# Neurodiversity Sensitive Algorithms in Inclusive Education: Towards real time cognitive load responsive learning environments

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**Abstract**
Inclusive education has expanded considerably, yet many of the practices currently in place seem unable to respond to the rapid and often unpredictable fluctuations in attention, cognitive load and emotional regulation that affect neurodivergent learners. These momentary shifts, now well recognized in cognitive psychology, can influence engagement long before any decline in performance is visible. Despite this, support strategies in both formal and non-formal settings tend to remain fixed throughout activities. This article considers the emerging idea of neurodiversity sensitive algorithms, a form of Artificial Intelligence designed to notice short term indicators of cognitive overload and to adjust learning conditions in real time. Drawing on research in neurocognition, learning analytics and inclusive pedagogy, it proposes a conceptual model called the AI CoReg framework. It also explores applications in different educational environments and reflects on the ethical questions that such systems inevitably raise. The argument presented is that real time responsiveness, if approached thoughtfully, has the potential to contribute meaningfully to inclusive practice.

**Keywords:** Neurodiversity, Inclusive Education, Cognitive Load, Real-Time Adaptive Learning, Artificial Intelligence in Education, Learning Analytics, Ethical AI.

## 1. Introduction

The move towards inclusive education has prompted schools, cultural organisations and community learning programmes to reconsider the kinds of support they offer to learners with diverse cognitive profiles. While policy developments have opened doors for many students, there remains a noticeable gap between policy and lived experience. Learners with attentional or processing differences, for example, may still find themselves struggling with tasks that are theoretically “accessible” but not responsive to the moment-to-moment variations that shape their engagement (Norwich, 2014).

One of the difficulties is that most accommodations, however well intentioned, are static. Extra time or simplified materials help to an extent, yet they do not shift when a learner’s concentration dips suddenly or when working memory becomes overloaded. Research suggests that these fluctuations can be quite rapid, particularly for students with dyslexia or attention difficulties (Gathercole et al., 2006; Booth et al., 2010). In many cases teachers are aware of this, but it is understandably hard to monitor subtle changes across a whole group.

Although digital tools and adaptive systems are now more common in classrooms and museums, they tend to respond to performance rather than state. A student may receive easier questions after a series of errors, but such adjustments come too late to prevent the frustration that preceded them. Meanwhile studies in affective computing indicate that patterns in gaze, response timing and micro pauses may reveal early signs of strain (D’Mello & Graesser, 2012). This gap between what can be detected and what is currently used in practice forms the basis for the idea explored in this article.

The aim, then, is to outline a conceptual model that describes how Artificial Intelligence might respond to cognitive load in real time. The intention is not to propose a technological fix or a fully developed system, but to sketch out a framework that could help guide future interdisciplinary work.

## 2. Theoretical foundations

### *2.1. Cognitive load and neurodiverse learning profiles*

Cognitive load theory offers a useful starting point for thinking about why some learners become overwhelmed more quickly than others. Working memory, as Sweller (2011) reminds us, has limited capacity. When demand exceeds its available resources, performance tends to deteriorate. In neurodivergent learners, however, this threshold can be more variable and influenced by factors such as sensory sensitivity, attentional regulation and emotional arousal (Booth et al., 2010).

Much of the research in neurocognition points to several behavioural cues that accompany rising cognitive load. These include increases in blinking, subtle changes in gaze behaviour and slight delays in responding (Beatty & Lucero Wagoner, 2000). Although educators may notice larger shifts, these smaller cues often slip beneath awareness in busy classrooms or museum galleries. Yet they may appear well before accuracy declines, which means they could help anticipate a learner's need for support (D'Mello & Graesser, 2012).

### *2.2. Beyond traditional adaptive learning*

Most adaptive learning technologies operate on a simple principle: if a learner performs poorly, the system reduces difficulty; if they perform well, it increases it. This approach makes sense in many situations, but it does not capture the realities of fluctuating cognitive load. Performance does not always reflect ability. Sometimes it reflects temporary fatigue, sensory overload or emotional regulation difficulties.

The field of learning analytics has shown that interaction data -such as pauses in writing or irregular cursor movements- can reveal significant information about a learner's cognitive effort (Ifenthaler & Yau, 2020). Taken together, these insights suggest that a different kind of system could be developed, one that responds to state rather than outcome.

### *2.3. Micro inclusive practices and the role of Artificial Intelligence*

Teachers and museum educators routinely make small adjustments in response to learners' needs. They slow the pace, reduce sensory stimulation or switch to a different mode of explanation. These micro inclusive practices are essential to inclusive pedagogy (Florian, 2015), and they recognise that learners' needs are fluid rather than fixed.

Artificial Intelligence cannot replace this relational and responsive aspect of teaching. What it might do, however, is complement it. It may help educators notice things that are otherwise easy to miss, especially when working with larger groups. The goal here is not automation but augmentation.

## 3. The AI CoReg model

### *3.1. Recognising cognitive load*

The AI CoReg model begins with the idea that Artificial Intelligence can recognise patterns associated with rising cognitive load. These patterns may include slower reading, hesitation in writing, unexpected errors or irregular navigation behaviour. Research across reading science and human–computer interaction indicates that such patterns are often meaningful (Wilkins, 2003; D'Mello & Graesser, 2012), although they must be interpreted cautiously.

### *3.2. Generating supportive adjustments*

If the system identifies a pattern that is consistent with rising cognitive load, it can offer a small, temporary adjustment. That might mean increasing spacing, reducing visual complexity or switching to audio. These sorts of adjustments, already used in accommodation plans, have been shown to reduce visual stress (Wilkins, 2003) and to support learners who experience anxiety in testing situations (Robson et al., 2023). The difference here is that the adjustments would be available dynamically and discreetly.

### *3.3. Ethical, privacy and equity considerations*

Any system that analyses learners' behaviours raises ethical questions. The data involved can be sensitive and must be handled transparently. Systems must comply with privacy legislation such as the General Data Protection Regulation and should be designed with attention to fairness, given the possibility of algorithmic bias (Floridi & Chiriatti, 2020). These considerations mean that such technologies must be developed collaboratively, involving educators, technologists and learners themselves.

## 4. Applications in formal education

Real time responsiveness could strengthen literacy support by offering adjustments before frustration builds. A learner who experiences visual stress may benefit from increased spacing without needing to ask for it, and a student who becomes anxious during assessment may find a slight slowing of onscreen pacing helpful. Evidence suggests that these forms of support can improve comfort and performance (Wilkins, 2003; Robson et al., 2023). Because the system operates quietly, support becomes less stigmatising, which may help foster a greater sense of belonging (Norwich, 2014).

## 5. Applications in non-formal education

Museums and cultural learning settings have long worked to accommodate diverse visitors, and many now offer personalised interpretation. Research shows that this approach can increase engagement and comprehension (Dierking & Falk, 2013). Real-time adaptation could extend this work. For example, digital labels or audio guides might shorten or simplify explanations when a visitor slows down or shows signs of fatigue. In virtual or augmented reality environments, temporary reductions in sensory intensity can make experiences more accessible (Radianti et al., 2020).

## 6. Policy implications

Introducing neuro adaptive systems into education would require thoughtful policy work. Teachers and facilitators must remain central decision makers. Artificial Intelligence should act as a supportive tool, not a prescriptive one. Policies need to ensure transparency, informed consent and respect for learners' autonomy. Interdisciplinary collaboration will be essential if these tools are to reflect inclusive values rather than only technological possibilities.

## 7. Conclusion

This article has explored the concept of neurodiversity sensitive algorithms as a possible future direction for inclusive education. The AI CoReg framework suggests how Artificial Intelligence might detect rising cognitive load and provide small, well-judged adjustments that support learners without drawing attention to their needs. While there are significant ethical and practical challenges to address, the idea offers a way of thinking about inclusion that acknowledges the fluidity of human cognition. Real-time responsiveness, approached carefully, may complement existing pedagogical practices and widen participation in both formal and non-formal educational settings.

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