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AI-Assisted Scaffolding for Inclusive CLIL in Higher Education

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Abstract. The CLIL courses in universities frequently combine students of varying levels of academic and English literacy. Consequently, not all learners engage in reading and are unable to communicate complicated ideas when studying disciplinary content using English. This paper examines whether AI applied in a narrow and teacher-directed form can serve more inclusive CLIL by scaffolding both content and academic language differentially. The research will be carried out in a six-week CLIL module of an undergraduate course in which the instruction will be in English. Two intact groups with around 50-70 students will be subjected to the same syllabus, activities and the same standards of assessment. The support package of the experiment group will be a curated AI support package monitored by the instructor. It will offer adaptive glossary of important terms, concept-check prompts, levelled language frames in discussion and writing and feedback prompts which are based on a CLIL-oriented rubric. The conventional scaffolding of the comparison group will be the use of instructor-prepared materials without AI. It will consist of pre- and post-measures of content comprehension, academic vocabulary task which is discipline specific, and rubric based assessment of student writing. The indicators of participation will also be analyzed, i.e. frequency of contributions and the use of academic language in the classroom. To clarify the experience of using the scaffolds and what assistance proves the most valuable, short student and teacher interviews will be used. It is assumed that AI scaffolding through the teacher will enhance conceptual learning, reinforce academic language in student writing, and engage more learners with lower proficiency. The research provides useful suggestions on the responsible introduction of AI in the university CLIL with focus on academic integrity and quality control.

Keywords: CLIL; Artificial Intelligence; higher education; scaffolding; inclusive education

Introduction

Content and Language Integrated Learning (CLIL) has emerged as one of the most important methods of combining disciplinary knowledge with intentional language performance, especially in situations when students are expected to learn content using English. At the tertiary education

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level, CLIL has been associated with internationalisation strategies and with the need for graduates to be able to engage in global academic and professional communities. However, in CLIL classrooms at universities, there are often students who demonstrate unequal levels of English language proficiency, as well as different degrees of academic literacy (Mammadova, 2024). Such differences can lead to unequal participation, a lack of confidence in interaction during seminars, and written work that may fail to reflect students' conceptual knowledge when cognitively challenging content tasks are presented in a second language. One of the main ideas of CLIL is that cognitive difficulty should be preserved and that language assistance should be a planned and intentional process rather than being left to immersion (Coyle et al., 2010; Dalton-Puffer, 2011). It is at this point that scaffolding becomes necessary. Scaffolding, which can be described as organized, temporary assistance allowing learners to act at a higher level than they can independently at present, consists of such techniques as pre-task concept clarification, vocabulary support, modelling disciplinary discourse, sentence and paragraph frames, and guided feedback (Gibbons, 2002; Vygotsky, 1978). Scaffolding in CLIL is not content simplification, but rather an accessibility and inclusion process that supports learners in coping with complex concepts and building the academic language required to communicate them (Mammadova, 2023). Nonetheless, scaffolding in university CLIL is challenging in terms of providing it in a timely and differentiated manner. Teachers also have to work with large numbers of students, busy timetables, and heterogeneous abilities, and it is difficult to support everyone. This issue can be addressed through formative assessment and feedback, which help explain expectations, facilitate revision, and provide advice on how to improve during learning, rather than simply judging performance at the end (Black & Wiliam, 1998; Hattie & Timperley, 2007). In practice, however, there are often time-related constraints in feedback cycles, and students are not always given maximum guidance to address gaps in participation and academic language. Recent developments in educational AI create new possibilities for micro-scaffolding: quick vocabulary and concept support, levelled language frames in speaking and writing, and feedback prompts aligned with rubrics. Studies of AI implementation in higher education indicate both growing interest in AI-based learning and evaluation and the necessity of keeping educators at the centre of design and regulation (Zawacki-Richter et al., 2019). This is a key issue in CLIL: unregulated application of AI may lead to false explanations, support shallow paraphrasing, and create academic dishonesty concerns. Thus, AI should not be discussed as a substitute for teaching or student thinking, but should instead be teacher-guided and limited in order to function as scaffolding. This paper discusses an AI-assisted inclusive CLIL scaffolding model in higher education. This model integrates four supports embedded within a CLIL unit: an adaptive glossary of key disciplinary concepts, concise concept-check cues, discussion and academic writing language frames at different levels, and rubric-congruent formative feedback, all of which can be regulated by the instructor. The following research questions guide the study: What will be the design of AI-assisted scaffolding to support university CLIL tasks without reducing cognitive load? What improvements will be made in content understanding, discipline-specific academic vocabulary, writing quality, and involvement?

What are the perceptions of students and instructors regarding the usefulness and integrity of AI-assisted scaffolding?

Methods

This research is based on a mixed-methods, quasi-experimental methodology in a CLIL course taught in English at a university. It has a comparison-group design because students are taught in intact classes, and random assignment would not be feasible in a real-life higher education setting (Shadish et al., 2002). Part of the study takes place during a 6-week CLIL unit in an undergraduate module in a subject such as Education, Geography, Business, or a similar field and involves about 50–70 undergraduate students with diverse levels of English proficiency and different levels of academic literacy. Two intact classes or seminar groups are assigned to an experimental group and a comparison group. The two groups follow the same syllabus, content input, tasks, and assessment criteria so that any differences that emerge may be attributed to the scaffolding approach rather than to other instructional content. The experimental group is provided with an AI-assisted scaffolding toolkit, which is limited, teacher-directed, and built into the unit at certain predetermined points. The toolkit consists of an adaptable glossary of primary disciplinary terms with brief definitions, examples of scholarly usage, and quick comprehension checks; brief concept-check prompts, which require students to explain concepts in their own words, contrast concepts, support claims, or identify misconceptions; levelled language frames, which support seminar discourse and academic writing; and rubric-aligned formative feedback prompts, which target content accuracy, application of disciplinary vocabulary, coherence and clarity of argument, and academic style. AI may be used to generate candidate glossary entries, frames, or feedback wording, although the instructor reviews and approves the materials and feedback before they are used by students, makes any necessary revisions, and ensures that this process remains consistent with the role of formative feedback in improving learning during the process (Black & Wiliam, 1998; Hattie & Timperley, 2007). The comparison group completes the same unit using traditional non-AI scaffolding provided through instructor-created materials such as a fixed glossary, teacher-provided frames, and teacher-generated practice feedback. To measure not only learning outcomes but also the experiences of participants, data are gathered from various sources in accordance with the principles of mixed-methods integration (Creswell & Plano Clark, 2018). Pre- and post-tests of content understanding aligned with unit outcomes, a discipline-specific academic vocabulary task, and scoring of a brief academic writing task, such as a mini-report or structured explanation with rubrics, are examples of quantitative measures. Participation is examined using classroom indicators that include frequency of contribution and use of target academic phrases, recorded through observation checklists or short transcript samples where feasible. Qualitative data are collected through short student interviews or open-ended questionnaires, as well as instructor reflective notes or a short interview aimed at documenting implementation issues and perceived value. Quantitative data are compared through pre/post gains and writing scores between the groups using relevant statistical tests, whereas qualitative data are analysed thematically to identify patterns regarding the usefulness of scaffolds, changes in confidence and participation, perceived fairness, and concerns about accuracy or integrity (Braun & Clarke, 2006). The integration of mixed methods is intended to explain not only whether a difference occurs between groups, but also how and why scaffolding may affect learning and inclusion (Creswell & Plano Clark, 2018). Voluntary participation, informed consent, and anonymised reporting are included in the ethical procedures. Because AI is used in the experimental group, explicit rules of academic honesty are enforced. The scaffolding processes to which AI may be applied include, but are not limited to, glossary support, planning, language framing, and feedback prompts; however, generating end-assessed texts is forbidden, which highlights the importance of keeping educators in control of AI application in higher education settings (Zawacki-Richter et al., 2019).

Findings

Due to the fact that the study is to be implemented in a current university CLIL course, the results are presented in the form of expected outcomes in relation to the intervention logic and the measures to be carried out. In sum, the AI-aided scaffold group is expected to demonstrate greater improvement than the comparison group in three interrelated domains, namely content knowledge, academic language growth, and inclusive engagement. First, students in the AI-assisted scaffolding condition are expected to show stronger content understanding. The adaptive glossary and concept-check prompts are intended to reduce misunderstanding of critical disciplinary terms and to encourage students to explain meanings in their own words, which fits the CLIL focus on integrating meaning-making with language support (Coyle et al., 2010; Dalton-Puffer, 2011). Second, improvement is expected in discipline-specific academic vocabulary and academic writing performance. It is hoped that repeated exposure to essential terms in writing through glossary support, together with the use of levelled language frames and rubric-based feedback prompts, will help students use disciplinary language more accurately and confidently in writing, especially when feedback is structured and revision-focused (Black & Wiliam, 1998; Hattie & Timperley, 2007). Third, participation patterns are expected to become more inclusive in the AI-assisted group. Levelled discussion frames are expected to reduce hesitation by providing entry points for asking for clarification, expressing agreement or disagreement, and adding evidence, which is consistent with the principles of inclusive scaffolding (Gibbons, 2002; Vygotsky, 1978). Qualitative evidence is expected to show that learners find AI scaffolding most beneficial when it reduces anxiety and provides understandable support in expressing complex content through academic vocabulary, while also emphasising the importance of educator supervision and clear limitations in maintaining integrity, which is supported by recommendations from AI research in higher education (Zawacki-Richter et al., 2019).

Results

Since the study is intended to be implemented in an ongoing university CLIL course, the results are presented as anticipated outcomes based on the logic of the intervention and the measures planned. In general, it is anticipated that the AI-assisted scaffolding group will demonstrate greater improvement compared to the comparison group in three interrelated domains, namely, content understanding, academic language development, and inclusive participation. To begin with, students in the AI-assisted scaffolding condition are expected to show higher levels of content understanding and greater gains. The concept-check prompts and adaptive glossary are intended to minimize linguistic misunderstandings of key disciplinary concepts, as well as to encourage students to develop meaning-making skills independently, which is consistent with CLIL principles focusing on the combination of meaning-making and language support (Coyle et al., 2010; Dalton-Puffer, 2011). Second, discipline-specific academic vocabulary and written academic performance are expected to improve. The glossary and rubric-informed feedback prompts should support more effective and confident disciplinary writing by helping students benefit from repeated exposure to key terms and from later writing practice, with feedback being structured and revision-oriented (Black & Wiliam, 1998; Hattie & Timperley, 2007). Third, participation is expected to be more inclusive within the AI-assisted group. Levelled discussion frames are predicted to reduce hesitation because they provide points of entry for requesting clarification, agreeing or disagreeing, and contributing evidence, which supports greater engagement in line with inclusive scaffolding principles (Gibbons, 2002; Vygotsky, 1978). The qualitative data are likely to show that AI scaffolding is perceived as most useful by learners when it helps reduce anxiety and provides clear support for expressing complex information using academic language, while also emphasizing the role of teacher control and limits in ensuring integrity, which is a key recommendation in AI-related research in higher education (Zawacki-Richter et al., 2019).

Discussion

It is expected that teacher-directed AI scaffolding will support inclusive CLIL in higher education by reducing language-based obstacles to disciplinary meaning-making. If students in the AI-assisted condition show better conceptual knowledge, stronger discipline-specific vocabulary, improved academic writing, and more balanced participation, this would align with the CLIL principle that cognitive challenge should be maintained while language support is explicitly planned (Coyle et al., 2010; Dalton-Puffer, 2011). The intervention will not simplify the subject matter but will instead focus on making complex content accessible through specific support in terminology, interaction, and academic discourse, reflecting scaffolding as organized assistance that enables learners to perform tasks that are more difficult than what they can do independently (Gibbons, 2002; Vygotsky, 1978). One implication concerns formative assessment. If the quality of writing and argumentation improves through rubric-aligned feedback, this would support the view that feedback is most effective when it is criteria-based and used to help students improve during learning (Black & Wiliam, 1998; Hattie & Timperley, 2007). The role of AI in this model is not to replace the instructor’s judgment; rather, it assists in accelerating differentiation and simplifying the language of feedback, while the teacher remains responsible for making accurate judgments that are acceptable and consistent with course outcomes. Governance and academic integrity are also central. The approach can be justified, even if the results are positive, only if it does not compromise the authenticity of student work. Bounded use and instructor control are directly related to educational AI research, which emphasizes that technology should not displace educators or shift fundamental pedagogical choices toward technological ones (Zawacki-Richter et al., 2019). Clear boundaries, process evidence through drafts and revisions, and teacher moderation are therefore viewed as conditions for success rather than optional additions. Finally, the limitations must be acknowledged. The intact-group design restricts causal claims compared with randomized designs (Shadish et al., 2002). The results may also be influenced by discipline, task type, and institutional context. In the future, the approach may be tested in other subject areas, and the question of whether scaffolds can be gradually withdrawn as learners gain independence may also be explored, which is an important principle in scaffolding-informed pedagogy (Gibbons, 2002).

Conclusion

This article proposed an instructor-guided and limited AI-assisted scaffolding model to support inclusive CLIL in the university setting. The combination of an adaptive glossary, concept-check prompts, levelled language frames, and rubric-consistent formative feedback under instructor regulation is expected to strengthen content knowledge, academic language production, and more balanced participation in mixed-proficiency university classes. If the anticipated results are confirmed, the study will offer practical recommendations on how AI can be integrated into university CLIL as scaffolded support without compromising academic integrity and while keeping teacher judgment central.

Limitations and Ethical Considerations

This study has several limitations. Intact groups do not allow strong causal claims, and the findings may partly reflect group differences or instructor bias. The results may also be context-dependent, as the research is conducted in a single course within one institutional setting and over a six-week unit; therefore, long-term effects and broader generalizability cannot be ensured. Because AI is involved, careful governance is necessary to maintain academic integrity and ensure that AI supports learning rather than generates assessed work; the success of the model therefore depends on clear boundaries, fair access, and consistency in instructor oversight.

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