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Affective co-regulation in hybrid learning environments: a critique of algorithmic relational adaptivity

Francesco Pio Sarcina [1,*] **and Michele Baldassarre** [1,§]

[1] University of Bari Aldo Moro, Italy; francesco.sarcina@uniba.it; michele.baldassarre@uniba.it
* francesco.sarcina@uniba.it

Abstract: Artificial intelligence (AI) is increasingly used in education not only to adapt content and feedback but also to respond to learners' emotional states. This theoretical paper examines what happens to affective co-regulation, the reciprocal modulation of emotional states within educational relationships, when adaptivity moves from the cognitive to the relational domain. Drawing on engagement research, embodied and enactive accounts of intersubjectivity, and critical studies of educational technology, it distinguishes cognitive from relational adaptivity along five dimensions: object of adaptation, direction of responsiveness, epistemic basis, treatment of friction, and accountability. Cognitive adaptivity is consistent with scaffolding and formative feedback, while relational adaptivity becomes problematic when it replaces reciprocal co-regulation with unilateral accommodation. The main risk is less that learners mistake machines for people than that they grow used to relationships that make no demands on them. The paper derives five design principles for hybrid learning environments and outlines an agenda for empirical research.

Keywords: Artificial intelligence in Education; Affective co-regulation; Relational adaptivity; Hybrid learning environments; Embodied intersubjectivity.

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1. Introduction

Adaptive systems, intelligent tutors and generative conversational agents are now used to provide individualized feedback and adjust instructional pathways (Holmes & Tuomi, 2022). A growing number of them also address the learner's emotional state: they detect sentiment,

§ Although this article was developed jointly by the authors, Francesco Pio Sarcina wrote the paragraphs 2, 2.1, 3, 4, 5 and 6; Michele Baldassarre wrote the paragraphs 1 and 7.

offer encouragement and present themselves as companions or mentors (Henriksen et al., 2025). Personalization is extending from what students learn to how they feel while learning.

The shift matters for engagement, a multidimensional construct with behavioral, emotional and cognitive components (Fredricks et al., 2004). Its emotional component depends on relationships: a meta-analysis of 99 studies found consistent associations between the affective quality of teacher–student relationships and students' engagement and achievement (Roorda et al., 2011). Existing work has examined how AI might support socially shared regulation (Järvelä et al., 2023) and how control can be distributed between humans and machines (Molenaar, 2022), while critical studies show how datafication and nudging reshape learning (Knox et al., 2020). Less attention has gone to a prior question: is adapting a relationship the same kind of operation as adapting a task?

This paper asks under which conditions the logic of algorithmic personalization, defensible for cognitive support, becomes problematic when applied to affective co-regulation. It follows a conceptual-analytic approach: the constructs of co-regulation, adaptivity and friction are clarified on the basis of the literature, examined against current uses of conversational AI, and translated into design principles. The central claim is that cognitive and relational adaptivity follow different pedagogical logics, and that relational adaptivity becomes problematic when it replaces reciprocity with unilateral accommodation.

2. Affective co-regulation and the relational nature of learning

Relationships shape how students take part in learning. In Hamre and Pianta's (2001) longitudinal study, the quality of kindergarten teacher–child relationships predicted academic and behavioral outcomes through eighth grade. In the classroom, teachers and students continuously interpret each other's actions and adjust their responses, and perceptions of competence, safety and belonging take shape within these exchanges. Co-regulation is the name for this process.

In the Vygotskian reading of McCaslin and Hickey (2001), regulation is not first an individual capacity later applied to social settings; it emerges through participation in relationships in which learners receive feedback, negotiate meanings and adjust to others. Research on collaborative learning distinguishes self-regulation, co-regulation, in which one participant temporarily supports another, and socially shared regulation, in which a group regulates its joint activity (Järvelä et al., 2023). On the affective side, Butler and Randall (2013) define emotional

co-regulation in close relationships as a bidirectional linkage of emotional channels between partners that contributes to emotional stability for both. Extending this definition to teacher–student and peer relationships is an analogy, yet two of its features are directly relevant. Co-regulation is bidirectional, since each partner is also regulated by the other, and it is dynamic, oriented to a shifting equilibrium that includes moments of tension.

2.1. Embodied intersubjectivity and hybrid learning environments

Gallagher (2005) argues that social understanding rests primarily on bodily and practical engagement with others rather than on inferences about hidden mental states. Gallese (2009) describes a complementary mechanism, embodied simulation, through which the actions and emotions of others are mapped onto one's own bodily repertoire and which underlies social identification. Enactive accounts go further: in participatory sense-making, meaning is generated by the coordination of two autonomous agents, and the interaction acquires a dynamic that neither partner fully controls (De Jaegher & Di Paolo, 2007). The enactive account supplies a criterion for what follows. Each partner can take the interaction in unforeseen directions, so the other remains partly opaque, and this opacity is what makes interpretation, empathy and negotiation necessary. It is a condition of relational learning rather than a defect to be engineered away.

The term *hybrid* can refer to the mix of face-to-face and online modalities or to the distribution of agency between human and artificial actors. This paper adopts the second meaning. Following Molenaar (2022), a hybrid learning environment is one in which the regulation of learning is shared among learners, teachers and AI systems at different levels of automation. The question is which regulatory functions can be delegated to the artificial component.

3. Algorithmic personalization and productive difficulty

Intelligent tutoring systems analyze students' interactions, provide diagnostic feedback and modify activities according to learner profiles; in VanLehn's (2011) review, step-based systems approached the effectiveness of human tutoring. The premise is sound, since learners do not approach a task with the same prior knowledge, pace or needs. In this domain personalization builds on established pedagogical principles. Scaffolding was first described as the tutor's control of task elements beyond the learner's current capacity (Wood et al., 1976), and formative

feedback works best when specific, timely and focused on the task (Shute, 2008). Adaptive systems that identify specific difficulties and adjust support apply these principles at scale, and this is where their contribution to inclusive design is clearest.

Digital design, however, brings its own values. Reducing friction is a standard goal of interface design. In education, Knox et al. (2020) show how the combination of machine learning and behavioral economics pushes platforms toward nudging learners to predefined outcomes. Removing arbitrary barriers, such as inaccessible materials or opaque procedures, is beneficial. Removing difficulties with formative value is a different matter, because some difficulties are part of how understanding is built. Kapur (2016) shows that initial failure followed by consolidation can yield deeper understanding and transfer than immediate success. Biesta (2013) makes a parallel point about the aims of education: it always involves a risk, because it engages subjects who respond in ways that cannot be fully controlled, and attempts to eliminate that risk turn education into a technology of production. The distinction becomes decisive when personalization moves into relationships. Adapting a task to a student's needs concerns access; adapting a relationship to a student's comfort changes how the student encounters other people.

4. From cognitive to relational adaptivity

Cognitive adaptivity adjusts learning resources to a learner's characteristics. Relational adaptivity, as used here, adjusts the behavior of an interaction partner, typically an artificial agent, to the learner's emotional states in order to regulate affect. The two are often implemented with similar techniques, yet they rest on different assumptions. Table 1 distinguishes them along five dimensions. The dimensions are analytical. In practice, cognitive support is always delivered within some relationship, and both forms of adaptivity may coexist in the same system.

Table 1. Cognitive and relational adaptivity: analytical dimensions.

Dimension	Cognitive adaptivity	Relational adaptivity
Object of adaptation	Content, pacing, representations and feedback on a task	Tone, emotional responses and availability of an interaction partner
Direction of responsiveness	Unidirectional by design: the system adjusts to the learner	Reciprocal in human co-regulation: each partner adjusts to the other
Epistemic basis	Performance data with a relatively clear relation to the learning goal	Inferred emotional states, weakly and contextually related to observable signals
Treatment of friction	Extraneous difficulty is reduced; productive difficulty can be calibrated	Disagreement, waiting and misunderstanding are part of what is learned
Accountability	Errors can be checked against the learning objective	Responses carry moral and relational weight that a system cannot assume

The first two dimensions mark the central difference. Teaching involves interpreting unforeseen situations, addressing tensions as they emerge and negotiating meanings in a shared ethical space, and peer relationships require learners to deal with perspectives that diverge from their own. In both cases the learner is regulated by a partner who is being regulated in turn. Fuchs (2024) argues that understanding another presupposes the implicit attribution of subjectivity, grounded in a shared embodied form of life, a precondition that artificial agents, however fluent, do not meet. A system can adjust to the learner indefinitely; it cannot be affected in return.

The third dimension concerns what the system can know. Barrett et al. (2019) concluded that facial configurations do not reliably and specifically indicate emotional states across situations and cultures. The AI Act accordingly prohibits AI systems that infer emotions in education institutions, except for medical or safety reasons (Regulation (EU) 2024/1689, 2024, Art. 5(1)(f)). The prohibition covers biometric systems; text-based sentiment analysis in chatbots falls outside it but faces a similar problem, since the same words may express irony, resistance or distress.

The last two dimensions return to pedagogy. The risk of algorithmic co-regulation does not lie in AI systems giving useful feedback or guidance. It lies in taking technological responsiveness for relational understanding. A system generating reassuring prompts cannot share responsibility for the relationship or be changed by it, and when it is

optimized to remove discomfort, it also removes the occasions in which learners practice handling ambiguity and difference, the very situations in which relational competence develops.

Two objections deserve attention. First, scaffolding was itself described as a relational practice (Wood et al., 1976), and task feedback has emotional effects; for this reason, Table 1 presents analytical dimensions, not two kinds of system. Second, human relationships often fall short, and a patient artificial interlocutor may seem less threatening than a dismissive teacher. The argument does not idealize human relationships. It holds that their shortcomings call for better relationships, which technology can support, rather than for their replacement.

5. Conversational AI and the risk of relational substitution

Generative agents are now presented as study companions or sources of socio-emotional support. A critical review identifies opportunities, such as personalized practice and feedback on emotional expression, alongside risks of depersonalization, cultural bias and loss of privacy (Henriksen et al., 2025). One argument in their favor is that they offer a space free of social evaluation, where learners may ask questions or reveal misconceptions they would hide in class.

Why such agents are received as social partners is well documented. The Computers Are Social Actors paradigm showed that people apply social rules and expectations to computers that display language and interactivity, largely without reflection (Nass & Moon, 2000). Epley et al. (2007) argue that anthropomorphism is strengthened by the desire for social connection, so learners who feel isolated are those most likely to perceive care in a responsive system. Fuchs (2024) calls the resulting stance a form of digital animism, in which the line between simulated and actual subjectivity becomes harder to draw.

Large language models add a further element. Models trained with human feedback tend toward sycophancy, agreeing with the user's stated views even when these are mistaken (Sharma et al., 2024). In a relational register this becomes constant validation: an agent that always agrees and replies instantly appears attentive, yet its attention costs it nothing and asks nothing of the learner.

Turkle (2015) describes the appeal of technologies that offer connection without the demands of intimacy and conversation without the risk of being misunderstood. The pedagogical concern is not mainly that learners will confuse AI with humans. It is that they may grow used to a model of relationship built on unilateral convenience, with a partner

who is always available and has no needs of its own, and carry this expectation into their relationships with teachers and peers. Whether this happens, and for whom, has not yet been adequately studied in educational settings; here it is treated as a plausible risk that design should anticipate.

6. Implications for hybrid learning environments

If the analysis holds, the question for hybrid learning environments is which functions benefit from algorithmic adaptation and which should stay anchored in human relationships. Five design principles follow.

The first is to keep adaptivity primarily cognitive: scaffolding, diagnostic feedback and alternative representations are where AI contributes most, while machine-generated affective responses should be limited, recognizable as such, and never the main channel of emotional support.

The second is human mediation of affective signals. When a system detects frustration or distress, it should in most cases inform a teacher who can interpret the signal in context, rather than trigger an automated reply; this corresponds to the lower levels of automation in Molenaar's (2022) model. The third is to exclude automated emotion inference from decisions about learners, both because of the AI Act prohibition discussed above and because the inference itself is weak (Barrett et al., 2019).

The fourth is to design productive relational friction. Agents can ask for justification, present an opposing view, acknowledge uncertainty, or direct learners toward peers and teachers, and in group work they can prompt socially shared regulation instead of replacing it (Järvelä et al., 2023). The fifth is to extend critical AI literacy to the relational dimension, so that learners and teachers reflect on why a conversational agent feels supportive and what that support lacks.

These principles bear directly on teacher education. As AI systems take on more informational and instructional functions, teachers' work concentrates on interpreting classroom dynamics, mediating conflict and sustaining dialogue. Preparing teachers to recognize when AI support strengthens relationships and when it stands in for them is a task for both initial and in-service training (Henriksen et al., 2025).

7. Limitations, directions for research and conclusions

The argument is conceptual and does not rest on new data, and the hypothesis advanced, that frictionless artificial interaction shapes learners' relational expectations, needs empirical testing. Its sources come

mainly from European phenomenology and Anglo-American educational research, while the meaning of emotional expression and of relational friction varies across cultures. Its implications are also likely to differ between primary school children, adolescents and adults in higher education. Classroom observation of co-regulation episodes in lessons with conversational agents, design-based research on agents built to introduce productive friction, and longitudinal studies of companion-like agents could address these limits.

The extension of personalization from tasks to relationships involves a change of logic. Cognitive adaptivity can be evaluated against learning goals; relational adaptivity, when it takes the form of unilateral accommodation, rests on a weak inference of emotional states and removes the reciprocity through which co-regulation occurs.

The practical consequence is a division of labor within hybrid learning environments. AI systems can take on a large share of cognitive scaffolding and feedback and can support the regulation of learning by making information available to teachers and groups. The regulation of emotion within educational relationships should remain a shared human task, carried out by people who can be affected by one another. Designing for engagement means preserving the situations in which students meet others who do not simply adapt to them.

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