Title: The role of working memory capacity in a self-regulated multi-dimensional categorylearning task for High School Biology

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A growing consensus in educational research propagates the integration of freer forms of learning into school curricula, by which students can train self-regulated reflections on learning content when generating and testing hypotheses (Lazonder & Harmsen, 2016). For instance, in a school class on biology, students should not only acquire knowledge about regular feature correlations and their names (e.g., animal categories). Rather, they should also learn to organize their reflections in an autonomous discovery of multidimensional category structures. On the other hand, the self-regulation of discovery learning activities puts much cognitive load on learning outcomes (e.g., Alfieri, Brooks, Aldrich & Tenenbaum, 2011). A deeper examination of the involved mental processes is therefore necessary to understand these differences and design learning technology that models learners as active agents in computer-based learning analytics (LA) tools could be informed in a more stringent way, which could identify individual cognitive constraints in the self-regulation of discovery learning and thus, provide the basis for adaptive pedagogical agents scaffolding self-regulation strategies (e.g., Bouchet, Harley & Azevedo, 2016).

The goal of this study is to investigate the cognitive-psychological underpinnings for realizing such LA tools and adaptive pedagogical agents. To this end, we introduce a cognitive-computational model, which brings together general-psychological (Love, Medin & Gureckis, 2004) and individual difference research on category learning (Sprenger et al., 2011) and allows for simulating performance differences among students who engage in a discovery learning task. More specifically, the model simulates the self-regulated learning of new categories as an evolution of clusters of exemplars (points in a multidimensional feature space) and attributes difficulties in the categories' retrieval to capacity limitations of a working memory component (number of clusters that can be attended).

To test this model empirically, the study introduces a new discovery learning task, where a number of 60 students (from three 10th grade classes) explore a given domain in biology, namely basic level and subordinate dinosaur categories. Students iteratively perform two interrelated learning activities: they select an exemplar (by choosing features from three binary dimensions, e.g. whether the dinosaur can fly or not) and attempt to correctly assign that exemplar to one of six category names (e.g. Pisanosaurus). This way, we can relate self-directed selection (i.e., choosing an exemplar dinosaur) and categorization to a student's working memory capacity (measured with an Operation Span Task; e.g., Unsworth, Fukuda, Awh & Vogel, 2014) and test the model's ability to account for the observed data patterns. As an experimental variation, we introduce task difficulty, i.e., whether students learn basic-level vs. subordinate category names.

As a first research question, we explore the relationship between students' working memory capacity (WMC) and their performance in the discovery-learning task, both in terms of the breadth of their selection behavior (number of chosen exemplars) and the rate at which their categorization (naming) accuracy increases in time. We expect that the strength of these

relationships is stronger under more than less difficult learning conditions. The second question addresses the model's goodness-of-fit to both aggregated group data as well as individual data points. Finally, we explore the model's ability to explain the relationship between WMC and discovery learning performance (first question) and, more specifically, whether individual parameter estimates (e.g. learning rate and scope of attention) can be found to mediate the observed correlations (third question).

The results of the study will have implications for basic research on human categorization under self-regulated learning conditions (e.g., Gureckis & Markant, 2012) as it allows for validating state of the art assumptions under more natural conditions of discovery learning in the school context. Second, understanding individual differences in cognitive-computational terms will help making progress in designing learning analytics tools and pedagogical agents for computer-based learning environments that adapts the extent of scaffolding and guidance to a learner's current cognitive constraints and self-regulation strategies.

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