AI and Self-Regulated Learning Theory: What Could be on the Horizon?

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Abstract: This commentary discusses the current state of theory in self-regulated learning (SRL). It discusses the properties of optimal theory in SRL, and compares that to the current state of theory in the area. This commentary proposes that SRL theory could possibly be enhanced through the use of large language models, and proposes several specific ways that large language models could be used. It then discusses several of the challenges present in using large language models in this fashion.

Keywords: Artificial Intelligence, Large Language Model, Self-Regulated Learning Theory

This special issue brings together an exciting collection of articles that illustrate the potential of artificial intelligence to bring forward advancements in self-regulated learning research. While this special issue represents an exciting and important collection of articles, it is worth noting that the research groups and perspectives included here represent only a small proportion of the current ferment of research at this intersection. Indeed, the recent pages of this journal – not to mention other journals and conferences such as *The International Conference on Learning Analytics and Knowledge* and *the International Conference on Educational Data Mining* – are full of articles using AI to study SRL.

This special issue captures the excitement of this moment in each of its articles – from work to identify trigger events and patterns in regulatory processes during collaborative learning (Järvelä et al., this issue), to work to classify students' behaviors during collaborative knowledge construction (Ouyang et al., this issue), to work to automatically differentiate cognitive and metacognitive strategies from narratives (Lin et al., this issue), to work comparing eye movement between novices and experts (Li et al., this issue), to work clustering students' learning trajectories (Dijkstra et al., this issue), to the use of SRL measurements to drive automated scaffolding (Lim et al., this issue). Ultimately, Molenaar and colleagues (this issue) summarize all of the currently known ways where a range of multimodal data sources can be used to study four categories of SRL processes, discussing how horizontal, vertical, and integrated approaches can be used in multimodal SRL research.

In its rich breadth of intellectual contribution, this special issue also demonstrates one of the challenges that has been present since the beginning of work on self-regulated learning: the sheer scope and complexity of this topic. The simplest way one can see this is by noting the dizzying array of constructs investigated solely within the papers in the special issue. And this is only a small subset of the constructs seen in the broader literature on measuring and studying SRL. Topics in the space of self-regulated learning that are near and dear to this commentator's heart – help-seeking (Aleven et al., 2016), gaming the system (Baker et al., 2004), and self-explanation (Winne et al., 2019) (although the closely-related behavior of self-questioning is seen in Lin et al., this issue), for instance, are entirely absent from this collection of articles. Overall, this number of constructs would no doubt be much higher if one was to do a systematic review on all of the articles involving the term "self-regulated learning" and one or more of

the terms “artificial intelligence”, “educational data mining”, “learning analytics” (although doing so would still miss a lot of constructs, given the wide variety of terms used – Reschly & Christenson, 2012) (the actual execution of this exercise is left to the many ambitious Masters students worldwide who are looking for a thesis topic).

How do we simultaneously measure – and connect –- all of these constructs together? Right now, as these articles show, Artificial Intelligence is helping us to measure these constructs, but can it go further? Can AI help us capture what constructs are missing? Can it help us better connect constructs together and show more fully how they interrelate over time (beyond the excellent work seen in Järvelä et al., this issue, and – for instance – Bannert et al., 2014 and Beheshitha et al., 2015)?

Current theory in SRL has several weaknesses relative to what optimal theory would be. Optimal theory is concrete, specific, and predictive – not just explaining existing findings but making predictions about as-yet-unseen experiments and conditions (Lakatos, 1968). Can AI help us turn current SRL theory – which is verbal and high-level -- into theory that is more concrete, contextual, rigorous, and ultimately predictive?

Articles in this collection do an excellent job of mapping out the space of (some) constructs and connecting back to theory (see Molenaar et al., this issue, in particular). The question is, can the next special issue on this topic in CHB (in 2030, say) do fundamentally better? Can it present models that behave more fully as theory – that integrate a range of constructs and phenomena and make predictions about unseen cases (Lakatos, 1968)?

Perhaps it can. Let me write out one possible idea, in line with the zeitgeist of our specific historical moment. This paper is being written at a moment where large language models are demonstrating a range of unexpected and emergent behaviors. Perhaps it would be possible to assemble a corpus of empirical results involving the type of self-regulated learning constructs described in this special issue, drawn from the full scope of research published in this area. This key findings of this corpus could be summarized in natural language – perhaps distilled by an army of graduate students; perhaps distilled automatically by a large language model from the papers themselves; perhaps (probably) by using a few carefully-curated examples to fine-tune a large language model to then distill the key findings automatically, with human feedback used to further tune the process.

However this corpus is developed, it is then input to a large language model in combination with existing theoretical models of SRL, and the LLM is asked to generate the key components of a new theory. For example, the LLM could be prompted to:

- generate new, more concrete models of the processes of SRL
- create diagrams of how SRL processes unfold over time
- identify explanations (across papers) for specific phenomena identified in the corpus
- identify phenomena in the corpus that the model cannot explain and propose possible explanations
- identify contradictory results in the corpus that the model cannot explain and propose possible explanations
- take scenarios and predict what would happen next

- take study designs (published but held out of the corpus, or not yet conducted) and predict the results

In other words, an LLM could be used to create new, more concrete models, to interrogate and explain those models, and make concrete, testable predictions – the hallmarks of good theory (Lakatos, 1968). There might be several limitations to such a model; the actual underlying model might be more complex than the interpretations it could provide, violating one of the key goals of theory (full human understandability) while nonetheless offering interpretations and predictions that are useful. Relatedly, such a theory would be likely to lack parsimony, given the nature of LLMs. However, this may not be a major limitation for this domain; as it seems unlikely that any complete theory of self-regulated learning will look parsimonious, given the complexity of the domain, whether developed solely by human reasoning or augmented by AI. Another drawback relative to optimal theory would be its flexibility – in Lakatos's (1968) approach, a theory that is modified according to new results must make more predictions than the number of known findings that an adjustment now accounts for. Adding this constraint to a large language model's theory could prove difficult to do, as consistency is already not a hallmark of these models. On the plus side, LLM-generated theory would be responsive to new findings – they would simply have to be input to the corpus and the fine-tuning process re-run. It is also possible that some of these limitations could be addressed by careful iterative prompt engineering – for instance, a model could be instructed to prefer more parsimonious explanations wherever multiple explanations fit the data equally well.

Ultimately, such a theory might become the actual theory used in research (to propose open questions and new experiments) or simply a tool used by humans to develop and test a theory ultimately written by humans. Despite some initial ideas as to what the limitations might be, it is unclear at the time of this writing what the core challenges in creating high-quality theories using LLMs will be. An idea, written in a commentary such as this one, is inherently hand-wavey. The challenges in getting large language models to function as intended are non-trivial (see, for instance, the Waluigi Effect – Nardo, 2023). However, an effort of this nature could break us out of our field's long-standing situation, where theory is verbal and vague and non-predictive, where machine-learned models apply only to very small scope of phenomena and context (typically single data sets), and prior attempts to systematize findings across contexts into previous-generation architectures (such as production systems – Andres et al., 2017) never really got off the ground.

Ultimately, the articles within this special issue demonstrate that AI can play a major role in *measurement* of self-regulated learning and in the discovery of new phenomena. The question is, can we go further? Can we use AI to help us build theory on top of these building blocks? Doing so may help us to build past our current situation in SRL research – where considerable amounts of very interesting work is occurring, but that work is not connecting together as much as it could – to a world where we begin to develop theories of self-regulated learning that guide our research and which ultimately guide our work to support students in developing self-regulated learning themselves (going beyond exciting preliminary work such as Lim et al., this issue, to much more broadly scalable solutions). In the world of today – and increasingly into the future – individuals must continually learn to succeed and what needs to be learned develops faster than curriculum can. For this emerging world, theory can help us to develop and design learning systems that help students learn to regulate their learning better, and ultimately learn faster and deeper. The potential of AI to facilitate this may be just at its beginnings.

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