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# Critical AI literacy for applied linguistics and language education students

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**Abstract:** Following the generative artificial intelligence (GenAI) boom of the early 2020s, research in applied linguistics has become preoccupied with identifying how artificial intelligence (AI) and GenAI can be used effectively in research and education. As we emerge from our initial reactionary perspectives, there is an increased interest in delineating AI literacies so as to support learners who wish to engage with AI and GenAI as part of their learning process. This paper adds to this growing body of work, offering insight into critical AI literacies for applied linguistics and language education. Based on the critical grounded theory analysis of a focus group with Spanish students of applied linguistics, this paper teases apart the students' technical understandings of AI, use of critical thinking when engaging with AI, awareness of the ethical concerns surrounding AI, and practical applications of AI. The discussions revealed a complex interaction of practical, ethical, and analytical considerations, emphasizing AI's potential to augment but not replace human expertise. Ethical considerations were linked with critical thinking, reflecting a deep integration of moral and practical dimensions in student discussions. Our analysis seeks to inform current research that develops both frameworks and theoretical models for language education and applied linguistics education.

**Keywords:** AI; AI literacy; GenAI; generative artificial intelligence; higher education; language education

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# 1 Introduction

With the recent proliferation of user-friendly generative artificial intelligence tools (GenAI; e.g., ChatGPT), the use of artificial intelligence (AI) and Generative AI (GenAI) in education has become increasingly widespread (see Curry et al. 2025 for an overview). Digital technologies have revolutionised how humans manipulate linguistic symbols, akin to numbers and data, which is crucial for cognitive functions such as calculation, decision-making, and problem-solving (Lévy 2025). These are processes that AI can arguably facilitate and, as a consequence, the use case of GenAI in academia and higher education has become a central topic of debate.

Those who advocate for the integration of GenAI into educational contexts note its potential for transforming existing learning paradigms, offering personalised learning experiences and real-time feedback, and supporting educators in and beyond the classroom (Adigüzel et al. 2023). Crompton et al. (2024) have noted that, among other affordances for language learning, GenAI can help language learners practice speaking by offering pronunciation practice, acting as a conversational partner, and providing adaptive, multimodal feedback. GenAI also contributes to reading by supporting vocabulary acquisition – sometimes through gaming environments – and to pedagogy by enabling personalized instruction and fostering self-regulation. For the authors, these systems can reduce anxiety by giving learners a non-judgmental space to experiment with language and set learning goals. While such potential affordances abound, they are complemented by a comparable collection of concerns about the use of GenAI in education. Ethical issues in the use of GenAI have become one such central concern, with evidence of GenAI reinforcing and reconstructing biases in educational contexts (Choi 2022; Khan 2023). Likewise, the "black box" nature of GenAI (Curry et al. 2024; Curry et al. 2025; Curry and McEnery 2025), the limited public knowledge of the data on which the large language models are trained (Nesi 2024), the growing understanding of the negative impacts of GenAI on the environment and the global south (Ligozat et al. 2022), and the widening technological and digital divide in education (Li 2023) raise questions about the social value and cost of such tools. Yet, while debates surrounding GenAI continue to unfold in academic spaces, many learners across the world are already engaging with these tools to conduct their studies (Daher and Hussein 2024). In essence, the horse has bolted (Sauerbrei et al. 2022), the ship has sailed (Saguil 2024), and the genie is out of the bottle (Szudarski 2025). For example, recent evidence has shown that learners are already using GenAI as a search engine, idea generator, and a tool for writing support (Escalante et al. 2023; Kohnke 2024; Pérez-Paredes et al. 2025). However, despite the uptake in the use of GenAI, it remains unclear as to whether learners truly understand what the tools are doing, how they work, and what the outputs from these tools represent.

With a body of work on AI in applied linguistics steadily emerging, there is now a need to move past initial reactions to the affordances and caveats of GenAI in education and to engage critically and comprehensively with its relevance and use in education, for the use of such tools has already become a central practice for learners (Daher and Hussein 2024), a valued competency for employers (Prohorov et al. 2024), and a practice legitimated by educational institutions across the world (Dai et al. 2024). For as long as GenAI tools remain in use in educational settings, we need to make sense of current perspectives on GenAI for education and construct a coherent, logical, and evidence-based agenda built around critical AI literacies (CAIL) for learners. This contributes towards the development of a form of augmented intelligence (Fulbright and Walters 2020) that centres the role of the human in knowledge-making and seeks to enhance human knowledge-making practices through the use of AI. Given that effective AI and GenAI technology use needs to be aligned with the epistemological, ontological, and ethical values of the disciplines in which they are used, we argue that any such critical AI literacy must also be disciplinarily-grounded (Pérez-Paredes et al. 2025). To support such an aim in the context of applied linguistics and language education, there is a need to better comprehend learners' understandings of AI and GenAI, the ways in which they use AI and GenAI, their perceptions of AI and GenAI, their engagement with the ethics of AI and GenAI, as well as any gaps in their knowledge of AI and GenAI.

Shedding light on these facets of CAIL, this study presents an analysis of a focus group with university undergraduate students at a Spanish university. The focus group was designed to access applied linguistics and language education disciplinary perspectives on AI and GenAI. The students are studying applied linguistics and language education-related modules in a Southern European English-medium education in multilingual university settings (EMEMUS) context (Curry and Pérez-Paredes 2021; Dafouz and Smit 2020) and in parallel, they are EFL learners, developing their English language competencies throughout their programme of study. These learners study English at upper-intermediate and advanced levels while they take a set of modules in computational and socially-situated approaches to language analysis. For example, they study corpus linguistics and discourse analysis, as well as fundamental concepts in linguistics (e.g., grammar, syntax, morphology). They also learn to translate and about the processes of translation, the English language and English for academic purposes, and theories in language acquisition, *inter alia*. Thus, these learners have a complex insight into language and linguistics that cuts across the field of applied linguistics and its prominent subfield of language education. To gain a clearer picture of these learners' CAIL, we adopt a critical grounded theory approach to analyse a focus group through the disciplinary lens of applied linguistics in order to reveal the extent of these learners' CAIL and identify potential gaps in their knowledge. Furthermore, AI-GenAI systems provide open-

ended, interactive, and context-sensitive responses compared to the structured, task-specific affordances of CAIL. This distinction is crucial as our analysis sets out to examine how the GenAI affordances can be critically scrutinised within the broader framework of CAIL. With this information in hand, we propose a number of criteria that can be used to guide the development of CAIL for those studying applied linguistics and language education.

## 2 Critical AI literacy

Since the rapid adoption of GenAI tools such as ChatGPT in 2022, GenAI has become pervasive. While in the past, the use of AI was largely limited to those with expertise in the area, contemporary GenAI tools are used by people with a range of technical knowledge and expertise. Several factors explain the rapid adoption of AI and GenAI tools by the general public: (a) their ease of use and conversational interface that made advanced AI capabilities accessible to individuals with limited technical knowledge (Fan and Zhang 2024); (b) their versatility in generating content, which catered to a wide range of user needs, from casual information-seeking to professional applications (Cogo et al. 2024); and (c) their immediate availability and free access at launch that allowed users to experiment with and integrate AI into their daily routines without financial or technological barriers (Kaya 2024). In sum, GenAI tools like ChatGPT seem to meet the conditions for optimal technology adoption in line with the likes of the Technology Acceptance Model (TAM; Davis 1989).

The sudden irruption of GenAI tools was initially met with some scepticism at institutions across the globe, especially in educational settings. One cause of such scepticism pertained to the perceived ease of use associated with chat-based AI interfaces like ChatGPT. From the outset, teachers and learners were able to interact with the AI's advanced natural language capabilities, which enabled it to process information and generate human-like[1] language with seemingly little effort. As a consequence, educational institutions exhibited concerns about academic integrity and plagiarism (Eaton 2023). For them, there was a rising fear that learners would misuse GenAI tools – a misuse that would potentially undermine traditional assessment practices (Cogo et al. 2024). Additionally, educators and scholars raised issues regarding the accuracy and reliability of AI-generated content, which implicitly incurs the risk of spreading misinformation in academic contexts (Kaya 2024; Kern 2021). This scepticism was further fuelled by the opaqueness surrounding how AI tools access their data and how said data is actually processed (Curry et al.

1 How human-like these responses are remains up for debate, as research, such as Sardinha (2024), has evidenced significant linguistic differences in texts produced by GenAI tools and humans.

2024; Nesi 2024). This evidenced an understandable lack of preparedness among the educators and institutions faced with the challenge of integrating GenAI responsibly and effectively within their practices (Sperling et al. 2024).

Over time, however, the academic milieu has started to pay attention to the affordances of CAIL in educational contexts (Kaya 2024). In fact, educational researchers and institutions across the world have begun to develop frameworks to guide the ethical use of AI and GenAI, arguing for providing effective training in the responsible use of GenAI by fostering CAIL (Creely 2024; Dai et al. 2024; Kong et al. 2024). Higher education institutions have even expressed public support towards both their staff and their learners becoming AI-literate (Marx 2024). Research has also found that the development of CAIL can help enhance interdisciplinary learning by encouraging learners to critically assess AI's social impact while leveraging its tools for research and innovation (Sperling et al. 2024). Elsewhere, there have been attempts to adapt curricula to include critical discussions around AI's societal implications and wider discussions on the potential for GenAI tools to augment thinking and learning, rather than replace human thought (Curry et al. 2025; Yim and Wegerif 2024).

One of the areas in applied linguistics that has been impacted the most by the potential of GenAI is that of language learning (Curry et al. 2025). GenAI tools have been found to facilitate personalised feedback, increase learners' willingness to communicate, create adaptive learning experiences, and support enhanced interaction with language materials (Cogo et al. 2024; Han et al. 2024; Zhang et al. 2024). These tools empower learners by developing autonomy, improving proficiency, and engaging in critical evaluation of AI-generated outputs, fostering the development of both linguistic and digital competencies (Fan and Zhang 2024). The development of AI literacy in such contexts can integrate these advancements with academic rigour and prepare learners to analyse AI-assisted tools, their products, and their role in global communication and translation critically. Thus, we can explore AI's potential for collaborative learning and research while staying true to wider disciplinary practices (Curry et al. 2024; Yim and Wegerif 2024).

The initial reaction towards the use of GenAI in educational and academic contexts has resulted in somewhat divided perspectives. Dealing with the material reality that many learners across the world use AI and GenAI to support their studies, it is important to bridge these perspectives and lead the conversation towards establishing a solid foundation from which we can ensure GenAI and other AI-based tools are being used responsibly to benefit and complement the development of disciplinary knowledge and linguistic competencies. As Marx (2024) notes, "we should not attempt to stop technology, but rather to use it in responsible and helpful ways" (p. 1415). Thus, we should, as Tsui and Tavares (2021) argue, take a critical approach to the use of technology in education that maintains a focus on

pedagogy while remaining open to possible innovations beyond current working practices. Yet, such developments should be contextualised within wider disciplinary practices and global realities. This requires the fostering of the appropriate literacies across all members of the education community – literacies localised within varied disciplinary epistemologies and ontologies (Curry et al. 2025; Pérez-Paredes and Curry 2024).

Basic notions of AI literacy can be extrapolated from Kern's (2021) digital literacies, that is, a set of "symbolically mediated practices that involve various kinds of knowledge, predispositions, and skills to deal with texts in electronically-mediated environments" (Kern 2021 p. 134). Building literacy on a specific tool is essential for the user to make sense of all the possibilities and caveats involved in the utilisation of that same tool. This localised approach to literacy is well established already in applied linguistics, with, for example, calls for teacher education programs to include a focus on a "corpus literacy" (Abdel-Latif 2020; Breyer 2009), based on a view that developing teachers' corpus literacy will allow them to acquire the necessary skills to search, prepare, manage, and analyse corpus data and to effectively utilise corpus-based software and corpus outputs for educational purposes (Pérez-Paredes 2020; Pérez-Paredes and Curry 2024).

A similar literacy is needed to support the use of AI in the context of applied linguistics and language education. Casal-Otero et al. (2023) note that the acquisition of such a skillset in primary and secondary education implies the development of knowledge about AI itself and about how AI works. Likewise, Curry et al. (2025) argue that such literacies will need to cut across the epistemological, ontological, and ethical foundations of applied linguistics. Thus, CAIL involves not only technical knowledge but also a conceptual understanding of AI's capabilities and limitations (Long and Magerko 2020), as well as an awareness of its social and ethical ramifications (Yim and Wegerif 2024) within and beyond disciplinary contexts. While CAIL is arguably more effective when situated reflexively within disciplinary contexts, it also can vary in terms of a person's role in educational contexts. For example, Yang et al. (2024) identify the differing needs of students, educators, and administrators with regards to the GenAI literacies, noting that students require training in both the effective use of AI and the appropriate reporting on the use of AI. For educators, concerns orbit around tool selection and their pedagogical framing, while administrators focus on issues of well-being, tool regulation, and access to training. UNESCO's reports on teacher (Miao and Cukurova 2024) and student (Miao and Shiohira 2024) literacies for AI reflect similar differentiations, with a focus on developing teachers' CAIL to facilitate pedagogically-situated AI use in the former and developing learners' CAIL in terms of both AI use and technical knowledge of AI in the latter.

This paper contributes to the discussion around the relevance and scope of CAIL among learners in Higher Education, EMEMUS contexts, responding to the need for a localised and situated CAIL for students of applied linguistics and language education. Specifically, this study focuses on four broad domains of CAIL to determine how learners in this specific section of higher education engage with, use, evaluate, and understand AI and GenAI. Drawing on Marx (2024), we propose the following four dimensions involved in CAIL: (1) technical understanding (TU); (2) critical thinking (CT); (3) ethical awareness (EA); and (4) practical application (PA).

In Marx's (2024) framework, TU subsumes knowledge of how AI systems such as large language models (LLM) are trained, how LLMs function, and the technical limitations of AI and GenAI tools. CT pertains to AI and GenAI tool users' capacity to assess the reliability and validity of AI-generated outputs. CT also governs users' capacity to avoid over-reliance on GenAI tools. EA consists of users' capacity to acknowledge the ethical implications of using AI and GenAI tools, to determine a responsible usage of such tools, to adhere to disciplinary principles of transparency and fairness, and to consider the environmental and societal implications derived from the continuous usage of these resources. Finally, PA pertains to users' knowledge of the effective use and integration proof AI into tasks such as data analysis, hypothesis generation, and problem-solving. PA also subsumes users' capacity to acknowledge the importance of human oversight when using AI and GenAI tools.

The reflexivity of these four broad areas is particularly valuable for this exploratory study, given their capacity to subsume the range of competencies and the wider knowledge base attributed to learners' CAIL in a range of existing studies (e.g., Casal-Otero et al. 2023; Long and Magerko 2020; Miao and Cukurova 2024; Yang et al. 2024; Yim and Wegerif 2024). They were selected owing to their breadth and relevance across disciplines as this reflexivity signals their potential to be localised within applied linguistics and language education. Using these arguably universal criteria of CAIL, this study analyses the perspectives of students of applied linguistics and language education on GenAI tools and the impact of such tools in their learning processes. The aim of this analysis is to delineate their emerging CAIL while also identifying potential gaps therein. In so doing, we identify the potential challenges for enhancing CAIL among Higher Education students while proposing criteria for the development of CAIL for applied linguistics and language education.

# 3 Methodology

This section presents a description of the data used in this study in Section 3.1. This is followed by a discussion of the analytical approach, in Section 3.2.

## 3.1 Focus group data

The data of this study derives from a focus group conducted with learners from the 4th year of the Bachelor degree in English Studies at a Spanish EMEMUS university that emphasises the development of disciplinary knowledge alongside academic literacies. These literacies are taught through workshops, modules, and sometimes tailored language support programs that support the development of skills like academic writing and critical reading. The group of learners who participated in the focus group were recruited through the module, *Discourse and English language mass media,* during the 2023/2024 academic term. In this module, the students analyse English language mass media communication using corpus-assisted discourse analysis (CADS) for the first time in the degree. The module sees students examining the representation of minorities and people with diverse sexual orientations, discourses related to political ideologies, the emergence of populism, the extreme right in English speaking countries, and discourse and identity, *inter alia*. Through this module, the students hone their undergraduate research abilities, analyse and evaluate language data collected from a variety of sources (mostly newspapers), and gain insight into the ways in which discourses around a variety of topics are found in mass-media texts. The module also presents opportunities for indirect advanced language learning.

As the module progresses, learners are required to work in groups and select a research topic that they will investigate in depth. They are given the freedom to choose the ideological issue they wish to analyse, the time frame (span of years) for the analysis, and the newspapers on which they focus (usually from the US, the UK, or both). To do so, students use corpus methods and language data analysis to gain insights derived from frequency patterns, facilitating the identification of prevalent and less common discourses within societies. The adoption of corpus methods in this module is premised on the view that querying corpus data enhances our comprehension of the materialisation of discourses in texts and the role of language in the representation of objects, individuals, concepts, and social issues (Pérez-Paredes 2024). This module is designed to be a culmination of the learners' undergraduate journey through applied linguistics and language education research. They are encouraged to draw on knowledge and experience from other modules in the programme and make use of all of their linguistic expertise.

Three learners took part in the focus group which took place in June 2024. Their profiles are shown in Table 1. They are similar in that they performed well in the module and showed advanced critical skills when analysing the language used in English-speaking mass media. However, Participants 1 and 2 showed a cline towards quantitative language data analysis and had completed the final degree project on

**Table 1:** Profiles of participating students from the module "*Discourse and English language mass media*".

| Participant | Sex | Age | Module grade | Methodological position | Final project topic |
|---|---|---|---|---|---|
| 1 | Male | 22 | A+ | More interested in quantitative analysis | Analysis of AI language |
| 2 | Male | 22 | B+ | More interested in quantitative analysis | Analysis of AI language |
| 3 | Female | 22 | A+ | More interested in qualitative analysis | To be decided |

the characteristics of AI-generated discourse. Participant 3, on the contrary, was invested in qualitative analysis methods and had not yet started her final degree project. The participants were informed about the nature of the research activity prior to their involvement. Each student willingly provided their consent to participate, understanding the objectives and methods to be employed. We adhered to the ethical guidelines prevalent in social science research, ensuring confidentiality and the right to withdraw from the study at any point without any repercussions.

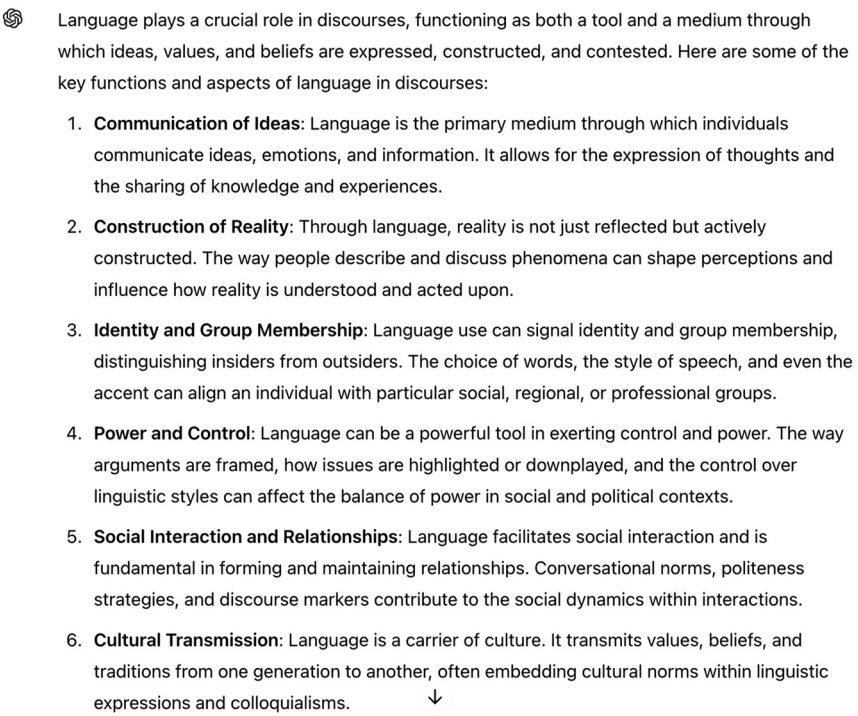
As the focus group progressed, the participants were asked a series of questions pertaining to applied linguistics, corpus linguistics, language education, and artificial intelligence. These questions addressed:

- Their experiences of using corpus linguistics to analyse English texts quantitatively and qualitatively;
- Their perception of the skills involved in language data analysis;
- Their perception of the impact of AI on language education and applied linguistics; and
- Their experience of using ChatGPT for language learning and undergraduate research tasks.

The rationale for engaging with questions of corpus linguistics in particular derives from two main lines of reasoning. First, the participants had all studied corpus linguistics recently, thus, this was a topic on which they could speak readily, allowing for conversation to flow. Second, as corpus linguistics is the most computational approach to language study and learning in which these learners engaged throughout their degree, we wanted to explore how participants would compare, contrast, or conflate corpus linguistics, AI, and GenAI. Such an insight would allow us to see where corpus literacy and CAIL align and how corpus literacies could be used to develop CAIL. Throughout the focus group, the discussion was reoriented towards AI, in order to keep the focus on learners' understandings of AI and GenAI, the ways in which they use AI and GenAI, their perceptions of AI and GenAI, and their engagement with the ethics of AI and GenAI.

As part of the focus group, participants were also asked to engage in an evaluative task, critiquing output from ChatGPT 4. The GenAI tool was asked to propose a response to an essay topic for the module. The participants were asked to reflect on ChatGPT's response to the essay question, "What is the role of language in discourse(s)?", and evaluate it in terms of quality. Figure 1 shows a screenshot of the output from ChatGPT. In our view, the AI-generated reply is vague and omits most of the contents and the insights from the compulsory readings of the module. As such, the response ignores the critical concepts involved in the analysis of discourses from a CADS perspective (e.g., Baker 2023; Partington 2006; Pérez-Paredes 2024).

We recognise that the small sample size ($N = 3$) undermines the generalisability of the findings we share in Section 4. As such, any arguments made should be viewed in light of what they are: part of an exploratory study endeavouring to situate CAIL within applied linguistics and language education disciplinary confines. As such, it is never our intention to generalise and it is important to note that this study is driven



Language plays a crucial role in discourses, functioning as both a tool and a medium through which ideas, values, and beliefs are expressed, constructed, and contested. Here are some of the key functions and aspects of language in discourses:

1. **Communication of Ideas**: Language is the primary medium through which individuals communicate ideas, emotions, and information. It allows for the expression of thoughts and the sharing of knowledge and experiences.
2. **Construction of Reality**: Through language, reality is not just reflected but actively constructed. The way people describe and discuss phenomena can shape perceptions and influence how reality is understood and acted upon.
3. **Identity and Group Membership**: Language use can signal identity and group membership, distinguishing insiders from outsiders. The choice of words, the style of speech, and even the accent can align an individual with particular social, regional, or professional groups.
4. **Power and Control**: Language can be a powerful tool in exerting control and power. The way arguments are framed, how issues are highlighted or downplayed, and the control over linguistic styles can affect the balance of power in social and political contexts.
5. **Social Interaction and Relationships**: Language facilitates social interaction and is fundamental in forming and maintaining relationships. Conversational norms, politeness strategies, and discourse markers contribute to the social dynamics within interactions.
6. **Cultural Transmission**: Language is a carrier of culture. It transmits values, beliefs, and traditions from one generation to another, often embedding cultural norms within linguistic expressions and colloquialisms. ↓

**Figure 1:** ChatGPT 4 reply to the prompt "What is the role of language in discourse(s)?"

by a qualitative agenda that allows us to conduct in-depth analyses of situated learner discourses that help us to make sense of emerging CAIL within a controlled context. In preparation for analysis, the focus group was automatically transcribed, then manually revised, anonymised, and checked for accuracy by the researchers. The transcript was parsed by speaker turn and the analysis centres only on turns produced by the participants. In total, the focus group lasted 97 min and produced a total of 7,698 words, after removing the interviewers' language from the count.

## 3.2 Analytical approach: corpus linguistics and critical grounded theory

For the analytical approach, we adopt a method outlined in Curry and Pérez-Paredes (2023) for interview and focus group analysis. This approach combines corpus linguistics and critical grounded theory with the criteria for AI literacy drawn from Marx (2024). First, the interview transcript was saved as a text file and analysed using Sketch Engine (Kilgarriff et al. 2014). Keywords and key terms were computed using a corpus of interviews and focus groups with English-Medium Instruction (EMI) lecturers from a Spanish university as a reference corpus – for details on this corpus see Pérez-Paredes and Curry (2023). This corpus was selected as it is composed of discussions about university education in the same EMEMUS Spanish context. Therefore, general language of university education would be less likely to appear key and, given that these data were collected in 2019, there were no discussions of AI. This means that language relating to AI and GenAI was more likely to appear as keywords and key terms. This is valuable as these are discourses we are interested in analysing. Once key words and terms were computed, an alpha cutoff of 0.05 was used to determine statistically significant keywords. This relatively low threshold was applied as the data for the target corpus (i.e., the focus group with learners) was quite small (7,698 words). Keywords and multi-word terms were then extracted with a total of 39 significant keywords and four significant key terms identified. These words are presented in the Appendix A. These key words and terms were used as field codes, following Curry and Pérez-Paredes (2023). To apply the field codes, each turn in which any of these words occurred was tagged with key words and terms. In Example 1 below, the keywords *parameters*, *text*, *like*, and *know* were tagged as field codes.

**Example 1 (Participant 3)**
probably to **know** which are the useful variables set **like**, that, **like** the **parameters** you have to use in order to find what you want to find, because you **know** it's there, but you don't **know** how to reach it. So, to have the tools to reach the amount of **text** you need that's —yeah.

Not all instances of field codes reflected discussions of AI or GenAI, e.g., *like* in Example 1 is simply a feature of spoken discourse. Yet, other words, such as text and parameters were effective at signalling sites in the discourse in which discussions of AI and GenAI emerge.

Using the field codes as a way into the discourse, CAIL codes, based on Marx (2024), were then applied. These codes are outlined in detail in Table 2.

Once these codes were applied, focused codes were then developed to tease apart the different themes and ways in which issues of CAIL were being evoked in the discussion of applied linguistics and language education. Table 3 presents an overview of these focused codes, linked to their overarching AI literacy code.

These focused codes were iteratively developed through the coding process, and applied to every turn in which their associated themes were found to occur. As Dafouz and Smit (2020) note, when using qualitative coding to understand a complex concept, there is an inevitable degree of overlap in the codes. We share their view that such overlap is a strength of qualitative coding as it affords insight into related and intertwined concepts. To ensure consistency of coding, Stemler's (2004) consensus estimates were used to iteratively and collaboratively apply AI literacy

**Table 2:** CAIL codes based on Marx (2024).

| Thematic AI codes | Codes | Definitions |
|---|---|---|
| Critical thinking | CT | Assessing the reliability and validity of AI-generated outputs, avoiding over-reliance on these tools, and applying critical judgment to results |
| Ethical awareness | EA | Recognising the ethical implications of using AI, ensuring its application is responsible and aligned with principles like transparency and fairness |
| Practical application | PA | Learning how to integrate AI into tasks such as data analysis, hypothesis generation, and problem-solving while acknowledging the importance of human oversight |
| Technical understanding | TU | Knowing how AI systems, such as large language models (LLMs), are trained, how they function, and their limitations (e.g., biases and hallucinations) |

**Table 3:** Focused codes.

| AI literacy codes | Focused codes | Definitions |
|---|---|---|
| Critical thinking | CT01 | Signals the use of critical thinking to engage with technology, data, etc. |
| | CT02 | Signals a lack of criticality when engaging with AI tools and technologies |
| Ethical awareness | EA01 | Signals thinking about sources of information and the responsibility to reflect on sources |
| | EA02 | Signals engagement with the notions of quality and reliability with regards to data and AI outputs |
| | EA03 | Signals reflection on the risk of AI for human knowledge production and how human knowledge is generated |
| | EA04 | Signals AI as not equating to humans |
| | EA05 | Signals human dependence on AI |
| | EA06 | Signals potentially unethical use of AI |
| Practical application | PA01 | Signals use of technology to solve problems |
| | PA02 | Signals engagement with notions like parameters/variables in analysis |
| | PA03 | Signals use of AI for support functions e.g., references |
| | PA04 | Signals use of AI for analytical purposes |
| | PA05 | Signals use of AI to carry out tasks/jobs |
| Technical understanding | TU01 | Signals the need for cleaning and preparing data |
| | TU02 | Signals a form of data literacy about understanding what data is being used |
| | TU03 | Signals a lack of knowledge of how LLMS work |
| | TU04 | Signals a partial knowledge of how LLMs work |
| | TU05 | Signals a good awareness of the texts AI produces |

codes and generate focused codes. Two of the authors coded the entire transcript and negotiated the final set of codes.

# 4 Results and discussion

This section discusses the results of the analysis offering an overview of the findings from the coding process. Participant 1, 2, and 3 produced a total of 19, 30, and 27 turns, respectively. On average, 1.6, 1.3, and 1.3 codes were applied per turn for Participants 1, 2, and 3, respectively. Figure 2 shows the percentage of CAIL codes applied per speaker. In terms of CAIL codes, CT is most frequent, accounting for 35 % of all codes, followed by EA, PA, and TU at 25 %, 22 %, and 18 %, respectively.

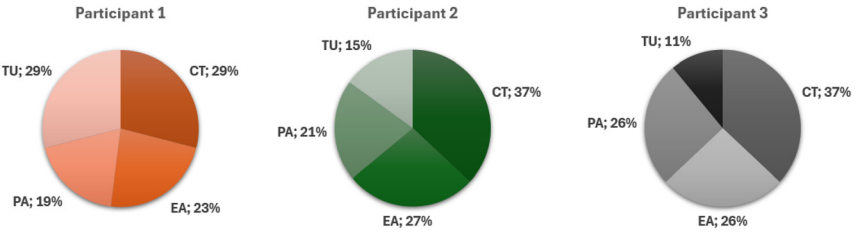



**Figure 2:** Percentage of CAIL codes per participant.

These themes occur most often in combinations with one another, as Table 4 illustrates.

In terms of focused codes, Table 5 demonstrates the prominence of engaging in critical thinking, reflecting on the risk of AI for human knowledge production, human dependence on AI and knowledge generation, the potential use of GenAI tools as a form of support, and a partial knowledge of how LLMs work. These focused codes can also co-occur, in different combinations and a full list of these combinations are presented in Appendix B.

Overall, what this initial overview of the coding frequencies indicates is that the participants demonstrate some degree of CAIL with regards to the use of AI in their studies. As they discursively and collectively construct their understanding of this knowledge, they demonstrate a complex engagement with AI and GenAI. There are evident gaps in their knowledge, for example no ethical code pertains to the environmental impact of AI (Ligozat et al. 2022) as this topic did not emerge from the focus group. Moreover, evidence of limited knowledge of LLMs, intermittent limited criticality, a varying understanding of the role that GenAI should play, and questionable ethical perspectives on GenAI use indicate a need for a robust and grounded CAIL.

In what follows, Sections 4.1–4.4 present a critical investigation of the participants' AI literacies in terms of critical thinking, ethical awareness, practical application, and technical understanding, respectively.

## 4.1 Critical thinking

Critical thinking is the most frequent code applied to the focus group data, accounting for 34 % of all CAIL codes. This prominence also exhibits small variability across the participants, representing 29 %, 36 %, and 37 % of codes applied to discourse produced by Participants 1, 2, 3. In total, 34 turns, accounting for 4,343 words, are attributed with a CT code (either independently or in combination with

**Table 4:** Percentage of combined CAIL codes per participant.

| Participant | CT | EA | PA | TU | CT & EA | CT & PA | CT & TU | EA & PA | EA & TU | EA & TU | CT & EA & PA | CT & EA & TU | EA & TU & PA | CT & EA & PA & TU | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 3 | 3 | 3 | 0 | 10 | 13 | 18 | 5 | 13 | 13 | 5 | 8 | 5 | 5 | 100 |
| 2 | 6 | 13 | 3 | 9 | 16 | 19 | 6 | 6 | 3 | 3 | 6 | 3 | 3 | 3 | 100 |
| 3 | 6 | 13 | 0 | 3 | 19 | 19 | 0 | 13 | 6 | 6 | 6 | 0 | 6 | 0 | 100 |

**Table 5:** Percentage of focused CAIL codes per participant.

| Participant | CT01 | CT02 | EA01 | EA02 | EA03 | EA04 | EA05 | EA06 | PA01 | PA02 | PA03 | PA04 | PA05 | TU01 | TU02 | TU03 | TU04 | TU05 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 22 | 8 | 3 | 0 | 3 | 11 | 3 | 3 | 3 | 3 | 8 | 6 | 3 | 0 | 6 | 6 | 14 | 0 | 100 |
| 2 | 23 | 11 | 0 | 0 | 11 | 0 | 11 | 3 | 0 | 0 | 17 | 6 | 6 | 0 | 0 | 3 | 6 | 3 | 100 |
| 3 | 30 | 14 | 5 | 3 | 3 | 0 | 3 | 3 | 3 | 3 | 14 | 3 | 8 | 3 | 5 | 0 | 3 | 0 | 100 |

other codes). Only 5 % of CAIL codes account for CT alone, indicating a propensity for discussions around critical thinking to co-occur with other themes. Most prominently, CT co-occurs with PA in 16 % of the tags applied to turns, followed by EA at 14 % and TU at 9 %. This kind of co-occurrence is evident in Example 2 in which participants demonstrate critical thinking skills while discussing the affordances of ChatGPT for supporting essay writing.

**Example 2 (Participant 2)**
"The fact is that ChatGPT is not an expert on this field. […] But because, as we said, like, we know how to answer questions and ChatGPT doesn't, really. Like, it for, I think it's a good tool, like if you read this then you can propose a good answer. But ChatGPT didn't answer your question at all, but at least I don't like the answer."

CT also co-occurs with multiple other codes, albeit to a lesser degree. For example 5.8 % of all tagged turns contained CT, ET, and PA tags, 4 % contained CT, ET and TU tags, and the co-occurrence of all four tags accounted for just 3 % of tags. Example 3 showcases a complex engagement with critical thinking as the learner evaluates the potential quality of responses but, at the same time, does not question the ethical issues with getting ChatGPT to write a response. The learner also indicates some ideas of the practical uses of GenAI tools as a writing support but the assertion of what the tools 'know' may indicate a limited understanding of how GenAI tools work.

**Example 3 (Participant 1)**
"I think it will be it will create a great response just for the question of the language. I think it's kind of simple question. So ChatGPT will be able to generate a response based on what it knows about language […] However, I don't think that the same result will be from the second question. I think that the sense, or the of the meaning, the meaning of representation in that sentence will be kind of a problem for ChatGPT to understand what this question really means."

Thus, questions of critical thinking abound in these data, as the participants endeavour to assess the reliability and validity of GenAI tools, question or fail to question their role in their studies, and consider issues of over-reliance.

Overall, 25 % of all focused codes pertain to CT01 and 11 % to CT02, rendering these two focused codes the most prominent focused codes in the data. Many different focused code combinations occur in the data, the most prominent being combinations of CT codes as well as CT and PA codes. In some instances, CT01 and CT02 co-occur, indicating a complex engagement with criticality among the participants. In Example 4, one participant demonstrates a critical perspective on analytical approaches, indicating that ChatGPT could not conduct an in-depth study of language that meets the rigorous expectations of corpus linguistics, which

reflects wider discussions in the literature (e.g., Curry et al. 2024). Yet, they also propose that ChatGPT can support learners in operating research tools, which is not always the case as ChatGPT has a propensity to also create issues in the learning process. Thus, the participant shows criticality from an analytical perspective, but when viewed as a supporting resource, more limited criticality is exhibited. As such, questions of quality may need to be addressed with learners, focusing not only on the importance of quality knowledge in analyses, but in every aspect of the research process – a central facet underpinning learners' understanding of AI, as reflected in Miao and Shiohira (2024).

**Example 4 (Participant 3)**
"I think that for example in the case that, for instance, a researcher forgets to use something like, for instance, I don't know, a database, you can ask ChatGPT to give you a sort of list to —of how to use it as such. And for that it can be useful for the researcher. But for corpus linguistics to make a full —a deep search for a topic or something like a database does, I think that it cannot be that useful but it can also offer some answers that can be, you know, resourceful."

In terms of CT and PA, CT01 and PA03 co-occur most often. When they do, participants discuss the need to be critical of GenAI tools when applying them as part of the analytical process. They draw on their wider knowledge of linguistics, citing scholars like Fairclough and Foucault, as means to explain their nuanced views on the use of GenAI, as demonstrated in Example 5. In that example, the participant critiques output from ChatGPT, assessing its quality favourably but determining the need for more information.

**Example 5 (Participant 2)**
"I would go for the —I don't remember right now, excuse me, if it was Fairclough, Foucault —the CDA perspective in which language and discourses and, well, especially the aim, once we have them, was to have like a critical awareness of what discourses could —were able to do with our identities and our ideologies and social structures and the ability they have to modify them."

Overall, the participants demonstrate a high degree of critical thinking when discussing and evaluating the GenAI tools. Notably, they often draw on wider disciplinary knowledge to substantiate their view and offer explanations and nuance. There remain issues with their engagement with GenAI tools, as they exhibit a lack of criticality at times, both in terms of their use of GenAI tools and their understanding of how such tools work. Given the potential affordances of knowledge transfer across disciplinary confines for advancing thinking and learning (e.g., van Peppen et al. 2022), developing conceptual links between different areas of applied linguistics,

language education and GenAI – as the learners instinctively do – may prove fruitful in helping learners map their critical perspectives against new and emerging GenAI tools.

## 4.2 Ethical awareness

The ethical implications of using AI in education environments was also a recurring topic among the participants. EA occurred in 25 turns, accounting for 3,328 words. When combined with other tags, questions of EA were raised mostly in combination with CT (14 %), while appearing less frequently alongside TU (8 %) and PA (8 %). The participants demonstrate mixed feelings towards the ethical considerations of using GenAI in educational contexts. Their perspectives range from seeing AI as a clear threat to both human cognitive development and the ability of humans to access or retain job positions to the opposite view, suggesting that research should focus on how we can work alongside AI instead of analysing the potential problems GenAI tools may pose.

For EA01, the participants highlight the importance of being able to access and understand the data on which AI and AI-based tools are trained. In their view, it is an ethical duty that users develop sufficient critical thinking skills to be able to discern useful from non-useful feedback. They argue that such a practice is fundamental for language research generally, and for being able to make sense of GenAI produced output specifically. In this way, participants appear to see greater value in using GenAI as a sort of companion tool to amplify information rather than using GenAI to generate text, as Example 6 illustrates.

**Example 6 (Participant 3)**
"[…]when I'm studying and I see that a summary that I have about a unit or something is, like, short, I […] look for information [in ChatGPT] to amplify what I have and that's all for now —I have also used it to translate the text and then to do the evaluation of the translation made by ChatGPT."

When faced with the question of to whom or what AI-generated data belongs, the participants struggle with finding a definitive answer, as in Example 7.

**Example 7 (Participant 3)**
"It's a kind of a difficult question to answer, because you don't know if it's the creator as such of the AI […] does ChatGPT owns text? I don't really know about that."

The literature remains similarly unsure as to how we can answer these questions effectively. The interplay between GenAI and both the data it uses as sources and the data it outputs has been the subject of discussion on ethical and legal grounds (e.g., Eshraghian 2020). Draxler et al. (2024), for example, note that people tend to avoid

assigning authorship to AI, especially when GenAI has been used as a 'companion tool' rather than the primary source of output. Given the immense complexity involved in addressing the question of data ownership in using GenAI, it is imperative that it form part of situated CAIL.

In terms of the quality of texts produced by GenAI (EA02), the participants seem confident in their ability to correctly distinguish AI-generated text from human-generated text, generally alluding to "mistakes" in AI pattern selection and organisation, which, in their view, are visibly different from the ones humans may make. This is evident in Example 8.

**Example 8 (Participant 3)**
"[…] we can distinguish [translations made with ChatGPT] by the errors that they made as such because […] they don't relate to context […] as well as we humans do. […] For example, humans, we make errors depending on […] how exhausted we are. We have made an error that then, when we revise the text, we see it and we change it. But for ChatGPT I translated the text and click like four, five times and it made the same error."

Regardless of their possible personal reluctance towards AI, they seem to deem GenAI tools useful for a handful of specific tasks, such as generating a short piece of text. They declare their clear preference towards managing the selection, cleaning and compilation of a corpus 'by hand', which, in their view, promotes their research skills and ensures an ethical engagement with the data.

For EA04, the participants seem to be aware of a growing dependence on GenAI. The ways in which GenAI could negatively affect humans were discussed in depth in several turns, with participants showing clear differences in perspectives. Participant 1 believes the capabilities of AI are yet to evolve and that the focus of AI-related research should be directed towards what they can offer rather than the problems they may entail. This suggests the current impact of AI tools in educational settings is not as dire as some may initially regard. In contrast, Participants 2 and 3 openly label AI as a "threat" to human cognitive development, especially in the case of very young users, as Example 9 illustrates.

**Example 9 (Participant 3)**
"I feel that it's making us lazy, kind of non-thinking students."

This same view is echoed by Participant 2, who implies that indulging in the yearning for constant stimulus and instantaneous feedback might potentially hinder human cognitive development, as people would not make "a real effort" in using their own capabilities to perform tasks when they can reach a potentially comparable result in mere seconds. From an educational perspective, such a use of GenAI risks

undermining efforts by teachers to develop process-driven and pedagogically-situated approaches to using AI in education (Yang et al. 2024).

The participants express deep concerns about how the existence of GenAI tools may affect future generations. For the unprepared users, they fear that GenAI will become a substitute for critical thinking processes, especially those related to written comprehension and production. In their view, children are not sufficiently educated at home to deal with the proliferation of different devices and tools available to them. Aside from the impact of GenAI on young users, Participant 2 was also concerned about the perceived threat that AI poses to certain jobs, especially those related to linguistic production, naming translation as an "at risk" area. Participant 3, in contrast, believes that there is no such threat, trusting that the quality and reliability of human translation will always overcome automatic GenAI translation. These perspectives underscore even further the sheer importance of providing an ethics-driven accessible and comprehensive CAIL to potential users of GenAI tools, especially at a very early age. Such literacy would provide the necessary tools for humans to manage both the potential tasks GenAI can perform reliably and, even more importantly, to critically interact with GenAI production instead of uncritically accepting.

The question of whether AI can be regarded as human also emerged from discussions with participants (EA05). While such a question has traditionally been a philosophical consideration reserved for science-fiction literature, the human-like production of GenAI has brought it into our realities. The participants agree in not considering GenAI production as human, suggesting that the process of thinking requires more than putting together words to form coherent sentences, demonstrating a capacity to make sense of AI through their applied linguistics lens. For the participants, the very act of creating something is inherently human, as GenAI is only able to replicate what other humans have already produced. As such, they argue that AI cannot form opinions by itself, unless prompted to it by a human beforehand.

## 4.3 Practical applications

The analysis of the focus group reveals a blend of enthusiasm, scepticism, and reflective insight about integrating AI into practical applications. Discussions span issues of data analysis and problem-solving. 22 turns tagged as PA were analysed, totalling 2,502 words. PA codes account for 22 % of all codes applied to the data. These codes occur alone only in 2 % of tagged turns and most often co-occur with other codes, including CT in 16 % of tagged turns, EA in 8 % of tagged turns, TU in 9 % of tagged turns, CT and EA in 8 % of tagged turns, CT and TU in 4 % of tagged turns, and

EA and TU in 5 % of tagged turns. PA also occurs with all other codes in 3 % of tagged turns. Thus, PA is a highly interconnected theme.

The participants' opinions collectively highlight the promise and challenges of using AI for practical applications. Key takeaways include the importance of robust support during the learning curve, the indispensable role of human oversight, and the value of hands-on projects in making AI tools meaningful and relevant. These insights underscore the view that an effective integration of AI in language education university programs requires thoughtful design, ethical vigilance, and a balance between technical capabilities and human expertise. The human-centred nature of their perspective reflects a more general trend at the intersection of AI and education (e.g., Miao and Shiohira 2024)

For PA01, the participants' reflections show the growing utility of AI in addressing complex challenges, particularly in language analysis and research. Tools like Sketch Engine exemplify how software facilitates textual analysis and pattern recognition, simplifying what might otherwise be arduous manual processes. The participants appreciated the systematic capabilities AI tools provide, allowing for an expanded comprehension of language use and discourse analysis by uncovering implicit meanings. However, they also highlighted the steep learning curve, suggesting that effective integration of AI-driven data analysis and the use of complex corpus analysis tools requires substantial initial investment in understanding and adapting their use to specific contexts, such as applied linguistics and language education, as illustrated in Example 10.

**Example 10 (Participant 1)**
"We worked with Sketch Engine a few years ago in another subject. We didn't get anything at all, and it was not really clear what we were dealing with and I think that for the first time we now are able to understand what Sketch Engine is capable of."

The initial struggles with Sketch Engine suggest a steep learning curve, particularly when tools are not adequately explained or contextualised. This capacity to critically engage with such tools demonstrates their willingness to persist in iterative learning when working with technology – a capacity directly transferable to their CAIL.

The participants' reflections highlight the cognitive shift that AI necessitates when engaging with the variables involved in the analysis of mass media texts written in English (PA02). Participants described the iterative process of refining their queries and datasets, which is critical for generating meaningful results. They noted that understanding and managing variables like time frames (years or months) or sources such as different newspapers or academic references impacts the reliability of their analysis – an issue of disclosure as identified in Yang et al. (2024).

Their reflections demonstrate how tools for data analysis such as Sketch Engine encourage a more structured and critical approach as they necessitate a research

methodology that facilitates critical analysis and makes users more meticulous in their planning and execution phases. For example, they value how the ability to manipulate large datasets and refine search parameters (e.g., time frames, genres, etc.) allows for detailed and precise linguistic analyses. Participant 1 noted a newfound appreciation for Sketch Engine after gaining a clearer understanding of its functionalities, despite earlier struggles in previous years (see Example 10). Once again, this knowledge and these skills developed in applied linguistics are directly mappable to CAIL, meaning that there are opportunities for transfer.

For PA03, AI's role in support functions, like generating references or summarising texts, has been lauded by the participants for its efficiency. For example, Participant 3 mentioned the use AI to amplify study notes and evaluate translations, indicating its utility in supplementary academic tasks. While these applications streamline workflow and reduce redundancy, the reflections also point to a dependency on human oversight. The importance of validation and cross-referencing AI outputs with established sources was emphasised by the students as an important means of ensuring academic rigor and accuracy.

For PA04, the importance of validating AI-derived insights with authentic sources and human judgment is a recurrent theme. Participant 2 raises a critical concern: without a credible source, they wonder how AI outputs can be trusted. This highlights the importance of providing AI with high-quality, reliable data. The reflective question about relying solely on AI-generated ideas emphasises the ethical and practical necessity of human involvement in AI-driven processes. Participant 1 reflects on the ability to infer meaning from what is explicitly stated and what is omitted, particularly in text analysis. This insight reveals an appreciation for AI's nuanced capabilities, such as outlining implicit ideas or even bias in textual data. This perspective aligns with AI's strength in processing large datasets to uncover patterns and meanings beyond human intuition. However, the same participant hints at the risks of over-reliance, particularly when AI tools such as ChatGPT fail to offer the "real source or sources". This is echoed by Participant 2, as Example 11 demonstrates.

**Example 11 (Participant 2)**
"I think it depends on how you use this tool, but if you don't have the real source, how can you really contrast the information?"

AI's analytical capabilities are recognised by the participants as a double-edged sword. On one hand, it aids in generating initial insights or hypotheses by synthesizing vast amounts of data. On the other hand, participants identified its limitations in critical areas like discourse analysis, where nuanced understanding is required. For instance, while AI can produce general summaries or responses, it struggles with deeper contextual or theoretical interpretation, often offering disjointed or overly

generalised conclusions. This highlights the complementary rather than replacement role of AI in scholarly analysis.

For PA05, participants reflected on AI's potential to perform increasingly complex tasks, from constructing corpora to assisting in translation. They speculated about its growing capability to outpace human performance in specific areas, such as machine translation. However, scepticism persists regarding AI's ability to replicate human expertise, especially in domains requiring critical thinking and contextual understanding. The reflections suggest a cautious optimism about integrating AI into professional environments, where it could function as a tool for augmentation rather than replacement. This perspective aligns with broader trends advocating for AI literacy to maximise its benefits while addressing its limitations (Yang et al. 2024).

Overall, the participants appreciated the relevance of their hands-on project, describing it as a "real project" and recognising the applicability of their learning to authentic contexts. The elective nature of the module seems to have attracted motivated individuals who value the subject matter, resulting in a generally positive perception. However, the participants acknowledged that interest in the module and AI tools may vary. Participant 2 emphasised that the module was engaging mainly for those who found the analysis of discourse interesting. The participants agreed that, while interest-driven learning is valuable, broader educational strategies should also aim to make AI accessible and appealing to a wider audience, given its increasing relevance in diverse fields. Taking such thinking on board, there may be a case of both disciplinarily situated CAIL that complements a more generic CAIL.

## 4.4 Technical understanding

Finally, TU, which pertains to what the participants know about AI systems, how they are trained, how they function, and their limitations, account for the most infrequent number of tags in the data. 18 % of all AI literacy tags were TU tags and these occurred across 18 turns in 2,823 words. TU occurs alone in 4 % of the tagged turns. Therefore, it mainly co-occurs with more prominent themes, including CT in 9 % of tagged turns, EA in 8 % of tagged turns, PA in 9 % of tagged turns, CT and EA in 4 % of tagged turns, and EA and PA in 5 % of tagged turns. TU also occurs with all three other tags in 3 % of tagged turns.

TU04 is the most common focused code, followed by TU03 and TU02. These focused codes also co-occur with focused codes from other CAIL codes, including EA04, CT01, and PA02, most prominently. Thus, once again, the role of technical knowledge in the participants' AI literacy is intertwined with questions of ethics, critical thinking and practical applications, illustrating the complex nature of CAIL and the need to address these issues holistically.

When combined with EA04, TU04 is tagged to utterances in which participants demonstrate a partial understanding of how GenAI tools and their LLMs work, drawing distinctions between human thought processes and that of AI, as Example 12 presents. In this case, the participant draws on their metalinguistic knowledge of LLMs, conceiving their processes as ones designed to produce a string of words. The participant challenges this process as not matching human intelligence, also signalling an understanding of how humans produce text.

**Example 12 (Participant 1)**
"Yeah, ChatGPT work with, as far as I know, with prompts and datasets and it's supposed to kind of learn about humans from all those samples […] It's just —it's not a brain who is thinking —it's kind of mixing words that ChatGPT knows that exist, knows that tend to appear in similar context or in the same context."

TU03 occurs with critical thinking in utterances in which participants offer a critical perspective on AI while also revealing a rather limited understanding of its mechanics. However, this combination, as Example 13 demonstrates, signals an effective critical perspective that accounts for the participant's lack of knowledge. Thus reflecting on a lack of knowledge can prove a useful means in highlighting gaps in knowledge around AI that can curtail inappropriate usage.

**Example 13 (Participant 1)**
"In my case when ChatGPT appeared I didn't understand what it really was, and I, at the beginning I didn't use it. I found it really difficult. I, to be honest, I kind of —I mean, I didn't understand how it work, how I was supposed to ask, or how the ChatGPT was supposed to answer the question, and I didn't know if the response was —were reliable enough."

Elsewhere in the focus group, participants demonstrate a greater understanding of data, more generally, indicating the kinds of technical knowledge (TU02) needed to put tools to use (PA02) – specifically corpus linguistics tools. In Example 14, one participant highlights the need for linguists to understand exactly what their data represents to perform effective analysis. This demonstrates a data literacy typical of the rigor of applied linguistics. Contrasting Example 13 with 14, it is clear that these participants have a complex understanding of language data and issues of representation and rigorous analysis. Using criteria established in the domain of text analysis, for example, may prove an effective means of illuminating challenges with GenAI when developing CAIL.

**Example 14 (Participant 1)**
"You might think what you are thinking or what you are imagining about your topic is enough, and then you just find around 50 texts and you know that's not enough […] So it's clear that you have to be as cautious as possible in order to, you know, that if you mess up that stage you are going to mess up all the project."

# 5 Critical AI literacy (CAIL) for language education and applied linguistics

In this study, we analysed a focus group with final-year students of the Degree in English Studies in a southern European University. Our data shows that learners frequently engage with GenAI tools in a critical manner. This is important for CAIL as it emphasises the need for users to evaluate the capabilities and limitations of AI tools. CT often appears alongside other themes such as PA and EA, suggesting that discussions about AI and GenAI are multifaceted, addressing practical, ethical, and analytical aspects. Addressing this complexity is essential for a comprehensive understanding of GenAI use. The learners seem to agree that GenAI is most effective when it is used to complement human expertise rather than replace it, ensuring ethical and accurate outcomes. Thus, one clear motivation of CAIL in applied linguistics and language education is the development of augmented intelligence (Fulbright and Walters 2020). While tools like Sketch Engine excel in aiding learners' hypothesis testing and language pattern recognition, the learners agree that human oversight remains critical for nuanced interpretation and ethical decision-making. The insight learners can glean about language through such corpus analysis software is extensive, while for them, many GenAI tools obfuscate data and processes. Thus, drawing learners attention to the issues of transparency in corpus linguistics and AI use may prove a useful means of expanding their CAIL through a process of transfer (van Peppen et al. 2022). Doing so through practical, real-world projects in language education and applied linguistics combined with disciplinary theoretical foundations, can enhance the relevance and impact of AI training and equip learners with both a conceptual and a practical toolkit to navigate appropriate uses of AI within their field. The learners emphasise the importance of embedding CT in real practice, which we believe is an important consideration when designing CAIL programmes.

Ethical considerations are a significant aspect of participant discussions, particularly in how they intersect with critical thinking. This overlap suggests that ethical reflections are deeply integrated with critical evaluations, emphasising the importance of considering both the moral implications and the practical uses of AI in education. The learners exhibit a spectrum of views on AI's role in education, ranging from concerns about AI's threat to human cognitive development and job retention to more optimistic views about AI enhancing human capabilities. This range highlights the complexity of AI's impact, suggesting that its effects are not universally agreed upon and depend heavily on the context and manner of AI implementation. There is also a critical focus on the origin of the data used by AI tools and the potential over-reliance on AI for educational tasks. Participants stress the ethical responsibility of GenAI users to discern the quality of AI-generated

output and the potential dangers of making AI the primary resource in research and learning environments. Participants agree that while AI can mimic human output, the processes involved are not equivalent to human thought, emphasising that creation and opinion formation are distinctly human traits.

Some learners show a nuanced understanding of the AI tools' limitations and capabilities, while others may not fully grasp the ethical implications. This variation highlights the need for more targeted education to enhance understanding and critical assessment skills among learners. The CAIL focused codes CT01 and CT02 differentiate between high and low levels of criticality, respectively. The analysis of the focus group suggests that linking applied linguistics and GenAI can advance learners' critical thinking, aiding them in applying theoretical knowledge practically and ethically. This interdisciplinary approach could enhance AI literacy by encouraging deeper understandings and critical evaluations. As for TU, the breakdown into subthemes such as data preparation, data literacy, and understanding of LLMs illustrates the specific areas where learners may lack or have only partial knowledge – knowledge deemed to be a central facet of learner development by UNESCO (Miao and Shiohira 2024). The focus group shows some TU with other facets of CAIL, promoting a holistic view of AI education in the module. By connecting technical details to ethical and practical considerations, the learners show a decent grasp of TU, which prepares them for informed and responsible use of AI in various settings. However, the presence of focused codes like TU03 and TU04 highlights prevalent gaps in understanding how AI operates, particularly in comparison to human cognitive processes.

Despite the integration of the four major components of CAIL addressed in the analysis of the focus group, the infrequency of some CT and TU focus codes might indicate a broader educational gap in AI intellectual and technical training. This gap could limit learners' ability to take advantage of AI capabilities and assess AI tools critically. The topics of academic integrity and the ethics of ownership are crucial, particularly as AI tools become more integrated into academic settings, raising concerns about plagiarism and, more significantly, about the true ownership of AI-generated content and the data that feed LLMs (Eaton 2023). However, the learners showed evidence that they felt that the attribution and identification of sources was a major flaw in some of the uses of GenAI to which they were exposed. Perhaps this is due either to the high standards of academic integrity in most undergraduate programmes or to the intensive training in the module to identify, classify and analyse texts from different sources. The use and analysis of corpus data has surely made learners aware of the importance of conceptualising texts as socially situated artifacts that may serve ideological purposes, hence the importance of understanding sources, citation and authorship.

On these grounds, we propose that a disciplinarily-situated CAIL can draw on issues of criticality, ethics, practice, and knowledge that are of inherent value to the fields of applied linguistics and language education. Specifically, we argue that despite the novelty of GenAI, some of the competencies required to unpack and assess it are already at our discipline's fingertips. In applied linguistics and language education, students are trained to recognise biases and understand the role of language data in the production and dissemination of knowledge. Thus, we can draw parallels with the language of LLMs and the language processing practices of GenAI tools to create opportunities for critical reflection and the development of CAIL. Likewise, in applied linguistics and language education, we help students to recognise the role that sources play in reporting research and typically we frame this as an ethical concern. We can draw on this competence when addressing the nature of the sources of information in LLMs and help learners develop an ethical awareness of data. In terms of practical application, we can make clear that some GenAI tools may be useful to students of applied linguistics and language education. Yet, any form of technology that facilitates language analysis is similarly useful. In our field, we have now developed effective means of critiquing tools in terms of their designs, assumptions, interoperability, *inter alia*. This same thinking can help develop CAIL for students of applied linguistics and language education who are engaging with GenAI tools. Likewise, while it may prove challenging to develop learners' technical understanding of LLMs, especially if our own understanding is somewhat limited, we can draw on research on representation, data collection, sampling frames, transparency, replicability, and reproducibility to highlight our gaps in knowledge surrounding LLMs and the kinds of questions we should be asking of the tools and data we are using. Appendix C elucidates this point further by offering an example of ways in which we can facilitate the transfer of competencies from applied linguistics and language education to each focused code identified. The motivation behind this alignment of applied linguistics and language education to each focused code is to offer concrete guidance on the development of a transfer-based and discipline-specific CAIL.

We remind the reader that our findings are somewhat limited by the sample size. Thus, there are evident gaps in our focused codes that should be addressed, such as the perceptual differences between AI and human cognition; understanding how AI models the world through language alone versus human approaches to making sense of the world through sensory and cognitive experiences. This distinction can provide deeper insights into both the capabilities and limitations of AI systems. Also, the focus group has overlooked discussions on bias and social justice – key areas given that AI systems can perpetuate existing societal biases if not carefully managed. The use of certain varieties of English, for example, was not present in the conversation and certainly the synthetic, non-organic nature of the language output

of tools like ChatGPT requires further attention. Finally, the environmental impact of developing and using AI has not been discussed, which is vital given the substantial energy demands and carbon footprint associated with training LLMs. Addressing these topics would enhance the learners' comprehensive understanding of AI and its broader implications in applied linguistics and language education. This would ensure a more ethically aware and socially responsible use of technology in their future linguistic careers.

# 6 Conclusions

Language and data are symbolic artifacts that reflect our evolution into a digitally-and-cognitively mediated species (Lévy 2025). AI is arguably the latest manifestation of this evolution: our analysis of the focus group has allowed us to reflect on some areas that, based on their absence in the conversation, may require attention and integration into the broader, four higher level categories involved in Marx's (2024) framework. Figure 3 shows specific areas of attention in each of the four CAIL dimensions.

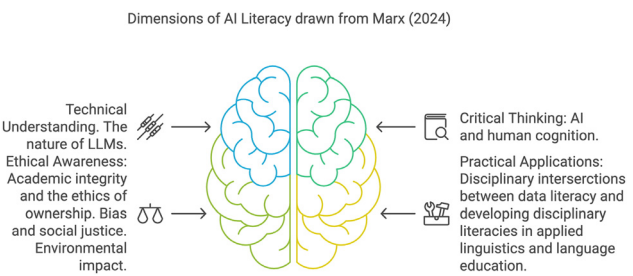



**Figure 3:** Some of the dimensions of AI literacy that need special attention in CAIL.

There remains, however, a need to reflect on how these dimensions interplay with broader trends in AI technology that also affect analyses and uses of AI in applied linguistics and language education. The four dimensions considered in this study intersect with what Lévy (2025) has recently conceptualised as two prevailing models in AI: symbolic and neural. Symbolic models are robust in reasoning, while neural models excel in pattern recognition and data processing. These two models are crucial in the context of language education and applied linguistics. For example, the generation of frequency information in language data through corpus tools

such as Sketch Engine requires some basic understanding of statistics and the role frequency in language data (Pérez-Paredes and Curry 2024). Symbolic artificial intelligence, on the contrary, has been key in the development of AI, providing a framework for reasoning and problem-solving that imitates both human logical thinking and human language production. While it has been overshadowed by the rise of machine learning and neural networks, symbolic AI remains a crucial component in hybrid systems that combine the robustness of rule-based logic with the adaptability of statistical models (see Figure 3). Understanding how such reasoning tales place and how language is generated is absolutely essential to address aspects such as language awareness, language learning, analysis of linguistic genres, or understanding variation in digital contexts.

As shown in this paper, the participants reflect on issues related to AI and its use in both models, substantiating Lévy's proposal for an integration of these models that combines their strengths. He suggests that this combination can overcome the dichotomy between human-like reasoning and machine efficiency – an aim that could guide CAIL for applied linguistics and language education. As such, we believe that both models need to be addressed in each of the four dimensions considered, as this integration may enhance the capabilities of AI and offers new ways to augment human cognition and facilitate complex decision-making and creative problem-solving (Lévy 2025) in a context where activities like writing will very likely become human-machine hybrid (Eaton 2023). Digital AI environments provide tools that streamline and extend cognitive functions beyond natural human limits and neural AI has enhanced machine capabilities in tasks requiring human-like perception and decision-making and despite challenges in interpretability and resource demands, its vast potential fuels ongoing interest and investment.

Access to CAIL in EMEMUS contexts will foster better informed thinking, better problem-solving skills, and increased innovative creativity in language education and applied linguistics. If developed effectively, it will also promote an ethical use of AI and a human-centred approach that works within established disciplinary strengths. Based on this discussion with learners of applied linguistics and language education, there is evidence that learners draw on methodological approaches (e.g., corpus approaches), knowledge of data and issues of representation, theoretical perspectives about language as a social product and artefact (e.g., references to Foucault), and language as a system (e.g., references to words, texts, syntax). This kind of knowledge is not generic. It is specialised and is central to the epistemologies and ontologies of applied linguistics and language education. We argue for a disciplinary perspective on CAIL not only as it responds to wider calls in the literature and discussions of linguistics and AI elsewhere (e.g., Curry et al. 2025; Grieve et al. 2025) but because learners of applied linguistics and language education appear to draw on this knowledge instinctively.

Situating criticality, ethics, practical applications, and technical knowledge within this paradigm means that learners can navigate their growing knowledge and apply it to their practices, generally. By developing an approach to CAIL that also draws on such situated knowledge, we can develop a mechanism for learners to use knowledge gleaned across their discipline to evaluate new AI tools and developments, critically and ethically. Drawing on Tsui and Tavares (2021), we can also encourage that learners reflect these criticism and critiques back at the discipline more generally. In these ways, AI becomes resource for generating critical thinkers and ethical humans who draw on technical and contextual knowledge to inform their activity. In a world shaped by increasing challenges in economy, society, ecology, and policy, these are the kind of thinkers we need to develop.

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# Appendix A: Keywords and key terms

| Rank | Keyword | Rank (cont.) | Keyword (cont.) | Rank | Key term |
|---|---|---|---|---|---|
| 1 | chatgpt | 21 | text | 1 | artificial intelligence |
| 2 | human | 22 | machine | 2 | social reality |
| 3 | artificial | 23 | nowadays | 3 | critical thinking |
| 4 | intelligence | 24 | analysis | 4 | constructing social reality |
| 5 | humans | 25 | texts | | |
| 6 | threat | 26 | dealing | | |
| 7 | realities | 27 | critical | | |
| 8 | response | 28 | translated | | |
| 9 | probability | 29 | topic | | |
| 10 | sketchengine | 30 | corpus | | |
| 11 | responses | 31 | answer | | |
| 12 | newspaper | 32 | look | | |
| 13 | parameters | 33 | final | | |

(continued)

| Rank | Keyword | Rank (cont.) | Keyword (cont.) | Rank | Key term |
|---|---|---|---|---|---|
| 14 | baker | 34 | example | | |
| 15 | constructing | 35 | really | | |
| 16 | disappear | 36 | now | | |
| 17 | paul | 37 | like | | |
| 18 | machines | 38 | know | | |
| 19 | sort | 39 | think | | |
| 20 | ai | | | | |

# Appendix B: Percentage combination of focused codes per student

| Combined focus codes | P1 | P2 | P3 | Total |
|---|---|---|---|---|
| CT01; CT02; EA05 | 0 | 0 | 8 | 3 |
| CT01; CT02; PA03; TU02 | 9 | 0 | 8 | 6 |
| CT01; CT02; PA03; TU03 | 0 | 9 | 0 | 3 |
| CT01; CT02; PA05; PA03; EA06; TU03 | 9 | 0 | 0 | 3 |
| CT01; CT02:PA03; PA05; EA06 | 0 | 0 | 8 | 3 |
| CT01; EA01 | 0 | 0 | 15 | 6 |
| CT01; EA02 | 0 | 0 | 8 | 3 |
| CT01; EA03 | 0 | 9 | 0 | 3 |
| CT01; EA04 | 9 | 0 | 0 | 3 |
| CT01; PA03 | 0 | 18 | 15 | 11 |
| CT01; PA04; TU04 | 9 | 0 | 0 | 3 |
| CT01; PA05 | 0 | 9 | 8 | 6 |
| CT01; TU04 | 0 | 9 | 0 | 3 |
| CT01; TU04; PA03; PA04 | 9 | 0 | 0 | 3 |
| CT02; EA04; TU04 | 9 | 0 | 0 | 3 |
| CT02; PA03 | 0 | 9 | 0 | 3 |
| CT02; PA03; PA04 | 0 | 9 | 0 | 3 |
| CT02; PA05 | 0 | 0 | 8 | 3 |
| CT02; PA05; PA03; EA06 | 0 | 9 | 0 | 3 |
| EA05; CT01 | 0 | 9 | 0 | 3 |
| EA05; EA03 | 9 | 9 | 0 | 6 |
| PA01; EA02; TU01 | 0 | 0 | 8 | 3 |
| PA03; PA04; CT02; EA02 | 0 | 0 | 8 | 3 |
| TU02; PA02 | 0 | 0 | 8 | 3 |
| TU02; PA02; EA01; CT01 | 9 | 0 | 0 | 3 |
| TU03; CT01 | 9 | 0 | 0 | 3 |
| TU04; EA04 | 18 | 0 | 0 | 6 |
| Total | 100 | 100 | 100 | 100 |

# Appendix C: ALLE competences for CAIL

| AI literacy code | Focused code | Definition | Applied Linguistics & Language Education (ALLE) competencies that may facilitate transfer |
|---|---|---|---|
| Critical thinking | CT01 | Signals the use of critical thinking to engage with technology, data, etc. | In ALLE, students are trained recognises biases and understand the role of language-driven data in the production and dissemination of knowledge. Students are aware that knowledge in ALLE is constructed through a variety of different paradigms, including qualitative, quantitative and mixed methods approaches. We can draw parallels between these competencies and the need for critical approaches towards AI. Such an explicit comparison can facilitate transfer. |
| Ethical awareness | EA01 | Signals thinking about sources of information and the responsibility to reflect on sources | In ALLE, we help our students to recognise the role that sources play in reporting research and knowledge generation. They come to understand that identifying sources in ALLE is key to offering context on how knowledge is generated. We can draw on this competence to ensure that the development of responsible professional habits involves reflexivity on the quality and appropriateness of the sources (or lack of sources) in AI output. |
| | EA02 | Signals engagement with the notions of quality and reliability with regards to data and AI outputs. | To what extend does AI use credible sources? In ALLE, students recognise that sources such as research papers, encyclopaedia entries, books or podcasts are likely to play different roles in ALLE research and knowledge generation. Assessing that the quality, the validity and reliability of linguistic research is mediated by the nature of the research methodology (corpus-based, experimental, ethnographic, etc.) and the publishing format where it is published. We can draw on this knowledge to facilitate transfer from ALLE to critical AI literacies. |

(continued)

| AI literacy code | Focused code | Definition | Applied Linguistics & Language Education (ALLE) competencies that may facilitate transfer |
|---|---|---|---|
| | EA03 | Signals reflection on the risk of AI for human knowledge production and how human knowledge is generated | To what extent can AI replace human cognition and knowledge? In ALLE, students become aware that the information generated with the aid of AI cannot just be copied and pasted somewhere else. Using content generated by AI tools is an unethical use that does not support the range of cognitive skills involved in producing for example an essay or putting together a critical literature review. Critical thinking, linguistic analysis, communication and language education-related cognitive skills are essential to develop responsible work habits, professional integrity and lifelong learning skills. These competencies can be highlighted to students to foster critical AI literacies. |
| | EA04 | Signals AI as not equating to humans | In ALLE, we often endeavour to make students aware that information and outputs are shaped by cultural norms. Taking this knowledge in line with developments in AI, we can encourage students to reflect the role of LLMs in training AI and shaping their outputs and draw attention to specific tools, such as ChatGPT, to increase ALLE students' awareness about the relationships between AI and register in particular and epistemologies in ALLE more generally. |
| | EA05 | Signals human dependence on AI | To what extend can AI replace agency? ALLE students are often trained to be aware that academic outputs must reflect agency, their growing expertise, and a critical awareness of linguistic issues. Drawing on this knowledge, we can encourage reflections on the nature of texts generated with the aid of AI, highlighting how they do not necessarily contribute to their growth as a student in ALLE. We can note that relying on AI for the generation of text can only negatively impact how the students conceptualise how knowledge is constructed in applied linguistics and language education. |

(continued)

| AI literacy code | Focused code | Definition | Applied Linguistics & Language Education (ALLE) competencies that may facilitate transfer |
|---|---|---|---|
| | EA06 | Signals potentially unethical use of AI | As we make our ALLE students aware of the negative impact of unethical decisions on linguistic research, we can also make them aware that unethical uses of AI can damage their growth as a student in ALLE and can potentially risk their individual and professional development in the field. Any gaps in knowledge can be addressed through a contextualisation of AI as both an process and an industry and we can draw on the likes of critical discourse studies to encourage reflections on neoliberal and capitalistic facets of AI, the relationship between AI and the environment, and the impact of AI on different people, globally. |
| Practical application | PA01 | Signals use of technology to solve problems | Some GenAI tools are certainly useful in ALLE. Is the student aware of how they can help them solve problems? If so, is the student aware of the procedure in place to report ethical uses of AI in their work? Using AI for problem solving complements the students' efforts to identify linguistic, literary, and cultural challenges and analyse them critically. They should engage with these technologies with the same criticality with which they approach any language analysis tool. |
| | PA02 | Signals engagement with notions like parameters/ variables in analysis | Who defines the variables and parameters in ALLE research? This same question should apply to AI use in ALLE. If students understand how linguistic data is collected, analysed, and interpreted across different methodologies in ALLE can they say the same of AI tools. For example, corpus linguistics uses large datasets to study patterns in language use and experimental methodology seeks to investigate cognitive or psycholinguistic aspects of language learning. The student should access this reflexivity and critical engage with the use of AI tools when completing tasks. |

(continued)

| AI literacy code | Focused code | Definition | Applied Linguistics & Language Education (ALLE) competencies that may facilitate transfer |
|---|---|---|---|
| | PA03 | Signals use of AI for support functions e.g., references | Some GenAI tools are certainly useful in ALLE. However, together with skills in citation and referencing, students need to develop skills to locate and evaluate the references provided by or with the aid of AI tools. These are foundational academic skills that underpin quality control in academic work. We should encourage a student-centred, not AI-centred, approach that draws on this knowledge and ensures critical engagement with AI tools. |
| | PA04 | Signals use of AI for analytical purposes | How are analyses done by GenAI tools? The generation of knowledge in ALLE is often interdisciplinary. Students require skills from linguistics, education, sociology, and digital humanities. Students and educators must navigate therefore quantitative and qualitative research methods, critical discourse analysis, corpus tools, and pedagogical frameworks while remaining ethically and technologically aware.<br>Drawing on this knowledge base, the student can critically evaluate AI-generated linguistic data, particularly in language assessment, language learning, language analysis, automated translation, and chatbot-based learning. This allows for direct knowledge transfer in the use of AI. |
| | PA05 | Signals use of AI to carry out tasks/jobs | In ALLE, it is essential that students gain familiarity with how relevant corpora, text analysis software, and digital humanities tools perform tasks and support their research and practice agenda. GenAI tools can be successfully incorporated into a wider toolkit to support students in carrying out certain tasks. Assessing the quality of the output from AI is, however, essential. Evaluating results and introducing iteration in developing quality prompts is also essential. We can draw parallels between similar processes in linguistic analysis to foster a critical use of AI. |

(continued)

| AI literacy code | Focused code | Definition | Applied Linguistics & Language Education (ALLE) competencies that may facilitate transfer |
|---|---|---|---|
| Technical understanding | TU01 | Signals the need for cleaning and preparing data | Some GenAI tools are certainly useful in ALLE. However, the student needs a basic understanding of computational thinking skills to be able to interpret how AI tools can facilitate data-handling. As students in ALLE are often aware of basic principles behind Natural Language Processing, text mining, algorithmic thinking, data analysis and visualization, we can draw on the affordances and challenges of these approaches to foster critical AI literacies. |
| | TU02 | Signals a form of data literacy about understanding what data is being used | When it comes to AI, transparency in how language data is used and produced is key. Tools like ChatGPT and the like use large neural networks trained on vast amounts of text. They are not humans so they don't really "think" but they predict words based on patterns they have "learned". However, the generation of knowledge in ALLE is often interdisciplinary. Students require skills from linguistics, education, sociology, and digital humanities. Students and educators must navigate therefore quantitative and qualitative research methods, critical discourse analysis, corpus tools, and pedagogical frameworks while remaining ethically and technologically aware. We must make students aware of the affordances of their own thinking and the advantages of leading with human cognition. |
| | TU03 | Signals a lack of knowledge of how LLMS work | While students may have varied knowledge of LLMs, their knowledge of language, issues of representation, challenges of data collection and developing sampling frames is growing. Likewise, the value of transparency, replicability, and reproducibility is also developing in ALLE. Drawing on these values, we can foster critical reflection in learners to pose questions about LLMs, identify gaps in their knowledge, and unpack their role in and impact on research processes. We can transfer their growing methodological expertise to address these concerns. |

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