 1999) offers a nuanced and comprehensive theoretical framework for analysing language function in context. The theory revolves around three interconnected metafunctions: ideational, interpersonal, and textual. Within SFL, the ideational metafunction focuses on how language constructs meanings about the world. TTR analysis, reflecting vocabulary diversity, aligns well here. The interpersonal metafunction in SFL is concerned with the social aspects of communication, emphasising how language is used to enact roles and relationships. While TTR and MLU may not directly tap into the interpersonal metafunction, their outcomes contribute to the broader understanding of how linguistic choices influence social interactions within educational settings. For instance, MLU, as a measure of linguistic complexity, can be linked to social roles and relationships. SFL's textual metafunction examines how language functions within texts to convey meaning and serve communicative purposes. The analysis of grammar patterns directly aligns with the textual metafunction. This involves exploring how language is structured and organised within specific educational contexts, emphasising the syntactic choices made by learners. Through this, the intricacies of grammar patterns become a lens through which the textual dynamics of a given discourse are deciphered. Finally, analysing writing samples through the use of an LLM familiar with SFL categories can assist in assessing how students express ideational meanings, or structure their texts in a cohesive manner.

Another integral part of SFL is the transitivity system, which looks at the processes, participants, and circumstances involved in linguistic expressions. When applied to textual analysis, this system allows for a deeper exploration of how learners construct and convey meaning through different processes, such as doing, sensing, or being, which has particular relevance for situations such as writing up fieldwork notes from a school trip, for example. SFL also incorporates comparable insights from Functional Sentence Perspective, which considers the functional roles of different parts of a sentence. In the realm of Mean Length of Utterance (MLU) analysis, this perspective can be leveraged to explore how learners structure sentences to achieve specific communicative functions, shedding light on their understanding and deployment of language in academic contexts.

Through the use of these two approaches, it is possible to develop a sociological framing for digital textual analysis. It enriches the understanding of how learners engage with text as they learn, and how the text they produce in their own right can reveal aspects of their learning over time. These tools therefore not only provide linguistic insights, but also contribute to a deeper comprehension of the intricate social dynamics inherent in language use within educational settings. By embracing this holistic approach drawing on educational sociology, digital textual analysis becomes an ethically informed practice, fostering inclusivity, fairness, accountability and reliability.

There is one important point to make here, however, if the approaches are to be used effectively. LCT and SFL are theoretical frameworks that are proposed here to inform natural language processing (NLP) methodologies. One of the fundamental reasons behind this proposition is the idea is that these theoretical considerations focus on understanding language in context. The reliability and validity of data supporting LCT and SFL are critical for their application in NLP. For that reason, addressing the issue of inter-rater reliability is essential to ensure consistent coding across different raters when building a model that is going to be of practical use in schools. Reliability in such situations is often measured using metrics such as Cohen's kappa[2] or Krippendorff's alpha[3]. For NLP tools, accuracy measures such as BLUE, METEOR, Perplexity, ROUGE and F1 score evaluate algorithm performance in tasks like text translation, classification or sentiment analysis. In addition to a strict statistical model, the robustness of LCT and SFL can be assessed through triangulation of methods, enhancing the credibility of findings and ensuring that the interpretations derived from data are both reliable and valid across varied contexts. However, as with any analysis of this type, limitations exist, such as potential biases in qualitative assessments and the challenges of adequately capturing the complexity of language in automated systems (as well as issues pertaining to non-native speakers, as we have already highlighted).

Connecting theory to classroom practice

The integration of Systemic Functional Linguistics (SFL) and Legitimation Code Theory (LCT) into classroom practice offers a powerful approach to enhancing both teaching and learning in the humanities and social sciences. By embedding these theoretical frameworks into everyday pedagogical strategies, teachers can more effectively assess and support student learning, ensuring that educational practices are both inclusive and responsive to the diverse needs of learners.

Systemic functional linguistics (SFL)

SFL's focus on the functional aspects of language—ideational, interpersonal, and textual—can be directly applied to classroom activities that involve reading, writing, and discourse. For instance, when students engage in writing tasks, teachers can use SFL to guide them in structuring their texts in ways that clearly convey meaning (ideational), establish appropriate relationships and tone (interpersonal), and ensure coherence and cohesion in their writing (textual). For example, in a history lesson where students are tasked with writing an essay on a significant event, SFL can help teachers instruct students on how to effectively use historical terminology, articulate complex ideas, and organise their arguments logically. This approach not only improves writing skills but also deepens students' understanding of how language shapes knowledge in specific disciplines.

Moreover, SFL can be used to analyse student work to identify areas where they may struggle with particular aspects of language use, such as the ability to articulate complex concepts or the appropriate use of specialised vocabulary. Teachers can then provide targeted feedback, helping students to refine their linguistic skills in ways that directly contribute to their overall academic development.

Legitimation code theory (LCT)

LCT provides a framework for understanding how knowledge is constructed and communicated within educational settings. In the classroom, this theory can be employed to design activities that help students navigate the complexities of academic discourse. For example, by analysing the semantic gravity (the degree to which meaning is context-dependent) and semantic density (the degree of complexity and abstraction) of tasks, teachers can scaffold learning experiences that gradually build students' ability to engage with more abstract and sophisticated ideas. In a literature class, for instance, a teacher might first engage students in discussions that connect a text to their own experiences (lower semantic gravity) before moving on to more abstract interpretations and theoretical analyses (higher semantic density).

LCT also emphasises the importance of recognising different forms of knowledge and ways of knowing. This is particularly relevant in diverse classrooms where students may bring varying cultural and linguistic backgrounds. By applying LCT, teachers can create a learning environment that values and incorporates these diverse perspectives, helping all students to access and contribute to the collective knowledge of the classroom. For instance, in a social studies class, students could be encouraged to share their own cultural narratives, which are then linked to broader sociological theories, thereby validating their experiences while also deepening their understanding of the subject matter.

Having a strong connection between theory and practice ultimately redefines teacher professionalism, positioning them as not just transmitters of knowledge, but also as facilitators of a deeper, more nuanced learning experience. It also underscores the importance of ongoing professional development, where teachers continually refine their pedagogical strategies. This can be amplified through further research as well, for example longitudinal studies that establish the longer-term impact of such analysis carried out by teachers, or comparative studies of how integrated digital and social methodologies such as these impact teacher professionalism and learner outcomes.

Conclusion

Systems designed with sociologically infused digital textual analysis can draw on a great deal of informal writing (in this case trace data such as emails, forum posts, and online messages composed using school learning platforms) and formal writing (in this case homework and coursework uploaded onto systems) to build a holistic profile of learners throughout their subject journey. Drawing on various key metrics and sociolinguistic approaches, digital textual analysis can act as adjunct to the teacher and potentially even as a kind of expert tutor to learners, if an inbuilt feedback loop is made available to them.

Four key metrics provide the basis for such an approach: **type token ratio**, used to track language proficiency and knowledge and understanding of technical terms; **low-frequency words**, used within informal and/or subjective writing to establish sophistication of expression; **mean length of utterance**, to track the development of sentence complexity over time, and **irregular vs regular grammar**, to indicate progress in terms of language construction and syntax. It is also technically possible to deploy Large Language Models, to analyse text, but this approach has greater limitations as they are not transparent and explainable for understanding models' decisions to craft effective feedback to learners. However any of these metrics on their own are insufficient for a truly holistic picture of a learner's journey, and it is here where sociolinguistics becomes particularly useful. Two leading theories allow for a more nuanced, socially orientated view of learners over time. There are Maton's Legitimation Code Theory, where concepts such as semantic gravity, semantic density and specialisation codes can be used to define the particular situation of a learner or school, allowing for a situational reading. This can be used alongside concepts such as autonomy to determine learner progress. The second theory is Halliday's Systematic Functional Linguistics, which allows for three areas of interest or metafunctions: ideational, demonstrating how a learner's language constructs meaning of the world, and how that might be expressed through vocabulary diversity; interpersonal, demonstrating how language enacts roles and relationships; and textual, demonstrating how language functions as a result of syntactic choices. Halliday's model also allows for an understanding of the learner's complex interrelationship with doing/sensing/being within the educational journey via his concept of transitivity. Taken together, such an approach allows us to develop a view of learners in the humanities and social sciences over time, adding to the teacher's conceptual toolkit and providing for greater learner continuity and support throughout the learning journey.

Notes

1. Although this would also vary by register and genre, depending on the disciplines. This variation applies to each of the metrics listed in this article.
2. Cohen's kappa is a statistical measure used to assess the level of agreement or reliability between two raters or observers who are classifying items into categories. It accounts for the agreement occurring by chance, providing a more accurate measure of inter-rater reliability than a simple percentage agreement. See Cohen (1960).
3. Krippendorff's alpha is a measure of how much agreement there is among multiple raters when they classify or code data, with a range from 0 (no agreement) to 1 (perfect agreement). See Hayes and Krippendorf (2007).

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