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How AI Agents Affect Student Learning in the Context of Self-Regulated Learning and Socially Shared Regulation of Learning

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Abstract. Artificial intelligence (AI) pedagogical agents are increasingly involved in helping learners plan, monitor progress and adjust strategies. It is not enough to evaluate based on performance or satisfaction alone. A more appropriate perspective is learning regulation. This study focuses on self-regulated learning (SRL) and socially shared regulation of learning (SSRL). SRL involves learners managing goal setting, time and strategy adjustment by themselves, while SSRL occurs when the group adjusts together through communication and consultation, which means that the role of the agent is different in individual and collaborative learning environments. In SRL, agents reduce unnecessary cognitive burdens by reminding learners of key points, checking understanding or prompting target deviations, thus promoting metacognition. In SSRL, the agent helps the team visualise the interaction process - highlighting the participation gap, task drift or consensus formation, to support process optimisation, not just the final result. However, positive effects do not occur automatically; they depend on the task, the agent design, and the learner's willingness to accept suggestions. Too frequent prompts will interfere with thinking, and rich group interaction data is only valuable when learners can interpret and apply it. In general, AI pedagogical agents reshape the way learners regulate learning: in SRL, they enhance self-monitoring and adjustment ability; in SSRL, they clarify interaction problems and improve collaboration. Future research should focus on how agents participate in the regulatory process, not just performance or satisfaction improvement.

Keywords: AI pedagogical agents, self-regulated learning (SRL), socially shared regulation of learning (SSRL), human-AI collaboration, metacognitive support

1. Introduction/background

The application of AI in education is becoming more and more popular, and it has also changed students' behaviour in the learning process. Early educational technologies are often used as additional tools to provide resources, feedback, or practice activities. In contrast, pedagogical agents based on large language models can now conduct multiple rounds of dialogue with learners, answer their questions, and adjust support according to the needs of learners [1, 2]. In this case, it may be too simple to just call them "pedagogical aids". They can also participate in the planning, monitoring

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and review of learners. Therefore, this article focusses on how these agents shape the learning process itself.

From the perspective of learning regulation, this problem can be understood through two related but different concepts. One of them is self-regulated learning (SRL), which refers to the process of learners monitoring, controlling and adjusting their cognition, motivation and behaviour over time [3]. The other is socially shared regulation of learning (SSRL), which focusses on how group members jointly plan, monitor and coordinate cognitive and emotional processes to achieve common goals [1]. The difference between SRL and SSRL is important because they do not need exactly the same support. In SRL, agents should support individual learners without depriving them of too much autonomy. For example, it may help learners find problems, reflect on strategies, or check whether the current plan is still valid. In SSRL, the question is not only whether a learner can regulate learning, but also whether the whole group can coordinate its work. Therefore, supporting SSRL usually requires making interaction, participation and progress more visible to team members. Based on this difference, AI agents may work through different mechanisms of SRL and SSRL.

However, existing studies do not always clearly explain this difference. A large number of literatures still pay more attention to agent design features, such as anthropomorphism, emotional expression or feedback style, and then examine their relationship with results such as achievement, participation or satisfaction [4, 5]. These studies are very useful, but they do not fully show how agents affect learning through the regulatory process. Some studies have discussed AI support for SRL [6, 3], and some have studied AI-based SSRL [7]. Even so, these two research directions are usually discussed separately. Therefore, within the same analysis framework, it is still difficult to compare how AI agents support personal regulation and shared regulation.

Against this background, the research questions are as follows.

how does the AI pedagogical agent support SRL?

how does the AI pedagogical agent support SSRL?

2. How pedagogical agents shape student learning processes

2.1. Mechanisms of agent support in SRL

Early studies on pedagogical agents usually describe them as tools to help learners manage tasks. For example, agents can provide step-by-step guidance to help them complete tasks while reminding students of the time [8]. This kind of support is useful, but it mainly stays at the level of task management. Recent research focusses more on the monitoring of the learning process. That is to say, when the student feels that he cannot continue, for example, when he does not understand the task and does not want to do the task, the agent should make an appropriate response.

Järvelä and Hadwin [3] described these moments as "triggering events". This concept is very important, because when the learning process is interrupted, monitoring may be relatively critical. Because when these impasses occur, it is important to give the agent an anchor point to judge the reason why the student is stuck and then give an appropriate response.

Another important question is whether the support provided by the agent matches the work done by the student at that time. Dever et al. [9] found that prompts and feedback are more useful when they are associated with learners' current sub-goals. This means that the built-in AI agent into the learning process itself will help students with their tasks. For example, the agent may be asked to check the student's understanding during the task. In general, SRL-oriented agents are shifting from simple reminders to support for regulatory processes that directly target learners.

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2.2. The effectiveness of AI agents in supporting SRL

The impact of AI agents on SRL is unevenly distributed at all stages of regulation. A review of 27 studies by Guan et al. shows that AI agents are most helpful in the mid-term stage of learning, especially when learners search for resources, use strategies and monitor their progress [6]. However, their support seems to be weaker before and after the main task. For example, the agent does not seem to be very effective in helping students set goals, make study plans or reflect on their previous work [6]. This shows that current AI agents are better at supporting learners when they are completing their tasks than helping them develop a complete regulatory cycle.

But this effectiveness also depends on how students themselves use the agent. Li et al. [10] found that the use of learners' own strategies is closely related to the performance of agents. This shows that the support brought by the agent itself is not enough. Tips may be useful for one learner, but unnecessary for another learner, and may even distract. Therefore, agent support is more likely to work in the current regulatory state of the learner than in providing general guidance to everyone.

2.3. Learners' perceptions and affective experiences

AI agent not only provides cognitive support. Students' views on agents will also affect the way they use agents. When learners regard AI as a partner rather than an authority, they may feel more willing to interact with it and may show higher participation and intrinsic motivation [11, 12]. Edwards et al. [13] also pointed out that learners are more likely to interact with agents they consider reliable partners for a longer time.

This is important for SRL, because students' perception of the agent can change the way students participate. If students trust agents, they may be more willing to ask questions and use feedback to adjust their learning strategies. But if they only regard agents as the source of the correct answer, their interaction may become more passive. In this case, the same AI tool may lead to very different learning behaviours.

This problem is especially evident in creative tasks. Allowing learning to access AI tools does not necessarily improve creativity. That is to say, learners need to judge, choose, modify and combine the ideas generated by AI with their own ideas in the process. In other words, students need to regard the output of AI as the material for further work, not the final answer [14]. From this point of view, meaningful knowledge construction depends on whether students themselves further judge the response of AI, rather than simply accepting its suggestions.

The agent's emotional expressions will also affect the students' reaction. Some studies have shown that compared with neutral agents, agents with positive emotional expression can improve students' participation and intrinsic motivation [5]. In addition, students can notice emotional cues from virtual tutors, which may in turn affect their own emotional state [15]. This kind of emotional support can help learners stay motivated when they encounter difficulties.

However, this research direction is still incomplete. It is not clear how agents should respond to the changing emotional state of learners in the learning process [16]. For example, frustrated learners may need encouragement, but they may also need specific strategic support. Learners who are too confident may need tips to check their understanding. Therefore, future research not only needs to explain whether emotional factors are useful, but also to explain when and how they intervene.

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3. AI pedagogical agents in collaborative learning

3.1. Foundations of AI agents-supported SSRL

When learning is conducted in groups, judgement is no longer just about how a learner manages the task. The focus has changed from "how I regulate my study" to "how we regulate our joint work". This change also affects the expected work of AI agents. In individual learning tasks, the agent may mainly remind students to plan, monitor or reflect. However, in collaborative tasks, it also needs to pay attention to how group members communicate, divide labour and deal with problems together.

Järvelä et al.'s hybrid human-AI shared regulation in Learning (HASRL) model provides a useful way to understand this problem [1]. In this model, AI is not regarded as a tool outside the group. On the contrary, it is described as a possible collaborator in the regulatory process. The model includes four main functions in the SSRL cycle: detection, diagnosis, action and learning [1]. These functions are important because collaborative regulation usually develops over time. It is impossible to fully understand just by looking at the final product of the group task. For example, two groups may submit similar results, but one group may be well coordinated, while the other group may struggle with confusion, unequal participation or repeated misunderstandings.

That's why multimodal tracking is so useful in SSRL research. Data such as speech, gaze, facial expressions and interaction records can help show the changes in collaboration during the task. Students' expectations of agents also reflect this. In a group environment, students usually expect agents to do more than just provide task-related help. They may want to act as mediators, mentors or even companions [17]. Therefore, SSRL-oriented agents need more than just procedural guidance. They also need to respond to the social and interactive functions of group learning.

3.2. Making collaborative regulation observable

One reason why AI is useful in SSRL is that many problems in group regulation are not easy to see when activities occur. A group may seem busy, but the members may have different understandings of the task. Some students may dominate the discussion, while others remain silent. The group can also continue to work without noticing that its plan is no longer appropriate. These problems are difficult for teachers to track, especially when several groups are working at the same time.

AI systems can help by collecting and analysing multimodal data, such as gaze, audio, facial expressions and interactive logs. Through these data, researchers can identify key indicators related to the quality of collaboration. For example, attentional synchrony and language coordination can often reflect the level of group collaboration to a certain extent [18]. Of course, this does not mean that AI can fully understand the complex situations in group cooperation like teachers. More precisely, the role of AI is to present some processes in group interaction that are not easy to be directly observed, so that learners and teachers can see more clearly the problems that may exist in collaboration.

The significance of this observation also depends on whether the system can provide support at the right time. The study of Järvelä et al. [1] found that the AI system can identify triggering events that require regulation with an accuracy rate of 81.46% by tracking the physiological synchrony between group members and changes in facial affective states. This result shows that AI may find abnormalities when collaboration problems first appear, instead of waiting for summary feedback after the task. For group collaboration, if many problems cannot be dealt with in time, it will often affect the subsequent discussion and task progress. Therefore, timely detection can provide a basis for the intervention of AI agents, so that when the group coordination begins to weaken, it can

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remind members to refocus on tasks, adjust the division of labour or improve communication in a timely manner.

3.3. From analysis to interaction strategies

To make SSRL work properly, the team members need to have some common understanding of what they are doing. This includes common goals and how to coordinate tasks. Without this shared mental model, group work can easily become fragmented. Members can complete a separate part of the task without working together.

AI feedback can help the group establish this kind of coordination. Zheng et al. [7] used sequence mining to find that the group receiving AI feedback showed a clearer SSRL cycle. Before starting a new cycle, these groups have experienced goal orientation, planning, execution and monitoring, reflection and metacognitive adaptation. This model shows that AI feedback can help groups organise their interactions instead of allowing the discussion to be carried out in a loose or disconnected way.

However, AI feedback does not guarantee adaptive collaboration. Dang et al. [19] distinguished between two models: the plan and implementation approach (PIA) associated with adaptive patterns, and the trials and failure approach (TFA) associated with maladaptive patterns. In the second model, groups may continue to try different actions without recognising deeper regulatory issues. This is a common problem in group work. Students may feel that they are "doing something", but they don't really learn from the breakdown. If the agent can identify this pattern early, it may help the team stop repeating ineffective actions and move towards more orderly collaboration.

3.4. Role across learning environments and practical boundaries

Even if the study does not directly use the term SSRL, many findings still show that AI agents have a similar role in collaborative learning. Among them, in the field of programming, the performance of AI-assisted groups is better than that of traditional online collaboration groups [20]. In addition, process-focused AI feedback is also related to higher work innovation and deeper use of tools [7]. These findings show that AI agents can improve students' collaborative learning in the learning process.

Nevertheless, AI should not be completely regarded as a collaborative partner. Because although AI can provide useful information, it is weaker than human partners in terms of empathy, active listening and rich social understanding [21]. This restriction is very important for SSRL, because shared regulation is not just a cognitive process. It also depends on trust, emotion, social awareness, and mutual response among group members. For this reason, AI agents are better understood as cognitive collaborators rather than substitutes for human partners.

The role of the agent will also change in the learning environment. In face-to-face classes, agent support must adapt to existing classroom routines and peer interactions. If the agent often interrupts, it may interfere with the natural communication between students [21]. In online learning, the situation is different. Because social presence may be weak, agents can provide continuous cognitive and emotional support [22, 5]. In immersive environments such as mixed reality (MR), the performance as an agent may look more like a partner in the learning space. Research on partner positioning shows that this design can enhance learners' awareness of active learning and participation [11].

In general, the AI agent in SSRL mainly helps by making the group process easier to observe and supporting diagnosis and timely intervention. Their role is most powerful when they help the group

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find problems, coordinate actions and adjust the learning process. At the same time, their limits should be recognised. AI can support cognitive collaboration and some emotional support, but it cannot completely replace the social understanding of the development among human learners. In this sense, the AI agent is best understood as a process enhancer in collaborative learning.

4. Discussion

4.1. The different role of AI agents in SRL and SSRL

AI pedagogical agents should not be understood as having a fixed educational role. Their role depends on what kind of regulation is needed in a specific learning environment. According to the above research, this role is different in individual learning and collaborative learning.

In SRL, the value of AI agent is mainly reflected in the immediate support in the task process. They can provide brief suggestions, targeted feedback, or remind students to check whether the current learning strategy is still valid. Although these interventions are usually small, they can help learners find and understand problems in time, adjust learning methods, and optimise the next step before the task is completed. Therefore, AI agent is more like a metacognitive support tool than a simple task management tool.

In contrast, the problems faced by SSRL come more from group-level coordination. The difficulties in group cooperation are not necessarily due to the members' lack of self-monitoring, but may be because they did not find the key clues in collaboration in time. For example, there may be differences in understanding among members without realising it, or the original plan is no longer applicable while the group continues to advance the task. In this case, the role of AI agent is to make the group interaction process more visible. They can identify potential regulation triggers through multimodal data, present member participation, or summarise collaboration problems during activities, to help the group adjust the cooperation process in time. Therefore, the relationship between the value of the agent and process visibility and group coordination is closer than with personal monitoring.

This comparison shows that the design of AI agents should meet the regulatory needs of the learning environment. SRL and SSRL are not just two different settings. They also involve different support mechanisms. In SRL, the agent mainly acts as a metacognitive catalyst. In SSRL, it is more used as a process enhancer.

4.2. From agent features to interaction dynamics

Many studies still start from the agent itself. They ask what characteristics the agent has, such as feedback style, emotional expression or anthropomorphic design, and then check whether these characteristics improve learning outcomes. This method is very useful, but it is easy to miss what happens during the actual interaction between the student and the agent.

The research reviewed in this article shows that the effect of AI agent is not stable in all cases. It depends on how the students understand the agent, what the task needs, and how the interaction develops. For example, in creative tasks, AI does not automatically improve creativity. Learners need to question, choose, combine and modify the ideas generated by AI, instead of treating them as complete answers [14]. This means that the more important issue is not only what the agent can provide, but also how learners regulate their learning when using the agent.

This transformation is important for both theory and design. Theoretically speaking, human-AI learning should be regarded as a constantly changing process. The learner's goals, strategies,

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emotions and decisions may change as the task progresses, and the agent's response may affect the process. In fact, this means that a stronger agent is not necessarily a better agent. Support is only useful when it meets the current needs of the students. When students encounter difficulties, tips may be helpful, but if the same prompt appears at the wrong time, it may be ignored or even distracted. Therefore, the timing, form and transparency of support are as important as the technical capabilities of agents.

4.3. Limitations and directions for future research

Although this review puts forward a comprehensive point of view, there are still some gaps in the literature.

First, we should pay more attention to micro-level interaction. Many studies still focus on the final results, such as achievement, participation or satisfaction. These results are important, but they do not fully show how regulation has developed during the interaction between people and AI. Future research can use methods such as dialogue sequence analysis or behaviour pattern mining to study how these small actions develop over time.

Furthermore, more clear modelling is needed at the emotional level. Existing studies often mention that emotional support can increase motivation and participation, but they do not always explain how agents should respond to the changing emotions of learners. Future work can combine affective computing and human-computer interaction research to establish a model that connects emotions, cognition and intervention timing.

Moreover, more long-term evidence is needed. Many current discoveries come from short experiments, laboratory settings or one-shot studies. These studies help to identify the possible impact, but they say less about whether AI support can improve learners' regulation over time. Longitudinal research and design-based research in real classroom and collaborative learning environments will help explain whether learners become more capable regulators or whether they are just more dependent on agents.

Finally, the autonomy of learners should be regarded as a core issue. As AI agents become more capable, learners may begin to outsource planning, monitoring and evaluation to the system. This may make learning easier in the short term, but it may also weaken the development of regulatory skills. Future research should study how to design human-AI collaboration in a learner-centred way. The goal should be to help learners expand their agency, rather than letting agents quietly take over the core work of regulation.

5. Conclusion

AI pedagogical agents are changing the way learning is organised, but their impact should not be simply understood as providing information or feedback. This assessment shows that they have different roles between SRL and SSRL. In SRL, agents mainly support learners by prompting monitoring, strategy selection and adjustment during tasks. This makes them closer to metacognitive catalysts than simple task managers. In SSRL, the agent makes the group coordination visible and helps the group deal with problems. In this sense, they are more as process enhancers.

These two roles help to connect discoveries that are often discussed individually. They also showed that the value of AI agents depends on the degree of adaptation of its support to the regulatory process. Therefore, future research should pay more attention to the interaction between people and AI itself, especially the timing of communication, emotional changes and intervention. It is also necessary to test agent design in a longer-term and more realistic learning environment.

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Finally, the educational value of AI agents should be judged by whether they help learners become better self-regulators and collaborators, rather than users who rely more on automatic support.

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