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LEARNING TO LEARN VIA ARTIFICIAL INTELLIGENCE AND LEARNING ANALYTICS

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Abstract

This paper addresses the issue of how artificial intelligence and learning analytics are used to help learners improve their self-regulated learning skills, in other words, "learn how to learn". Two broad approaches are described. The first approach involves artificial intelligence systems that both teach content as well as support self-regulated learning by means of dynamic adjustment to various aspects of the interaction, including dynamic advice and feedback. Such systems are characterised as either purely reactive, explicit or pro-active. The second approach involves learning analytic systems based on artificial intelligence techniques that capture and analyse learning data from various kinds of educational interactions and later feed that back to learners in a form that enables them to visualise and reflect on their learning behaviour. Whilst the first approach is described by reference to the literature, the second approach showcases experimental work conducted by two of the authors. This involved the analysis of audio transcripts of students' weekly group discussions and the development of different machine learning techniques to capture the challenge moments, triggers of regulation of learning, that would form the basis for feedback implemented in real-world contexts. This informs the future design of the learning analytics and artificial intelligence system to promote awareness and support learners' subsequent regulation of learning.

Keywords: Self-regulated learning, learning to learn, artificial intelligence, learning analytics

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1. Introduction

One of the most important outcomes for an educational institution is that its learners get better at "doing" learning. Central to "learning to learn" is the skill of self-regulated learning where the learner focuses on the processes of their learning in addition to the content of that learning. These processes include planning, goal setting, monitoring and reflection, not just in terms of metacognition, but also in terms of their meta-affective and meta-motivational facets.

One of the contributions of artificial intelligence (AI) has been to assist human teachers in developing their learners' metacognitive, meta-affective and meta-motivational processes. AI has played different roles, each implying a different division of labour between the artificial intelligence (AI) systems and human teachers. These roles lie along a continuum from AI doing both the teaching of content and fostering self-regulated learning to AI solely undertaking the learning analytics:

The AI teaching system acts as both a content teacher as well as promoting self-regulated learning. This involves the human teacher introducing the AI system into their teaching and then priming and motivating the learners into using it effectively. The AI system then (i) adaptively chooses learning tasks, (ii) gathers and analyses learner data as the learners work on those tasks, (iii) adaptively reacts to how well the learners progress on the tasks, and crucially (iv) *adaptively reacts to the way the learner has gone about their learning.* Finally, handing back to the human teacher a summary of how things have gone for the teacher to provoke whatever analysis, discussion and remedial teaching is then needed.

The AI Learning Analytics system does not interact directly with the students while they learn but simply gathers and analyses data on the learners' learning and self-regulated learning, which it then hands over later to the human teacher and/or the learners for analysis and discussion. This data might have been derived from learners working in a classroom, either with or without any computer-based educational technology.

This paper is divided into 6 sections. The next section gives a brief overview of the notion of learning to learn, tracing it from early work by Bandura and Zimmerman on self-regulated learning through the development of static and dynamic models to the present day. Section 3 explores one end of the continuum mentioned above, namely the role that AI has played in providing platforms that support students in both their learning and their learning to learn. Sections 4 and 5 concentrate on the other end of the continuum mentioned above, namely AI systems that collect data on students' learning (not necessarily learning with an AI platform) and make use of learning analytic techniques to process that data into forms amenable to interpretation by learners and/or teachers in support of learning to learn. Section 6 offers a conclusion.

2. Learning How to Learn

In the context of student learning in educational contexts, "learning how to learn" can be regarded as the student improving some aspect of their self-regulated learning skills. Broadly, these skills involve the student thinking about and acting on both the "how" of learning as well as on the "what" to be learnt. For a recent overview of the field, see Tinajero et al. (2024) and for an overview of the role of AI in supporting metacognition (a central component of self-regulated learning), see Azevedo and Aleven (2013).

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2.1. Self-regulated learning

Zimmerman (1989) offered an early definition of self-regulation based on the general psychological notion of "self-efficacy" as a determinant of "whether coping behavior will be initiated, how much effort will be expended, and how long it will be sustained in the face of obstacles and aversive experiences" (Bandura, 1977).

> "In general, students can be described as self-regulated to the degree that they are metacognitively, motivationally, and behaviorally active participants in their own learning process . . . Such students personally initiate and direct their own efforts to acquire knowledge and skill rather than relying on teachers, parents, or other agents of instruction. To qualify specifically as self-regulated in my account, students' learning must involve the use of specified strategies to achieve academic goals on the basis of self-efficacy perceptions. This definition assumes the importance of three elements: students' self-regulated learning strategies, self-efficacy perceptions of performance skill, and commitment to academic goals. Self-regulated learning strategies are actions and processes directed at acquiring information or skills that involve agency, purpose, and instrumentality perceptions by learners. They include such methods as organizing and transforming information, self-consequating, seeking information, and rehearsing or using memory aids . . . Self-efficacy refers to perceptions about one's capabilities to organize and implement actions necessary to attain designated performance of skill for specific tasks . . . Academic goals such as grades, social esteem, or postgraduation employment opportunities can vary extensively in nature and in time of attainment." (Zimmerman, 1989, p.329)

As Bandura points out above, a crucial element is the students' existing "commitment to academic goals", and this takes effort and thus requires motivation. If the student wants to learn the concepts or the skills, they are likely to self-regulate their learning. Learning to learn, i.e. *improving* self-regulation skills, requires further effort and therefore further motivation, not just to the current academic goals but also to the more general aspiration of becoming a better learner for the future (Howell et al., 2018).

Efklides and Schwartz (2024) argue that:

> "the SRL conception of learning [mentioned above] represents what successful students (regardless of level, e.g., senior high, college, or university) do when actively learning. . . However, it is a common observation that this conception of learning does not easily generalize to younger or less successful students . . . Moreover, SRL often fails despite one's efforts or does not transfer from one knowledge domain to another."

In other words, it offers the goal but not the route to acquiring and improving self-regulated learning.

Work on self-regulated learning is described by both static and dynamic models. Static models identify the many different sub-parts and facets of self-regulated learning. For instance, Table 1 of Pintrich (2004) offers a detailed static model of the main facets of self-regulated learning as cognition, motivation/affect, behaviour and content. These are organized in terms of 4 phases, namely: Phase 1: Forethought, planning and activation, Phase 2: Monitoring, Phase 3: Control, and Phase 4: Reaction and Reflection. For example, in Phase 2, under motivation/affect we find "awareness and monitoring of motivation and affect."

By contrast, dynamic models go beyond simply identifying phases as in Pintrich above, to examine when and how the different components of self-regulation interact. For instance, Winne and Hadwin (1998)

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offer a "recursive, weakly sequenced system" as a dynamic model of metacognitive monitoring and control, named COPES (**C**onditions, **O**perations, **P**roducts, **E**valuations, **S**tandards). This model contains arrows showing influences and outcomes, such as monitoring produces cognitive evaluations that take different values, such as "on target", "too low", "too high" and so on.

In addition to the narrower focus on Monitoring, a further difference between the Winne and Hadwin model and the Pintrich model, is that the latter allows for more flexibility in the sequence of stages in the sense that a later stage might be interrupted with the student going back to an earlier stage, or a stage apparently skipped altogether.

2.2. Motivation and affect in self-regulated learning

Although only mentioned obliquely in the Zimmerman quotation above, self-regulated learning involves motivation and therefore affect plays a role. So, learning to learn includes the notion of learners (i) improving their capability to recognize and anticipate both the positive and negative affective and motivational states that accompany learning as well as (ii) developing strategies for managing these affective states, "in the face of obstacles and aversive experiences", as Bandura puts it.

The specific role of motivation regulation has been explored by Miele and Scholer (2017). This expands the level of detail in the Motivational/Affect Area of Pintrich's model, described above. Rather than treating the type and degree of a student's motivation as having relatively fixed values throughout a task, it indicates how the costs and obstacles encountered *during* a learning task may trigger a number of reflective, planning and monitoring processes with respect to motivation. These, in their turn, may have effects on the metacognitive self-regulated learning aspects of the task.

For a model that gives prominence to metacognitive experiences and to the affective side of self-regulated learning, we turn to Efklides (2011). Her Metacognitive and Affective model of Self-Regulated Learning (MASRL) is based on the task and the learner components and their interactions. In a later paper, Efklides and Schwartz (2024) emphasise the importance of helping learners to improve the accuracy of their understanding of their metacognitive experiences and the importance of teachers and/or systems in providing metacognitive feedback. They argue that this feedback must be carefully calibrated to be "developmentally appropriate as well as informative of students' learning process" and to take account of the fact that "metacognitive feedback regarding children's judgment of their own performance may have motivational and affective repercussions that might interfere with their regulation of learning."

2.3. Coregulation and social regulation

The notion of *self*-regulation has also been developed to cover collaborative and social regulation (see, e.g. Martínez-López et al., 2023). For instance, Järvelä and Hadwin's (2013) dynamic model illustrates how two learners can support and develop each other's self-regulated learning. In contrast to the Miele and Scholer (2017) model of self-regulated learning which zooms in to focus on the details of regulating motivation, the Järvelä and Hadwin (2013) model zooms out to compare two learners' overall models of self-regulated learning.

The model of Järvelä and Hadwin (2013) shows Learner-A's and Learner-B's individual self-regulated learning viewpoints of a shared task. Each learner has their own viewpoint as well as, through

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dialogue and other means, a perception of the other learner's viewpoint of the task. Similarities and differences of viewpoint provide triggers for exploring self-regulated learning for each learner. So, the model shows the two instances of self-regulation, the resultant co-regulation arising from the shared task, and the possible shared regulation emerging from the co-regulation.

2.4. Improving self-regulated learning

The key to improving self-regulated learning is that the student wants to improve it and is willing to put effort into doing so. One way to improve the quality of self-regulated learning is to transfer existing strategies and insights to a new learning context, but this is not always easy (Raaijmakers et al., 2018).

Central to all the models of self-regulated learning are the metacognitive, meta-affective and meta-motivational feedback processes of identification, selection, reflection and monitoring. Any or all of these processes can fail to work optimally and can be improved upon. For example, identifying one's state of understanding and feeling of knowing may be over- or under-estimated. Improving the accuracy of these estimates leads to a more accurate sense of self-efficacy. The selection of which goal to work on can be improved by either broadening the range of goals considered or by selecting a goal that is a better fit for the current situation. Reflection and monitoring can be improved by improving one's ability to focus both on how one is managing a task as well as on how the task is progressing.

The following section focuses on how systems based on artificial intelligence have been deployed to develop learners' self-regulated learning skills.

3. The AI System Acts as Both a Content Teacher As Well As Promoting Self-Regulated Learning

Artificial intelligence-based systems in education have a long history of personalising learning by dynamically adjusting (i) the difficulty of the learning task, (ii) the interface features of the learning environment, and (iii) the feedback and help in response to the systems' estimation of the learner's degree of understanding and skill, as well as their affective and motivational states. We distinguish three kinds of systems with respect to the degree that the dynamic adjustments address issues of self-regulation.

Purely reactive systems dynamically make the kinds of adjustment mentioned above and these may well help the learner progress better, but they do not in themselves directly address the learner's self-regulation. This is because such adjustments are made without explaining why they are being made and thus the focus for the learner is likely to remain on the task rather than on how they are learning. For example, at an affective level some systems display a screen-based, pedagogical agent playing the role of an empathetic teacher whose facial expression changes from smiling when the learner is working correctly to frowning when the learner makes a mistake (e.g. Dias et al., 2006). This change of facial expression provides an ambiguous signal that something is not quite right but does not indicate what that is.

Explicit systems dynamically make adjustments, as above, but also offer some kind of metacognitive, meta-affective or meta-motivational commentary or feedback to the learner. They may also request information from the learner about, for example, their confidence in their answers or their affective

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state (e.g. Arroyo et al., 2009). Such systems may or may not generate a log file for the human teacher to use in any post-task interaction with the learners.

Arroyo et al. (2014) describe the evaluation of a system for teaching mathematics that interacts with learners at the cognitive, affective, metacognitive and motivational levels. For instance, it measures learner effort as well as success and failure. Depending on their progress, for some students it explicitly praises their effort and for others it de-emphasises the importance of success. Based on Dweck's (2002) theory of learning and mindset, it also explicitly provides feedback to try to persuade students that mathematics is learnable and not impossible.

A commonly used method of providing metacognitive feedback is for a system to display a "skillometer" of some kind that indicates the system's estimation of the learner's progress in acquiring the skills or concepts to be learned (for an early example, see e.g. Koedinger et al., 1997). A contemporary and more elaborated example is Area9 Rhapsode (White & du Boulay, 2024). This system asks learners to make judgements of their learning (JOLs) on each segment of the course being taken and the system relates those JOLs to the learner's success or otherwise on that segment. The system then generates a diagram contrasting (i) the degree to which the learner was conscious of how much they had understood and of how much they had not yet understood, against (ii) the degree to which the learner had seemed unconscious of how much they had understood and of how much they had not yet understood. These metacognitive diagrams were aimed both at the learners and at the human teacher who would then use them for classroom discussions about the nature of learners' individual differences in the trajectories of their learning and understanding.

Betty's Brain, is a system designed to help learners develop their understanding of scientific concepts and processes, e.g. the ecology of a river system (Biswas et al., 2016). The learner is provided with various online materials to read and then starts to construct a node and arrow concept map, where arrows represent processes and nodes represent entities, e.g. plants produce dissolved oxygen. The learners can work at their own pace and in any order. They can submit a partial concept map at any time to have it evaluated. If they submit the same concept map for evaluation again, having made no changes to it, they are offered the metacognitive advice to return to the online materials and update their concept map before requesting it to be evaluated again.

MetaTutor is one of the most sophisticated systems that addresses the learner and reacts both at the cognitive and at the metacognitive levels (Azevedo et al., 2022). The basic system aims to teach blood circulation, but it also contains 4 agents monitoring the way the learner is managing their learning: (i) "helps students to navigate through the system and orient the students about the task", (ii) "guides students in setting appropriate sub-goals", (iii) "helps students to monitor their progress", and (iv) "helps students deploy SRL learning strategies, such as summarizing and note-taking, making inferences, re-reading, and generating hypotheses".

> "For example, students are prompted to self-assess their understanding and are then given a brief quiz. Quiz results allow the PA [agent] to provide feedback according to the calibration between students' confidence of comprehension and their actual quiz performance. Learners can also self-initiate and express these same system-initiated metacognitive judgments and learning strategies through an SRL palette of actions." (Azevedo et al., 2022, Page 6)

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With the advent of generative AI, in particular LLMs such as ChatGPT, there is renewed interest in the roles that they might play in education in general (see, for example, Giannakos et al., 2024; Pulk & Koris, 2025; Wang et al., 2025) and in support of self-regulated learning in particular. For example, Lai (2024) argues that "chatbots present the ability to be a virtual tutor in the absence of an instructor, adult, or peer. GenAI chatbots can operate as virtual tutors that engage in personalized conversations with learners by providing an interactive and adaptive learning environment to answer questions, explain, and offer instant support, assistance, and guidance." In the terminology of this section, these roles are largely reactive with respect to self-regulation. By contrast, when an instructor was present, Xu et al. (2025) explored how students were assisted to operate when using generative AI tools in an educational technology course. The ChatGPT-based system generated prompts for planning, monitoring and reflection as well as for evaluation, but was not as sophisticated as MetaTutor in terms of personalising the metacognitive prompting to the learning trajectory of the learner.

Pro-active systems go beyond Explicit systems but are a work in progress. Rather than simply responding to a learner's self-regulatory development needs as they manifest in a given learning session, pro-active systems initiate new learning situations designed specifically to develop aspects of the learner's self-regulated learning skill-set that need attention. For example, in terms of metacognition this might mean exposing a learner to much more open-ended problems than they are used to, in order to strengthen their ability to set goals, monitor progress and reflect in this new context. In terms of meta-affect and meta-motivation, Goldin (2000) argues for:

> "a curriculum in which affect is considered may include generating problems from the curiosity of students, in order to develop their sense that intense feelings are appropriate, and teaching them to apply heuristics when these feelings occur. Anxiety, fear, and despair (but not puzzlement, bewilderment, and frustration) maybe regarded as essentially undesirable affective states; yet we need to provide appropriate, domain-specific ways for students to handle the negative affect when it (inevitably) occurs. We also need to provide productive experiences with and uses of desirable affect, including the affect of frustration. Students should occasionally experience frustration- not too much, of course-and then be brought back from it, guided to make progress in the problem with processes suggested by the frustration, and feel subsequent pleasure, elation, and satisfaction that is heightened by the earlier experience of frustration. We give students too little experience with intensely positive affective states, rarely connecting them with their own, genuine mathematical achievements." (Goldin, 2000, pp. 217-218)

Such a curriculum might, one day, be implemented in a pro-active AI-based system aiming to improve learners' meta-affect and meta-motivation.

The following sections explore the other end of the continuum mentioned at the start, namely the use of learning analytics to support improvements in self-regulated learning.

4. How AI and Learning Analytics Can Be Leveraged to Infer Students' Regulation of Learning, Potentially Supporting Reflective and Effective Collaborative Learning

Learning analytics (LA) is an emerging field at the intersection of artificial intelligence and education, which aims to measure, collect, analyse and report data "*about learners and their contexts, for*

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purposes of understanding and optimising learning and the environments in which it occurs" (Romero & Ventura, 2020, p.2). This field leverages both learning sciences theories to guide data collection and interpretation while also leveraging data analytics techniques to analyse data, model educationally meaningful constructs and offer insights for educational stakeholders, including students and teachers. This interdisciplinary approach combines the theoretical grounding of learning sciences with the data-driven analytical power of data sciences, offering complementary strengths for understanding and supporting learning processes.

Multiple data sources and analytics approaches have been used in the learning analytics field to convert low-level data collected from learning platforms or environments to high-level educationally meaningful constructs. This process is known as a mapping "From clicks to constructs," offering meaningful insights, aligning with educators' pedagogical interests. For example, Cukurova et al. (2020) utilised supervised machine learning models, as decision trees, to detect students' listening, watching, making and speaking behaviours as well as predict groups' collaborative problem-solving competence from video data. Kent and Cukurova (2020) leveraged social network analysis to analyse the collaborative learning process of learners' communities from their online discussion interactions.

Advances in natural language processing (NLP) help computationally recognise patterns in texts (Dowell & Kovanovic, 2022), for instance, group discourse, which is pervasively available in collaborative settings. Various NLP techniques have been used in extracting features from discourse. The conventional approach involves the use of bags-of-words (Aggarwal & Zhai, 2012), analysing word frequencies, or linguistic features, grammatical structures in sentences, such as part-of-speech (POS). For instance, Emara et al. (2021) leveraged POS trigrams obtained from group discourse to identify group patterns of regulation in collaborative open-ended problem-solving contexts. These NLP-based features can be utilised, particularly in conjunction with machine learning (ML) techniques, to build predictive models from annotated datasets. To illustrate, Zheng et al. (2019) created a semi-auto ML pipeline combining human coding and NLP features to identify self-regulated learning (SRL) vs socially shared regulation of learning (SSRL) constructs from group chats. Large Language Models (LLMs), which are advanced NLP models pretrained on extensive datasets, offer capabilities to understand patterns in human language, enabling them to receive natural language instructions and respond accordingly (Liu et al., 2021), and potentially effectively even when confronted with unseen data (zero-shot learning) or when provided with minimal training (one-shot or few-shot learning). Despite the potential of NLP and recent developments in analytic techniques, there are insufficient studies and pragmatic implementations of NLP in SSRL research (Villa-Torrano et al., 2025). While some studies applied NLP to unravel the regulatory process (Emara et al., 2021; Zheng et al., 2019), none of them target the emergence of the regulatory process, i.e., predicting challenges and identifying challenge dimensions.

To understand shared regulation of learning in collaborative settings, data about learners' situations and regulation could be gathered from students' interactions to infer targeted constructs. Since collaboration requires learners to engage in regulation of learning (ROL) processes, it involves collective planning, monitoring, evaluating, and taking control of their own learning to achieve set goals (Hadwin & Oshige, 2011). As the group navigates through the collaborative task, members can individually regulate themselves (self-regulated learning, SRL), co-regulate others (co-regulation, Co-RL), and/or collectively regulate as a group (socially shared regulation, SSRL) to overcome the wide range of challenges that may arise (Hadwin et al., 2011; Kreijns et al., 2003). For regulation, group members must first acknowledge the challenge moments that might hinder effective collaboration and develop suitable strategies to overcome these challenges together (Järvenoja & Järvelä 2009; Malmberg et al., 2015). The use of ROL strategies has been linked to higher academic outcomes (Broadbent & Poon, 2015; Richardson, Abraham and Bond, 2012), with research showing groups highly engaged in SSRL processes negotiated shared task perceptions, goals, plans, and strategies (Hadwin et al., 2011; Malmberg et al., 2015) while maintaining positive socio-emotional interactions, or establishing “mutual trust” to overcome challenges collectively (Fransen, et al., 2011). Without awareness of one’s own SRL and where the group stands as a whole, various perceptions of the challenges can lead to inappropriate or misaligned regulatory processes by group members (Gutwin & Greenberg, 2002; Järvelä et al., 2015). However, due to differences in personal socio-historical experiences situated in various contexts (Hadwin et al., 2011), recognising challenge moments and aligning task perceptions and goals to coordinate SSRL strategies may require external regulatory support (Järvelä et al., 2015). Research has shown that groups who failed to recognise challenge moments accurately tend to activate procedural and behavioural (i.e., “routine-level”) strategies, while highly regulated learners focus more on deep-level processes such as cognitive and metacognitive strategies to overcome challenges collectively (Järvelä et al., 2013; Malmberg et al., 2015).

Although researchers have begun to develop computer-based pedagogical tools or pedagogical agents to support SRL (Azevedo & Hadwin, 2005; Perry & Winne, 2006), gathering SRL data through macro-level self-reports may not accurately reflect SRL strategies (Rovers et al., 2019). Such global measures also limit the study and support of regulation processes “on the fly” (Winne et al., 2002), hindering real-time and ongoing support for regulation in CL. To mitigate the validity concern and the lack of fine-grained information in self-reports hindering timely regulatory intervention, we propose a first step, contributing to the lack of research in the emergence of SSRL by leveraging NLP models to identify the dimensions of challenge moments exhibited through group discourse. An accurate identification of challenge moments is a crucial prerequisite to the deployment of appropriate ROL strategies, which would support the alignment of strategies amongst group members for successful collaboration (Järvelä et al., 2015). Three different NLP modelling approaches, namely a rule-based, supervised ML, and LLM approach, were compared in terms of their performance.

4.1. Methodology: Data processing and model building

Our study involved the analysis of audio transcripts of students’ weekly group discussions working in small group collaborative contexts recorded from a real-world postgraduate programme in educational technology. The recorded audio (n=28 sessions) underwent automatic speech recognition (ASR) and speaker diarisation. Through a conventional coding process, two researchers compiled dimensions of challenges and regulatory processes from the regulation of learning literature (Bakhtiar & Hadwin, 2020; Hadwin et al., 2018; Järvelä & Järvenoja, 2011; Malmberg et al., 2015; Näykki et al., 2021; Ucan & Webb, 2015) in combination with emerging patterns in the context. They labelled initial codes and discussed to finalise coding schemes (Table 1), yielding a training dataset for modelling. There were four overlapping dimensions of challenges, namely cognitive challenges (C: comprehension struggle), metacognitive challenges (M: difficulties in monitoring and controlling tasks), emotional/motivational challenges (E: expression of negative/demotivated feelings) and technical/other challenges (T). For regulatory processes, three mutually exclusive processes were conceptualised: task analysis (TA: engagement in task perception,

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goal setting and planning), task enactment/monitoring & control (MC: group strategies and coordination), and large/small-scale reflecting & adaptation (RA: reflection upon past processes, progress or products and adaptation of strategies).

Two approaches, supervised machine learning (SML) models, namely random forest (RF) and support vector machine (SVM), across different aggregation levels (utterances vs episodes) with and without engineered features, and OpenAI's GPT4 LLMs with few-shot training, were compared to detect dimensions of challenges and regulatory processes from student discourse. Five-fold cross-validation with stratified sampling was implemented in Python to evaluate the test performance of the models. For the generative model, OpenAI's GPT APIs were leveraged by prompting to identify any challenges and regulatory processes as specified with examples in the coding schemes (Table 1). Suraworachet et al. (2024) documented the full protocol used in building the predictive models of dimensions of challenge moments, which was subsequently applied to cover the detection of regulatory processes.

Table 1. Final coding schemes of challenge dimensions and regulatory processes with their relative frequency

Construct	Dimension (% in utterances and episodes)	Sub-dimension	Example
Challenges	Cognitive challenges (C): struggling to comprehend (7.5%, 52%)	Expressing confusion either about the task, contents, or task expectation (C1)	"What's the meaning of…?", "I'm confused about …"
		Expressing concerns over the brainstorming ideas (C2)	"Maybe the solution already existed.", "It may not work in other contexts."
		Questioning one's ability to communicate clearly (C3)	"Does it make sense?", "I'm not sure if this makes sense", "I am not sure that I have explained myself clearly."
		Struggling to understand peers in terms of the terminology used or the proposed ideas (C4)	"What do you mean by…?", "In terms of what?", "You mean to... or...?"
	Metacognitive challenges (M): struggling to monitor, execute or control the task (3%, 36%)	Raising concerns over time/progress (M1)	"We have to finish it in.. minutes.", "we have 2 tasks left.", "Where are we?", "Shall we move on?"
		Expressing confusion when executing tasks in the brainstorming platform (M2)	"Who's blue? (blue refers to a blue sticky note in this context)", "What should we do?", "So we focus on one, two, or we do everything, right?"
		Expressing concerns over the strategies/approaches that the group used (M3)	"I don't think that is the right approach."
	Emotional challenges (E): expressing negative feelings. (1%, 10%)	Expressing emotion or frustration. (E1)	"I'm lost.", "I'm confused.", "I'm not really happy.", "I'm not good at…"
		Expressing non-interests. (E2)	"I don't want to…", "I'm not motivated in this."
		Experiencing difficulty. (E3)	"That's hard.", "It's complex."
	Technical/other challenges (T): experiencing external/ environmental/ technical challenges (1.8%, 18%)	The faced challenges were related to environmental situations, technical issues or personal circumstances which haven't been identified above.	"It's not working on iPad.", "I have a problem with Miro.", "I can't make it.", "How to add stickers?"

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Regulation	Task analysis (TA) (3%, 8%)	Students construct interpretations or perceptions of the task (TA1)	"Just thinking, the purpose of this activity, task 2, maybe it wants to express some idea that there's some correlation, there's some connection between the demographic and the skill and the expertise."
		Students draw on their perceptions of the task to set personal goals to attain during the task and make plans regarding how to strategically approach the task to reach them (TA2)	"Because they're asking what this thing is she's struggling with. We should not select a particular feature, we should select the top two features which she needs to work, you know?"
	Task enactment/Monitoring & control (MC) (61%, 80%)	Students engage in a joint task, drawing flexibly upon a range of strategies to achieve goals (MC1)	"Just a concern of time, we have two tasks. -> The other two is my point, so I try to be quick.", "You can't actually include both those two issues together because it's from different aspects. -> It's true that we have different stakeholders but there should be. Because teachers and parents, they do need to communicate."
		Students respond to a friend's question, help clarify points, elaborate reasons, demonstrate procedure, or suggest ideas/strategies for the group (MC2)	"Should we move on? -> Yes", "Where's the stickers? -> Sticker, if you go to this and then the sticker."
	Large and small-scale reflection & adaptation (RA) (1%, 2.5%)	Processes, progress, and products of each phase are metacognitively monitored and evaluated, leading students to exercise metacognitive control by strategically adapting task perceptions, goals, and engagement when needed (RA1)	"We can check it. Yeah, yeah. Week one."
		Students reflect upon what has been done in the past (RA2)	"Yeah. So, if so, we need to change them a little bit in the last stage about writing stuff. Because our cases talk about collaborations in English, right? Discussions. Isn't it?"

4.2. Model performance and discussion

Through experiments with aggregation levels (utterance vs episode level), features and ML techniques, an SML model built either from SVM or RF performed on engineered features and aggregated at an utterance level revealed the most promising results with an F1-weighted score of 0.82 for detecting challenges and 0.81 for determining challenging dimensions (SD = 0.09). Conversely, the best model performed in the regulation identification task (F1-weighted = 0.81) was RF utilising typical n-gram features and aggregated at an episodic level. For determining regulatory processes, the model had an F1-weighted = 0.86 and an SD = 0.10.

For the generative AI approach, an aggregation at an episode level was used to supply context for generative AI in determining constructs. Prompts were designed to inquire about GPT-4 to first determine the presence or absence of challenges within episodes (F1-weighted = 0.82), followed by an identification of challenge dimensions (F1-weighted = 0.78, SD = 0.10). With a similar protocol, the GPT-4 model obtained an F1-weighted at 0.82 in recognising regulation and an average F1-weighted at 0.81 (SD = 0.11) in identifying specific regulatory processes.

In general, the two approaches show comparable and acceptable performance in detecting dimensions of challenge moments and regulatory processes. This suggests the potential technical capabilities of the state-of-the-art NLP models to effectively capture complex learning processes as

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dimensions with challenge moments and regulatory processes. Since the goal is not necessarily to improve the state of the art in NLP but to improve educational practice with applied AI, the relative advantages and disadvantages of each approach for teaching and learning, particularly for offering meaningful reflective feedback to students and/or teachers to close the feedback loop, should be considered. Next, we will discuss how such detection of key constructs could be used to directly support learners in developing regulation of learning in a real-world context and potentially support teachers in offering complementary insights into their teaching practices, promoting evidence-based self-adaptation.

5. An AI System for Real-World Collaboration and Regulation of Higher Education Students: Lessons Learned

Collaboration analytics (CA), a subfield of LA, focuses on collecting, analysing and supporting group interactions by enabling data-driven decision-making for stakeholders (Schneider et al., 2021). Similarly, CA employs multimodal data sources and diverse techniques to infer collaborative constructs and realise group dynamics (Martinez-Maldonado et al., 2021). Based on our prior models built to detect challenge moments and extend them to cover a detection of regulatory processes, these inferred constructs could be presented as feedback by mirroring information back to learners, closing the feedback loop (Martinez-Maldonado et al., 2021), triggering awareness enhancement of groups by fostering mutual understanding and self-reflection (Chen et al., 2024). Empirical studies have shown that mirroring group constructs such as member knowledge, amount of contribution, member interactions and peer perceptions could improve collaboration, including group awareness, discussion, positive climate, satisfaction, participation and performance (Janssen & Bodemer, 2013). Beyond the mirroring of simple information, tools could be extended to initiate metacognitive monitoring by representing current group states in comparison to desirable states and providing suggestive feedback towards productive group interactions (Soller et al., 2005). Due to its flexibility in presenting information, CA holds promise for simultaneously supporting group awareness through a reflection on current group interactions, enhancing metacognitive monitoring of situational challenges and facilitating regulation through suggested strategies—thereby acting as mediating feedback that fosters a transactional loop in collaborative learning.

Despite extensive research in understanding collaborative processes, few studies (the exception includes Echeverria et al., 2019) have implemented CA feedback as support and evaluated it with stakeholders, particularly in real-world collocated small-group collaborative settings. Moreover, CA implementation in an ecologically valid setting has several challenges, ranging from technological, design, deployment, and ethical issues (Martinez-Maldonado et al., 2024). This underscores the urgent need for further exploration of the ethical implications of CA, particularly in authentic face-to-face (f2f) settings.

To address these gaps, our work proposed the implementation of a collocated CA feedback intervention to externalise group regulations, accompanied by actionable suggestions to ultimately promote group awareness and trigger effective collaboration (as documented in Suraworachet et al., 2025). Through a human-centred design approach, the study investigates a post-hoc evaluation of students' perceptions of the proposed CA in authentic small-group collaborative environments, exploring the extent to which challenge moments and regulatory processes were externalised, recognised, and triggered regulation among members, leading to an improvement in collaboration. Ethical considerations on the practical application

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of the CA feedback, along with future suggestions, were also examined to inform the development and implementation of a more ethical and practical version of CA.

5.1. Methodology and feedback design

The study was conducted from a post-graduate module in educational technology where students participated in a 1-hour in-person group activity weekly, discussing their educational technological design. They were purposefully assigned to a fixed small group according to their variation in background of study, years of working experience, gender, and English as a first language. The sessions were video and audio recorded for analysing their group interactions and regulation.

Due to technical challenges in capturing and analysing data in real-time, this study demonstrates the feasibility of the proposed CA by collecting real-world data from one week to be processed and displayed for feedback in the subsequent week. Following the protocol described in Suraworachet et al. (2024), students' discourse was processed to predict the dimensions of challenge moments and extend to cover the prediction of regulatory processes. Due to the similar performances of the two language models (SML and LLM) with different explainability features, we applied both techniques in analysing the current dataset for generating feedback. The RF model and GPT4 were selected to represent SML and LLMs, respectively. RF's feature importance and GPT4's decision explanations were utilised to investigate students' perceptions of model explainability. A web application was created to provide the predicted results in the form of a dashboard featuring both visual representations and textual feedback, targeting awareness enhancement in their challenge moments and socially shared regulation of learning. The feedback was designed according to Hattie and Timperley's (2007) and Soller et al.'s (2005) feedback guidance. Feedback on the detected constructs and suggestions included explanations on what students have done well, as detected from data (learning progress) and what needs to be further improved for better collaboration (prospective activities towards learning goals). Collaboration and regulation theories, combined with expert rules, were used to formulate multiple criteria (e.g., detected challenges, etc.) for textual feedback to help students determine directions for improvement.

Figure 1 shows the analytics feedback on group challenges and regulations proposed in the study delivered at the students' discretion. The group regulation feedback started with an introduction of constructs (challenging dimensions and regulatory processes) due to unfamiliar concepts of regulation. Bar charts were utilised to present the frequency of self-reported preparation and motivation levels vs detected challenges and regulations in the session, whereas a timeline was used to present detected challenges and regulations over time. The textual feedback criteria include (1) a prevalence of specific dimensions of challenges in conjunction with self-report data on the level of preparation or motivation, and (2) regulatory patterns found in learning sessions. For example, if cognitive challenges are prevalent in conjunction with a low level of reported preparation, students receive feedback suggesting higher preparation for the next sessions. Similarly, if there is a low self-reported motivation level alongside high motivational/emotional challenges, the feedback would attribute the cause of high motivational challenges to low motivation among members, suggesting the promotion of a positive group climate. Additionally, to promote student agency, aligning with regulatory skills, model transparency and explainability were explored within this context. The feedback interface allowed students to select a model (either SML or GPT4), which then populated the results accordingly. The actual transcript of a learning session, along with predicted results and decision

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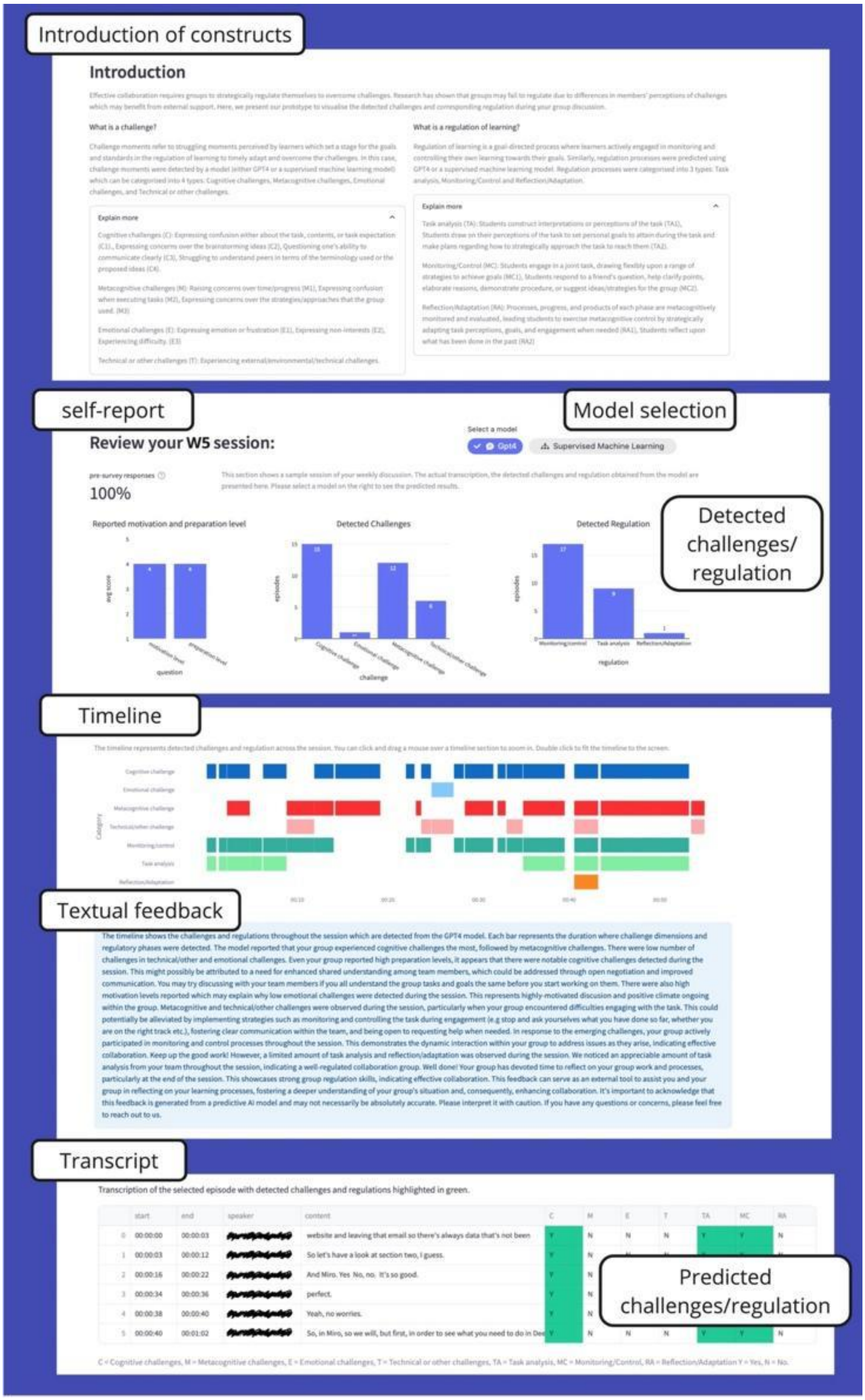
explanations, was included to promote students' model inspection and evidence-based reasoning. While GPT4 generated a sentence explaining its reasoning, the SML model outputted a list of important features dominating the model decision, as shown in Figure 1(b).



(a)

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(b)

Figure 1. (a) Group challenges/regulation page; (b) decision explanation generated based on the selected model (GPT or SML model).

To investigate students' perceptions of the feedback, students' weekly reflections and follow-up voluntary focus groups were utilised and qualitatively analysed.

5.2. Key findings and discussion

Several key findings were highlighted to demonstrate the value of CA Feedback as a reflection tool for students, which can make regulatory processes more visible and foster situational awareness and regulation, thereby offering the ethical and design implications of CA Feedback in real-world contexts.

Making Regulatory Processes Visible. Through students' reflection, they reported the value of feedback in helping them be aware of the situations through the recognition of excessive challenges exhibited (e.g., high motivational challenges). Resonating with Wise and Schwarz (2017) on the potential value of CA, the proposed CA could be viewed through a transactional lens, emphasising the process nature of collaboration beyond performance. The feedback could trigger reasoning based on external evidence and help them account for individual differences, such as language issues or low domain knowledge, as well as learning context (e.g., unfamiliarity with the tools leading to technical challenges). While CA feedback only presented the chosen constructs, students recognised nuances of regulation of learning currently unaccounted for. To illustrate, they pointed out the subjectivity of the challenge moments beyond externally

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detected or non-verbally expressed. This highlights the analytics' role in group settings as a mediating tool or an 'object to think about learning' (Cukurova, 2024), where interactions encompass individual understanding to transactional communication of attribution.

Fostering Regulation. The findings suggest that CA feedback acted as a transactional mediating tool, supporting students' reflection on their behaviours and prompting self- and co-regulation (Hadwin et al., 2017). To illustrate, students reported adjusting their strategies or observed peers offering help to them/others. These responses demonstrated how the proposed feedback could hold students accountable and motivate them to make personal changes or help others change. However, perceived group changes were relatively low, suggesting limited regulation at the group level. One explanation for this could be the provision of the CA feedback at students' disposal, which they appeared to access individually rather than collectively. Therefore, this may hinder opportunities for the feedback to trigger transactions and coordination among members, ultimately limiting the emergence of socially shared regulation. As Stahl (2004) emphasised, effective collaboration extends beyond individual thinking towards externalising ideas to develop mutual understanding and coordinate actions. Moreover, students' low reported engagement with the CA feedback suggests other barriers, such as a lack of personal interest in collaboration and regulation, as well as external demands, such as feedback on their individual engagement and written performance delivered during the same week. This could altogether influence their engagement with the CA feedback. These competing priorities also highlight a lack of commitment to collaboration imposed by the module design, which warrants further investigation. It is also worth noting that personal changes could be constrained by dominant peers as reported, reflecting the social dynamics that affect both self and socially shared regulation.

Ethical and Design Implications of CA Feedback. While students generally appreciated the transparent research practices, valuing their contribution to the field and reported low judgmental concern due to low-risk collaboration, the major concern lies in model accuracy, undermining their trust and limited behavioural changes. Feedback was often dismissed due to perceived errors, such as noisy classrooms and unrecognised challenges, which, in fact, had been verified. However, this information was not communicated to students but rather emphasised the derivations of the AI outputs. This may have reinforced students' negative perceptions of AI (Cukurova, Luckin, et al., 2020), which should be systematically investigated and handled.

Design and deployment suggestions. Students suggested several design improvements for the feedback, including simple analytics, predictive behaviours and feedback variants. To cope with cognitive loads, data storytelling techniques, a combination of textual or visual cues to progressively reveal information and direct users' attention, could potentially aid students' interpretation (Martinez-Maldonado et al., 2020). In addition to feedback clarity, students called for adaptable feedback to account for individual differences and context. CA offers potential to be extended towards a customisable dashboard, equipped with customisable indicators to accommodate learners with different learning goals and needs (Jivet et al., 2021). While students prefer performance-based feedback to determine "correct" direction of engagement, there might be no clear-cut optimal patterns of collaboration in complex socio-constructivist contexts (Cukurova, 2024). This raises concerns over students' simplified conception of collaboration and regulation. Beyond the CA feedback design, the success of CA highly depends on the deployment of feedback as a system, especially in real-world settings. Fostering transactions between the CA feedback,

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students' reflections and regulation requires an effective integration of learners, learning design and learning objectives, beyond the analytics itself, to reduce potential confusion, disengagement and increase trustworthiness and adoption of CA. One suggestion is additional group or teacher-led interpretative sessions with the analytics to promote understanding and group coordination. Scaffolding as a learning intervention could also be implemented. For instance, D'Mello et al. (2024) proposed a scaffolding intervention integrating the analytics with learning design, including the introduction of complex constructs, followed by practice sessions, to ensure students' understanding of constructs before the actual implementation of feedback. Such a pedagogical approach could offer a promising step in promoting CA adoption in the real world.

While CA feedback, built on the language models to detect challenge moments and regulation, could potentially offer an evidence-based tool for learners to externally validate their interactions and regulate their learning in collaborative settings, these mechanistic measures, such as exhibited keywords, are only a proxy of learning phenomena and may not fully capture human learning's complexity. With the growing presence of AI, there are also pressing questions of how teachers should synergistically engage with AI to harness its benefits as well as support mutual growth opportunities for both AI and humans towards a complementary future.

6. Conclusion

This paper has contrasted two approaches for using artificial intelligence to develop students' self-regulated learning capability. In one approach the artificial intelligence system takes on two roles: (i) teaching the content, making dynamic changes to task selection, interface features, provision of help and feedback with respect to the learner's understanding of that content, and (ii) to monitor how the learner is going about their learning and offer dynamic feedback and advice as to how they might be more effective in their learning.

The other approach is to separate the monitoring of and reacting to both the progress in understanding that content and the progress in getting better at learning from the teaching of the content. This involves using artificial intelligence techniques to analyse data from the learning, typically after the event, and transforming it into an actionable visualisation that the learner can use to reflect on how they went about their learning with a view to improving their learning methods the next time.

The first approach has to deal with the issue of dividing the learner's attention between thinking about the content and thinking about their learning. The second approach solves that problem but then faces the issue of the learner needing to relate the post-hoc visualisation of other learning to when their experience when learning occurred, and then carrying forward any insights from their reflection to future learning opportunities.

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Conflict of Interest Statement

The authors declare that they have no competing interests.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy or ethical restrictions.

Ethical Statement

Ethical approval for this study was obtained from the IOE Research Ethics Committee (IOE UCL's Faculty of Education and Society) (Approval Code: Z6364106/2024/06/68 social research). Informed consent from participants was acquired prior to data collection.

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