How working memory capacity limits success in self-directed learning: a cognitive model of search and concept formation

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ABSTRACT

With this work we intend to develop cognitive modules for learning analytics solutions used in inquiry learning environments that can monitor and assess mental abilities involved in self-directed learning activities. We realize this idea by drawing on models from mathematical psychology, which specify assumptions about the human mind algorithmically and thereby automate a theory-driven data analysis.

We report a study to exemplify this approach in which N=105 15-year-old high school students perform a self-determined navigation in a taxonomy of dinosaur concepts. We analyze their search and learning traces through the lens of a connectionist network model of working memory (WM). The results are encouraging in three ways. First, the model predicts students' average progress (as well as difficulties) in forming new concepts at high accuracy. Second, a simple (1-parameter) extension, which we derive from a meta-cognitive learning framework, is sufficient to also predict aggregated search patterns. Third, our initial attempt to fit the model to individual data offers some promising results: estimates of a free parameter correlate significantly with a measure of WM capacity.

Together, we believe that these results help demonstrate a novel and promising way towards extending learner models by cognitive variables. We also discuss current limitations in the light of our future work on cognitive-computational scaffolding techniques in inquiry learning scenarios.

CCS CONCEPTS

• **Human-computer interaction** → User models; Empirical studies in HCI; • **Applied computing** → Psychology; Education.

KEYWORDS

Self-directed learning, concept formation, working memory capacity, cognitive-computational modeling

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1 INTRODUCTION

Scientific inquiry has become a central notion in our vision of a next-generation school curriculum – an educational practice, by which young students can develop skills needed to arrive at valid conclusions in an autonomous manner. Though many different approaches surely need to complement each other, virtual environments where students can formulate their own questions and then, gather and analyze data on their own, are regarded as one promising path to get there [4, 18].

At the same time, empirically well-grounded consensus exists that this type of self-directed learning is challenging and quite often exceeds the cognitive capabilities of the learners (e.g., [1]). Effective scaffolding techniques are therefore necessary that meet the students at their current level of understanding to provide a personalized assistance in their inquiries [19]. In case of computer-supported learning scenarios, these techniques can draw on model-based analyses of learning traces (e.g., [31]) to put more weight on monitoring and understanding the learning process. Corresponding techniques of analyses (e.g., cluster analysis, machine-learning) are applied both in the fields of learning analytics (e.g., [20, 26]) and educational data mining (e.g., [5, 35]) and are key for adaptive interventions (e.g., [4]).

With our own research, we would like to shed some new light on learning analytics by developing cognitive-computational components for inquiry learning environments, which could become part of existing models for analyzing and scaffolding student learning: While already available approaches towards inquiry learning can accurately predict and assess the current degree of skill acquisition (e.g., [4, 36]), cognitive-computational modeling (e.g., [10]) would enrich the assessment by a mapping of observable skills (e.g., goal-directed search) and mental variables. The latter comprise such

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constructs as mental structure (e.g., long-term memory traces) and executive processing (e.g., attention control during self-directed learning). So far, cognitive-computational modeling has received little attention from the learning analytics community, and only few attempts have been made to apply statistical models with parameters that directly represent cognitive constructs (e.g., [20, 31]). The prediction accuracy of current models, however, would probably improve strongly through the integration of such parameters as these would make clearer the impact of cognitive constraints (e.g., attention control) on a given learning process.

In the present paper, we aim to illustrate this endeavor by the example of an experimental study that we have conducted in the high school context. As a first approach to *cognitive learning analytics*, the study's design aims to keep things as simple and controlled as possible and to constrain both the observed behavioral phenomena and the potentially involved cognitive processes to a smaller subset of elements relevant for the inquiry learning cycle (e.g., [30]). More specifically, instead of having students complete an entire cycle, they only cycle between the formation of new concepts (i.e., mental representations of dinosaur categories and their names) and the search for corresponding concept information (i.e., navigating a dinosaur taxonomy). The reason for our focus on concept formation is that students' understanding of how object features (e.g., having wings, being small) go together to form categories (e.g., different types of animals) is central to any learning activity and a prerequisite for a shared understanding and effective communication among learners [12]. Beyond that, the "search-as-learning" research (e.g., [11, 17, 39]) demonstrates that the activities of learning and searching are coupled to one another through dynamically evolving knowledge structures (see also [34]). Therefore, successful learning benefits effective searching (and vice versa), and gaining an understanding of the mediating knowledge structures, such as concepts, should benefit the modeling and support of the two activities.

Our theoretical considerations are grounded in cognitive research on self-directed category learning [13], which demonstrates that individuals (across different age groups) differ greatly in their rate at which they can acquire concepts (e.g., [22]) and in their ability to perform corresponding goal-directed search processes (e.g., [23]). An important source of these individual differences is working memory capacity (WMC; [7]), an integral part of the human cognitive system, which orchestrates a set of cognitive functions for the control of attention in the face of distraction [32]. Accordingly, the model that we are going to introduce here to explain differences among high school students in learning and searching draws on a cognitive-computational framework [28], which allows parameterizing WMC-related processes based on behavioral data, such as answer patterns or search paths. So what we do here is to establish a direct mapping between learning traces typically gathered for learning analytics and a theoretically grounded model of cognition. This should allow us a much better and theory-based understanding of those traces and also lead much more directly to evidence-based interventions (such as scaffolds). With this we aim to contribute to a theory-driven focus in Learning Analytics research.

The model is a 2-layer connectionist network that learns to mimic and predict a student's search and categorization behavior. We start with a set of mathematically formalized learning assumptions and thereby guide the development of more specific and falsifiable expectations to the data. The model we use as a starting point has thus far been applied to model observations made under controlled lab conditions. The goal of the present paper is to demonstrate that the framework can be employed as a learning analytics technology to model traces of self-directed learning behavior performed by high school students in the classroom. To address this goal, we have structured the study along three research questions (RQs).

The first two RQs aim at validating the model based on aggregated group data. In particular, they refer to two aspects of the data that we deem essential against the backdrop of the search-as-learning framework, namely characteristics of the average learning performance and of the average navigation behavior:

- Does a cognitive-computational model of WMC allow for predicting learning progress and difficulties of students searching a taxonomy of dinosaurs (RQ1)?
- Does an extension of the model by a search component also account for self-determined search decisions (RQ2)?

RQ1 mainly refers to the adaptation of certain model features to the self-directed learning context, such as adjusting the number of units within the connectionist network. Addressing RQ2 requires an extension by a mechanism, which enables an autonomous search, i.e., a goal-directed navigation within the dinosaur taxonomy. The cognitive assumptions for this extension are detailed in Section 2.2. Again, they are motivated by research on human category learning, in this case dealing with people's self-directed scheduling of learning content (e.g., [24]).

RQs 1 and 2 characterize our current research focus to find a cognitive model for learning analytics, which can explain general (i.e., aggregated and average) search and learning behavior by means of WMC-related parameters. Beyond that, we explore its applicability as a measurement model and raise the third research question:

- Can we fit the model against individual data to get parameter estimates that correlate with individual WMC scores (RQ3)?

The decisive advantage of such an approach would be that individual abilities could be inferred directly from recorded learning traces. Effortful invasive external tasks were no longer necessary.

Together, these three RQs specify the aforementioned research goal. If it were met, then we would be one step closer to a scaffolding technique that would monitor the learning progress of students, diagnose cognitive constraints and autonomously make recommendations about effective study choices.

2 WORKING MEMORY CAPACITY IN SELF-DIRECTED CONCEPT FORMATION

We proceed in two steps to present the theory and derive the model. In step one (Section 2.1), we elaborate on why forming concepts is so central to learning and communication between learners, and why it is related to WMC. In this context, we also outline a simple search-as-learning task (with the details provided in Section 3.1.2), by which self-directed concept formation can be observed. In step two (Section 2.2), we then specify the mental processes underlying concept formation and the impact of WMC in connectionist terms.

2.1 Shared Categorization and Inference through Self-Directed Concept Formation

In order to correctly understand an inquiry goal and form a hypothesis as well as to effectively collaborate with other students, an important learning objective for novices is to acquire the terminology of the associated knowledge domain. Within science disciplines (e.g., zoology), this typically requires to internalize already developed classification systems, like the dinosaur taxonomy in Figure 1 (left graph), on which we are drawing for the present high school context. Among others, internalizing a zoological taxonomy involves several aspects, such as getting to know its phylogenetic dimensions (e.g., locomotion) and every dimension's feature values (e.g., "can't fly" vs. "can fly"), figuring out the typical combination of features that form the taxonomy's categories (e.g., the feature triple of "can't fly", "is small", and "has no crest"), learning the categories' labels (e.g., "Pisanosaur"), and forming a mental representation of how their members (i.e., exemplars) look like.

To succeed, a student needs to develop correct concepts. For the purpose of the present paper and to simplify matters, we use the term concept to refer to associations in long-term memory that maintain encountered correlations between the phylogenetic features of a category and the features of the category's label, such as the orthographic and phonological characteristics of the label "Pisanosaur". Knowing these concepts is essential for participating in inquiry learning activities because they mediate two interrelated phenomena of shared understanding:

- shared categorization, i.e., using the same label for a given set of phylogenetic features, and
- shared inference, i.e., anticipating the same set of phylogenetic features given a perceived or conceived label.

According to these considerations and in order to investigate our research questions empirically, we have developed and applied a "search-as-learning" task, in which high school students can train these two processes in a self-directed manner. The task consists of several cycles, each consisting of students selecting one dinosaur category by making three binary choices of dinosaur features (e.g., whether they can fly or not). Thereby, students perform a self-guided search of the taxonomy. As depicted in the right graph of Figure 1, the three binary choices are made one at a time on consecutively presented pages, so that the entire taxonomy is never visible to the students. Below, we will explain why this step in the cycle (self-guided search) is driven by the inference of the category's features given that their selection is goal-directed. Then, after having selected the category, the picture of one of its members is shown. To train the process of categorization, the student tries to choose the correct label that is presented below the picture together with five distractor labels. Finally, and before a new cycle begins, feedback is given, which reveals the correct label for the selected category and helps the students adjust the already formed concept (mental associations between phylogenetic and label features).

Starting off with almost no prior knowledge, students' initial learning activities can be expected to be unsystematic and driven by processes of random decision-making. Due to the continuous feedback provided in every cycle, however, the categorization of dinosaur exemplars should in time become more accurate and the self-determined selection more goal-directed. With the term "goal-directed" we are referring to cycles, which start with a self-generated hypothesis, such as: "In the next cycle I would like to test my assumption that a 'Pisanosaur' indeed has no crest". That is, goal-directed cycles start with hypotheses that require an already developed understanding of the underlying concept (e.g., [37]), by which at least parts of the category features can be inferred to search the taxonomy systematically. Drawing on one's own knowledge to formulate hypotheses and search in a goal-directed way is a fundamental science inquiry competence. We therefore believe that it needs to be practiced in any type of discovery learning task.

Learning progress should manifest in both labeling and selecting the dinosaurs and, beyond that, should manifest differently depending on a student's WMC. The rationale behind expecting this interaction is that learning difficulties typically arise when to-be-studied concepts share similar features and are hard to differentiate in form of distinct memory representations (e.g., [3]), such as the concepts of PISANOSAUR and RINCHENIA (see Figure 1). The cognitive consequence are competing associations (e.g., Rinchenia–small and Pisanosaur–small) that interfere with one another whenever one of them needs to be retrieved. Thus, an important cognitive mechanism that supports the study of new concepts is effective control over interfering associations (e.g., [14]). And because inhibitory control is an important component of working memory (e.g., [28]), students who do better in a task requiring WMC should also exhibit advantages in a task on self-guided concept formation.

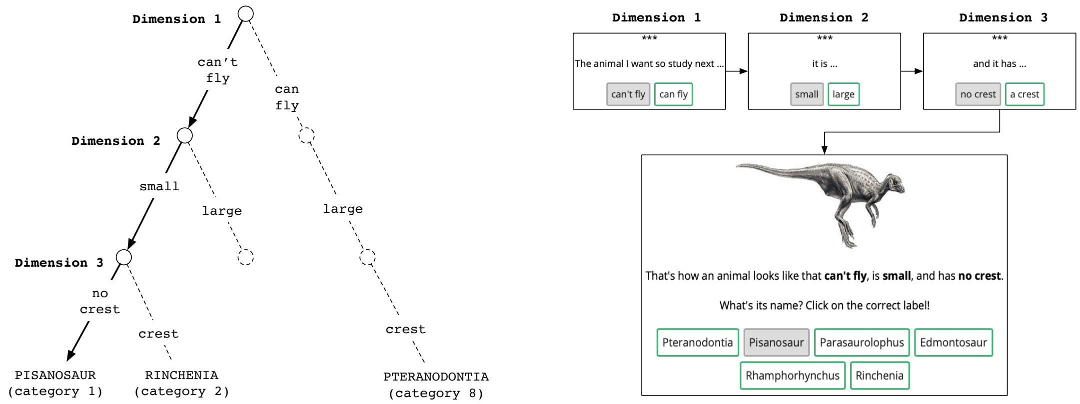
Summarizing, by drawing on research on human category learning, we are identifying a cognitive construct (WMC) that benefits the development of long-term memory structures (concepts), which we assume to mediate the dynamic coupling between goal-directed search and learning performance (categorization accuracy). That way, this work contributes to the search-as-learning research (e.g., [11, 17]). In the next section, we formalize our cognitive assumptions in form of a connectionist network model that we introduce here as a cognitive approach to learning analytics and on which we will base our predictions and analyses.

2.2 A Cognitive-Computational Account of Self-Directed Concept Formation

2.2.1 Model architecture. For modeling the formation of concepts, we are using a 2-layer connectionist network (see Figure 2), which in time learns to connect two types of information: a category's phylogenetic features (encoded in layer F) and linguistic (e.g., orthographic) characteristics of its label (encoded in layer L). The process of forming a concept is defined as arriving at a connection pattern within the weight matrix $\mathbf{M}$ that connects every unit in F with every unit in L and supports two processes of pattern completion: Categorization and inference, with information flowing from layer F to L and from L to F, respectively.

The network belongs to the class of Hebbian associators with a distributed representational scheme (e.g., [16, 28]). This means that a stimulus, such as a presented picture of a dinosaur with certain features, is represented not by a single unit (taking on the value of either +1 or -1) but by an activation pattern across the entire set of binary (±) units included in F. In this study, 3^*n units are used to code for a dinosaur category, i.e., n units per dimension x (see Section 3.1.2 for more details on simulating the study material).

Figure 1: Sketch of taxonomy used in the study (left graph) and what students see during navigation (right graph)



Similarly, a label is represented by an activation pattern in L with m binary (±) units. At a given point in time t, the activation patterns in F and L are represented by the feature vectors $\mathbf{f}_t$ and $\mathbf{l}_t$, respectively.

To form new concepts, the network learns to map the two states in F and L by tuning the weights in $\mathbf{M}$ such that $\mathbf{l}_t$ reinstates $\mathbf{f}_t$, and vice versa. The tuning is accomplished through Hebbian learning, by which a connection weight increases in strength whenever the corresponding units in F and L are concurrently active (+1) or inactive (-1), and decreases in strength, if their activation states differ in sign. In this study, such learning occurs in response to the feedback that is provided after categorization and used to determine the degree at which the predicted pattern, i.e., $\mathbf{l}_t$, deviates from the target pattern (correct label, denoted $\mathbf{w}_c$). A larger deviation is considered as a signal to increase the current encoding strength.

2.2.2 Categorization and Learning. Perceiving a pictured dinosaur exemplar evokes $\mathbf{f}_t$, i.e., the pattern in F which codes for the present exemplar. Based on $\mathbf{f}_t$, the network makes a prediction of how the corresponding label pattern $\mathbf{l}_t$ could look like by passing the probed activation through $\mathbf{M}$. More formally, this passage of activation (from F to L via $\mathbf{M}$) corresponds to taking each column of $\mathbf{W}$ and calculating the inner product with $\mathbf{f}_t$:

$$\mathbf{l}_t = \mathbf{M}\mathbf{f}_t \tag{1}$$

The outcome is used by the network to judge each of the six candidate labels (one target and five distractors) for how well it matches the pictured dinosaur (see Section 3.1.2 on why six rather than eight labels, i.e., one per taxonomy category, are presented). To this end, it determines the similarity between $\mathbf{l}_t$ and each candidate i by computing and transforming the Euclidean distance D according to

$$sim(\mathbf{w}_i, \mathbf{l}_t) = \exp[-\tau D(\mathbf{w}_i, \mathbf{l}_t)^2] \tag{2}$$

where $\mathbf{w}_i$ is the feature pattern that codes for the candidate label i, and τ is a free parameter controlling for how easy it is to discriminate between the candidates. Above, we have argued that inhibitory control is a working memory subfunction that helps counteract interference by the suppression of associations that compete for being retrieved. By controlling the noisiness in selecting the correct label from a set of competing candidates, τ is one important inhibitory control parameter.

The similarity (outcome of Equation 2) then translates to a choice probability for candidate i:

$$P(i) = \frac{sim(\mathbf{w}_i, \mathbf{l}_t)}{\sum_{j=1}^{J} sim(\mathbf{w}_j, \mathbf{l}_t)} \tag{3}$$

where J is the number of candidates, i.e., 6. After having made its choice, two processes take place: *output interference* and *learning by feedback*. The former process is an important property of connectionist networks to account for human behavior and consists in an unspecific impairment of the connection weights in response to the retrieval of information (e.g., a concept's label). Drawing on [28], we model *output interference* by adding Gaussian noise (with a standard deviation N_o) to every element in $\mathbf{M}$.

The second process – *learning by feedback* – is implemented by providing feedback in form of the correct label pattern, denoted $\mathbf{w}_c$, allowing the network to adjust $\mathbf{M}$. Note that the F-L associations of different concepts partially overlap (i.e., the vectors are not orthogonal) and are superimposed in the same weight matrix. As a consequence, $\mathbf{l}_t$ cannot be a perfect replicate of $\mathbf{w}_c$, no matter how well-trained the network is. To increase the accuracy of future predictions, the associations between $\mathbf{w}_c$ and $\mathbf{f}_t$ are stored in form of the outer product of the two vectors (Hebbian learning):

$$\Delta\mathbf{M} = \eta_t \mathbf{f}_t \mathbf{w}_c^{\mathrm{T}} \tag{4}$$

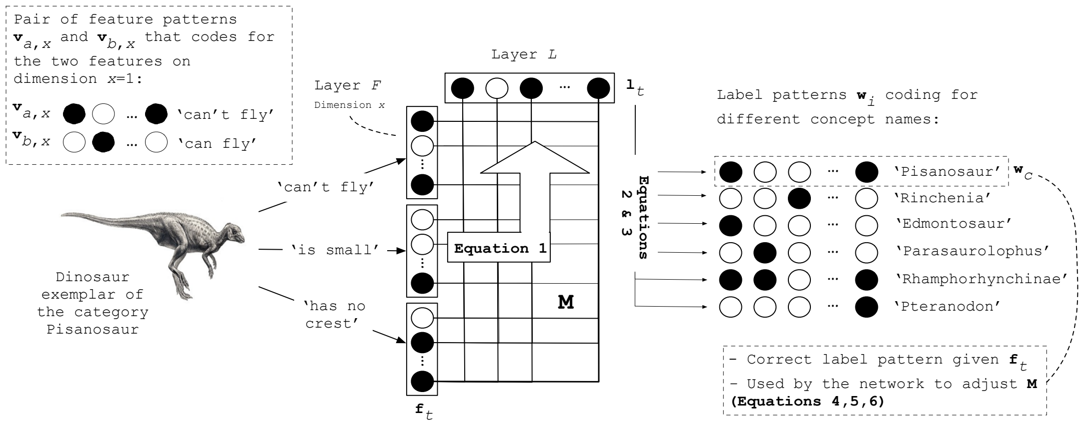
where η_t is the current encoding strength that gets smaller as the prediction gets more accurate. The accuracy can be operationalized as the degree to which the network expects $\mathbf{w}_c$. Denoting this momentary expectation E_t and defining it as the inner product of $\mathbf{w}_c$ and $\mathbf{l}_t$, we can insert it into the following logistic function to determine the current encoding strength:

$$\eta_t = \frac{1}{1 + exp[-(E_t - e)g]} \tag{5}$$

where e and g set the threshold and gain of the function.

As stated earlier, superimposing $\mathbf{M}$ by new F-L associations causes interference that slows down the just described learning process. In addition to the parameter τ (controlling interference suppression during retrieval), in a connectionist network, response suppression can further be realized through Hebbian antilearning (e.g., [2]). In the present model, it takes place, if the selected label

Figure 2: Schematic network architecture and the process of categorization



$\mathbf{w}_t$, which has been sampled from the probability distribution as defined by Equation 3, is wrong, that is, if $\mathbf{w}_t$ is not $\mathbf{w}_c$. To decrease the probability of making a wrong choice given $\mathbf{f}_t$ in future cycles, the corresponding connection strengths are suppressed by the following operation (Hebbian antilearning):

$$\Delta\mathbf{M} = -\rho\eta_t\mathbf{f}_t\mathbf{w}_t^{\mathrm{T}} \tag{6}$$

where ρ is a free parameter, which further controls the strength at which erroneous associations are removed from $\mathbf{M}$. ρ is therefore the second main model parameter (besides τ) that governs the network's ability to enact inhibitory control over interference.

2.2.3 Self-guided Search. To simulate students' category selections, we further equip the model with the ability to make its own study choices. Remember that we assume searching the taxonomy to be guided by a feature inference process: Based on a focused label, the student tries to infer the category features to navigate the taxonomy.

Hence, the question arises how a particular label gets into focus. Some answers can be found in models of "metacognitively guided study-time allocation" ([24], p. 161), and, in particular, in the region-of-proximal-learning framework [25]. In brief, research on it shows learners to attend to those to-be-learned items, for which they perceive a positive learning rate. Especially when they study under time pressure and if well-learned items are eliminated, they select "easy but as-yet-unlearned items" as these are "likely to yield a near-certain payoff for the small investment of study time needed to propel them into a learned state." (Metcalfe, 2009, p. 162).

In the present learning situation, where students study novel dinosaur concepts within a short time frame (about ten minutes), we can also expect a preference for easier concepts, that is, feature-label mappings that, after some study time has passed, have been visited more frequently and are therefore already in a transitional learning state. This would accord to Metcalfe's reasoning on empirical findings that "speak to people's perseverance once an item is chosen for study".

We can implement a mechanism that lets the network perseverate on studied concepts by coupling its study choices to the expectancy value E. At a given point in time t and for a given concept i, $E_{t,i}$ reflects the extent to which the network is already able to expect the concept's correct label and thus, reflects the "perceived easiness" of it. We have chosen the following softmax function (e.g., [10]) to transform $E_{t,i}$ into the concept's selection probability:

$$P(i) = \frac{exp(\phi E_{t,i})}{\sum_{j=1}^{J}[exp(\phi exp(E_{t,j})]} \tag{7}$$

where the parameter ϕ controls for the noisiness of responding.

Then, the label pattern that corresponds to the chosen concept initiates the goal-directed search by evoking a new activation state in layer L, i.e., $\mathbf{l}_t$. Inverse to the process of categorization, $\mathbf{l}_t$ is passed through M to update the pattern in F and form a new $\mathbf{f}_t$:

$$\mathbf{f}_t = \mathbf{l}_t\mathbf{M} \tag{8}$$

As illustrated in Figure 2, $\mathbf{f}_t$ consists of three subvectors, denoted $\mathbf{f}_{t,x}$ each representing one of two features (e.g., "can't fly") on one of the three binary dimensions x (e.g., locomotion). Now, to make a choice on x, $\mathbf{f}_{t,x}$ is matched against each of the two feature patterns $\mathbf{v}_{a,x}$ and $\mathbf{v}_{b,x}$. For example, on x=1 (dimension of locomotion), the latter two vectors code for the two features "can't fly" and "can fly", respectively. The probability of choosing the first feature is:

$$P(a,x) = \frac{sim(\mathbf{v}_{a,x}, \mathbf{f}_{t,x})}{sim(\mathbf{v}_{a,x}, \mathbf{f}_{t,x}) + sim(\mathbf{v}_{b,x}, \mathbf{f}_{t,x})} \tag{9}$$

where the similarities are calculated in the same way as given in Equation 2 with τ fixed to unity.

The outcome of this pattern matching process corresponds to the network's feature choice, i.e., to either clicking on the left or right button (see right graph in Figure 1). As soon as the network has made its third choice, it has defined a feature triple, i.e., the category for the next cycle $t + 1$. Sampling a new exemplar leads to $\mathbf{f}_{t+1}$, a new activation pattern in F that enters Equation 1 and triggers the next categorization attempt. A summary of the model parameters and their interpretations are given in Table 2.

3 STUDY

Having detailed our assumptions on how WMC-related mechanisms support concept formation, we now examine whether the model keeps its promise and accounts for observable behavior. In the following, we report from a study by which we have tested the model's validity. After describing the methods (Section 3.1), we present the main benchmark effects, i.e., reliable data patterns against which the model can be fitted (Section 3.2.1). We then draw on these effects to examine the model's goodness-of-fit with respect to students' learning performance (RQ1) and search behavior (RQ2; Section 3.2.2). Finally, we explore whether the model can also be utilized as an individual measurement model yielding student-specific parameter estimates (RQ3; Section 3.2.3).

3.1 Methods

3.1.1 Design and Participants. N=105 7th and 8th grade students from two local high schools are examined in their performance in *dinoNimi* (search-as-learning task) and in *Ospan* (complex span task to measure WMC). The average age of the sample is $M = 15.1$ years ($SD = 0.61$, $range = 14 - 17$ years). Participation is voluntary and not motivated by any financial incentives. Only students, whose parents have given informed consent, are allowed to participate.

3.1.2 Materials.

dinoNimi. The search-as-learning task is denoted *dinoNimi* and has already been outlined in Section 2.1. It has been programmed for the purpose of the present study as a Web-based application by drawing on the JavaScript library *JSPsych* [9]. With respect to the task's search component, the *dinoNimi* taxonomy spans eight search paths, each corresponding to one of eight mutually exclusive dinosaur categories (feature triples). In every cycle, the selected category is instantiated and illustrated by a schematic picture of a representative category exemplar. The picture is sampled randomly by the program from a set of ten unique and category-specific pictures.

In the simulation, these ten exemplars are derived from a prototype (representing a given category), which is a binary (±), $n * 3$-element vector. From this prototype, the ten exemplars are derived independently of one another, each being a noisy replicate of the prototype, with whom it shares a portion of $1 - \omega$ feature values. ω is a further free parameter taking on a value between 0 and 1.

With respect to the task's learning component, i.e., learning to correctly label the presented picture, the same set of $\mathcal{J}$=6 labels (one target label, five distractors) is reshuffled and displayed in every cycle t. The set of $\mathcal{J}$ labels consists of four subordinate terms ("Pisanosaur", "Rinchenia", "Edmontosaur", and "Parasaurolophus" for the four non-flying dinosaurs) and two basic-level terms (i.e., "Rhamphorhynchus" and "Pteranodontia", respectively, for the two flying-and-small and the two flying-and-large dinosaur categories). This variation of a label's specificity serves as an experimental variable, whose effects are not relevant to the present study and are therefore not reported. The entire task consists of seven 1-minute study phases (i.e., self-determined and self-paced search-and-learning cycles) each followed by an additional 1-minute test phase. In the latter, picture-label pairs are presented and have to be judged for whether they are correct or not. As we are still in the process of extending the model to account for these test-phase data too, in this paper, we only report the results of the study phases.

Ospan. The Operation Span Task (denoted *Ospan*) is a standard measure to index WMC (e.g., [8]), in particular, the ability to accurately perform a primary task (remembering a sequence of consecutively presented letters) that is interspersed with a secondary distractor task (solving simple arithmetic equations). The secondary task provides a threshold (85% correctly solved equations) that participants need to exceed for their response behavior to be deemed valid. The performance in the primary task (number of correctly recalled letters) serves as the actual test score (for details see e.g. [38]). Again, we have implemented this task as a Web-based application by making use of *JSPsych* [9].

3.1.3 Procedure. The experimental sessions are conducted in groups of about 20 students in the course of biology classes held in a seminar room at the university. The students are sitting on separate tables each equipped with a desktop PC computer. At the beginning, one of three experimenters provides a verbal instruction and on-screen demonstration of how to generate a personal username (for an anonymous treatment of the data) and how to perform *Ospan* in a first step and *dinoNimi* in a second. The other two experimenters take care that everyone understands and is ready to complete both tasks. During the session, all three of them are taking care that everyone is working individually and staying focused. At the end, the students are debriefed and granted with a small gift (chocolate). An entire session approximately lasts 45 minutes.

3.2 Results and Discussion

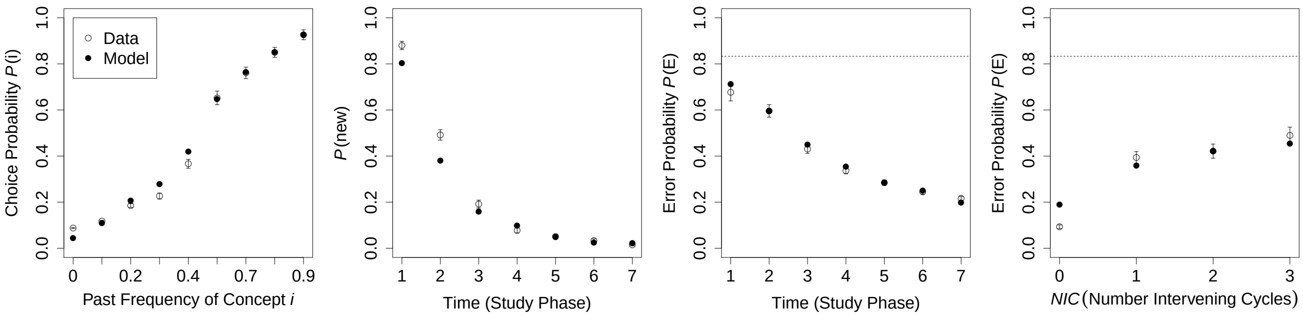
As benchmark effects we are using data patterns that have turned out to be reliable in the sense of yielding means with relatively small variances. These are shown in the four diagrams of Figure 3, in which every point represents an average score (mean) that results from aggregating across the entire student sample. Error bars indicate the standard error of mean. We first describe the empirical data before turning to the simulated model data.

3.2.1 Benchmark effects: average search & learning behavior.

Students' search behavior. Diagram (a) in Figure 3 draws the average probability $P(i)$ of a student choosing a particular category i, i.e., feature triple, against i's frequency in the student's previous study cycles. It reveals an S-shaped curve and hence, a category's past frequency to be a strong predictor of being re-visited in future cycles. This result lends strong evidence to one above-stated implication of the region-of-proximal-learning framework [24]: students tend to perseverate on those items (feature triples), for which they are perceiving a positive learning rate due to having chosen them at a relatively higher frequency. We regard this outcome as an empirical justification for extending the model by a search component according to the newly proposed Equations 7, 8 and 9.

The second diagram (b) shows students' average exploration rate by representing $P(new)$ – the probability of choosing a new concept – as a function of *Time* (study phase). In line with our interpretation of diagram (a) that frequently chosen categories increasingly determine future choices, diagram (b) uncovers a steep decline of students' exploration rate: an initially high estimate of about $P(new) = 0.9$ quickly drops off and starts approaching an estimate close to zero. Thus, both diagrams confirm the expectation that students' self-determined study choices are driven by "*perseverance once an item is chosen for study*" (Metcalfe, 2009, p. 163).

To test these descriptive results for statistical significance and to examine potential relationships with students' WMC, we have run



(a) Search: study perseverance **(b) Search: exploration rate** **(c) Learning curve** **(d) Retroactive interference**

Figure 3: Students' Search Behavior (diagrams a and b) and Learning Performance (diagrams c and d). Error bars represent the standard error of mean. Dashed horizontals representing $P(E)$ based on guessing.

Table 1: Summary of Logistic Regressions

Criterion	Predictor variable	β	*SE*	Wald *z*
$P(i)$	Intercept	-2.652	.116	-22.823***
	Past Frequency	4.967	.105	47.311***
	Ospan	0.000	.002	-.015
$P(new)$	Intercept	2.035	.318	6.393***
	Time	-1.097	.042	-26.137***
	Ospan	0.004	.005	0.717
$P(E)$	Intercept	0.822	.276	2.983***
	Time	-0.308	.027	-11.239***
	NIC	0.172	.011	16.310***
	Ospan	-0.018	.004	-3.988***

*** significant at .1% level

one logistic regression of $P(i)$ on i's *Past Frequency* and *Ospan*, and a second logistic regression of $P(new)$ on *Time* and *Ospan*. The outcomes of both regressions are presented in Table 1 and underscore our interpretation of diagrams (a) and (b): The corresponding beta-coefficients indicate a positive relationship between *Past Frequency* and $P(i)$ (Regression 1) and a negative relationship between *Time* and $P(new)$ (Regression 2). With respect to *Ospan*, however, none of the two models yields a significant result. In other words, the general search pattern as predicted by Equations 7, 8 and 9 does not seem to be affected by a student's WMC.

Note that we have also examined potential interactions between the variables in each of the Table 1 regressions but have not found significant results. That is, including an interaction neither improves the goodness-of-fit of a given model nor does it change the size of any of the reported effects significantly.

Students' learning performance. Diagram (c) shows the average learning curve by drawing $P(E)$ – the probability of choosing a wrong label for the selected feature triple – against study phase (*Time*). The curve's decline is indicative of a continuous learning progress as $P(E)$ decreases in time in a monotonous fashion. This result is particularly interesting as the fourth diagram (d) shows clear signs of interference, i.e., of an effect, which competes with the positive learning rate. In particular, the diagram plots $P(E)$ as a function of *NIC*, the Number of Intervening Cycles that separate the current re-study of a given concept from the concept's most recent study cycle. E.g., if *NIC* is zero, the concept has been studied in cycle t and in the immediately preceding cycle $t-1$. As *NIC* gets larger, so does the number of competing feature-label associations (i.e., concepts) and the harder it should be to retrieve from memory the correct label for a given feature triple. The apparently positive relationship between $P(E)$ and *NIC* as shown in diagram (d) provides direct evidence of that assumption. We therefore conclude that *dinoNimi* provides a paradigm that allows to evoke processes of interference that slow down but do not prevent concept formation.

To examine a potential relationship between these two learning-related measures and WMC, we have performed one further logistic regression of $P(E)$ on *Time*, *NIC*, and *Ospan* (see the results for the $P(E)$ criterion in Table 1). This time, all of the entered predictors have proven significant. The negative and significant β coefficients for the predictors *Time* and *Ospan* underline the observed increase of categorization accuracy across the seven study phases and suggest that the accuracy gets higher as a student's WMC increases, respectively. The positive and significant β coefficient for *NIC*, on the other hand, confirms the variable's detrimental effect on students' categorization accuracy. Overall, this third regression implies that students with higher WMC estimates tend to exhibit steeper learning curves because they are more effective in copying with interference arising from competing feature-label associations.

3.2.2 RQs 1 & 2: Testing overall model fit based on aggregated search and learning data. To increase the constraints for the model evaluation and to demonstrate that one and the same set of parameter estimates can account for a range of different data points, we aim to fit the model against all four data patterns (diagrams a-d) simultaneously, i.e., across 27 data points. For fitting the full model, which comprises nine free parameters (see Table 2), we are using a genetic algorithm (drawing on the R-package GA [33]) to minimize the root-mean-square deviation (RMSD) between students' data and model simulations. In case of complex and stochastic models, genetic algorithms have been found to be an effective way to tune parameters and minimize the problem of local minima (e.g., [15]).

The best-fitting parameter estimates are presented in Table 2 and underlie the simulated curves in Figure 3 (see the black-filled

Table 2: Summary of model parameters

	Description	Range	Estimate
n	# units per dimension in F	1-100	22
m	# units in L	2-150	55
$\omega^{\dagger}$	Dissimilarity between category prototype and exemplars	0-1	0.379
τ^*	Discriminability (retrieval)	0-3	2.459
g	Gain for logistic function	0-0.01	0.008
e	Threshold for logistic function	-2000-0	-967
ρ^*	Removal rate	0-1	0.744
ϕ	Discriminability (search)	0-1	0.124
N_o	Output interference	0-2	1.826

† Parameter is described under *Materials* (Section 3.1.2).
* Inhibitory control parameters.

circles). Qualitatively, the model appears to account for the data well and is able to reproduce the mathematical form of each of the four empirical curves. Using a χ^2 statistic with $df = 18$ (27 data points minus nine parameters), we have tested the goodness-of-fit also quantitatively and have found it to be adequate: $\chi^2(18) = 0.18$, *n.s.*. The diagrams (a) and (b) demonstrate that the extension of the model by our suggested 1-parameter search component (Equations 7, 8, 9) is sufficient to simulate aspects of students' study choices in a realistic way: Both the probability of perseverating on already studied concepts (diagram a) and the probability of switching to a new one (diagram b) is explained well by a mechanism that selects a to-be-studied concept based on the expected retrievability of the correct label. That way, we gain further evidence of a self-directed learner model, whose study choices follow principles derived from the region-of-proximal-learning framework. The estimate of the parameter ϕ (noisiness in the selection process) is rather small – an outcome of the estimation process that seems important to account for the observed temporal dynamics in the exploration rate as depicted in diagram (b): Initially, the unsystematic selection of single concepts already leads to a slight increase of these concepts' E-values. Were the value of the parameter ϕ large, the model's subsequent study choices would be more or less focused on this small subset of the taxonomy. By contrast, a small ϕ value makes the model start perseverating on frequently visited concepts only at a later phase, when several concepts have already been tried out and the distribution of E values is no longer uniform.

With respect to the learning curve in diagram (c), the model-based predictions are very accurate. This implies that the implemented encoding mechanisms (Equations 4, 5, and 6) and controlled retrieval processes (Equations 1, 2, and 3) allow to simulate a development of cognitive structure that mimics the students' average learning progress. From a working memory perspective, the most important parameters are τ (discriminability during retrieval) and ρ (removal rate for erroneous connections) that together influence the network's control over interfering associations [28]. As can be seen in Table 2, both of them take on relatively high estimates within the pre-determined range of possible parameter values. This suggests a high difficulty for the network to learn new competing feature-label associations from scratch, and that it aims to compensate for it by "turning up" its executive control mechanisms.

Despite utilizing these compensatory mechanisms, diagram (d) shows that the network's learning behavior is compromised by retroactive interference too: the probability of not being able to retrieve a concept label studied a certain number of intervening cycles (NIC) ago increases as NIC gets larger. Note that in the simulation, this process of forgetting can only be attributed to the impact of competing associations learned in between the repetition of a particular concept and not to the length of the retention interval, as no time-based decay is explicitly implemented. Overall, the simulated results reflect the NIC-dependent empirical increase of $P(E)$ well, and we can see an adequate goodness-of-fit especially for $NIC > 0$. In case of $NIC = 0$, the model tends to underestimate the students' actual categorization accuracy – a deviation from the data that we aim to reduce in our future work by refining the retrieval mechanism. E.g., the applied connectionist network formalism would also be compatible with a time-based decay component (e.g., [15, 16]), which would boost the availability of recently studied items and thereby improve the categorization accuracy at $NIC = 0$. For the present study, however, we prefer a model variant that tolerates a slightly decreased goodness-of-fit in favor of an increased parsimony (smaller number of parameters).

Summarizing, we regard these results as providing enough evidence to answer our first two research questions: the suggested model appears to make valid cognitive assumptions about students' average learning performance (RQ1) and search behavior (RQ2). Therefore, we can go one step further and demonstrate its applicability for individual data analyses.

3.2.3 RQ3: Modeling individual student data. In this final step, we limit the model-based analyses to a student's learning curve (see diagram c). The other three patterns must be excluded because for several students, not sufficient data is available to determine a reliable score for every point of the predictor variable (x-axes). Hence, seven data points, i.e., $P(E)$ values, remain per student. To maintain identifiability, we have decided to apply a model variant, in which only two parameters vary freely, namely τ and ρ. All of the remaining parameters are fixed and set to those values, which we have obtained in the course of the general model validation (previous section) and which are given in Table 2. For now, we also refrain from modeling individual search behavior (i.e., we skip the processes formalized in the Equations 7-9) and instead, let the model go through a student's self-determined sequence of study cycles. That is, in every cycle, the feature triple selected by the student is provided as input to the model, which then aims to categorize and learn from it according to the Equations 1-6. To determine the student-specific estimates of τ and ρ, again the parameter space is searched by minimizing the RMSD between the model predictions and the student data. This time, we use the *Simplex* method [27], which is more efficient than a genetic algorithm and applicable given the two continuous parameters.

With this just-described model and estimation method, we can explore RQ3. First, we aim to identify the percentage of students, for which an adequate data-model fit can be achieved. To this end, we are drawing on a statistical procedure that is described in [15] and helps objectify whether the deviation between a student's data

Table 3: Means and SDs of individual parameter estimates as well as their (Spearman) correlations with *Ospan*.

Parameter	*M*	*SD*	*Ospan*
τ	2.18	2.19	.21*
ρ	.55	.62	.07

* significant at the 5% level

and the model, denoted $RMSD_{model}$, is significant. Based on the student's empirical learning curve (i.e., *M* and *SD* across the seven study phases), a number of 100.000 curves are simulated, and each of these curves is quantified in terms of its RMSD from the empirical curve. This leads to a distribution of $RMSD_{data}$ values against which $RMSD_{model}$ can be compared: only if the latter statistics is found to be smaller than the 95th percentile of the $RMSD_{data}$ distribution, the model fit can be deemed adequate.

After having identified the percentage of students, whose learning curves can be fit, we are able to correlate the student-specific parameter estimates (τ and ρ) with their scores in the *Ospan* task, serving as an external validation criterion.

The results reveal a portion of 98% of the students (103 out of 105), for which the goodness-of-fit is adequate. Put differently, the model fits almost all of the individual learning curves well and thus, allows to infer two cognitive control processes on a student level: the ability to deal with interference during retrieval (parameter τ) and to remove erroneous feature-label connections in response to feedback (parameter ρ). Table 3 shows the means and standard deviations for the two parameters as well as their correlations with the *Ospan* score. As the coefficients indicate, the correlation is positive and significant for the parameter τ. No significant relationship, however, can be found for parameter ρ.

Summarizing, we can answer RQ3 by concluding that the model is appropriate to perform data analyses on an individual level: The resulting parameter estimates are reliable for the majority of students and, in case of parameter τ, demonstrate a systematic relationship with a general measure of a student's WMC (i.e., *Ospan*). Ways to increase this relationship and to clarify the cognitive-psychological reality of the parameter ρ will determine our future work and will be discussed next.

4 CONCLUSION AND FUTURE WORK

The vision underlying this work is to complement existing learning analytics with cognitive-computational components. Learning traces could henceforth be interpreted through parameters with a cognitive meaning, e.g., serving the control of automated adaptive support (e.g., [4, 13]). The present results suggest that such a cognitive conception of learning analytics and educational data mining has the potential for being realized.

The results provide a clear 'yes' to RQ1 by showing an existing model of WMC [28] to allow for simulating the effects of practice (study time) and interference on students' average concept formation progress (see diagram c and d in Figure 3, respectively). Prior work on traditional cognitive tutoring systems (e.g., vocabulary trainer) has shown that it is these very two variables, whose interactions need to be considered to optimize individual learning schedules (e.g., [29]). Therefore, a model that is able to accurately simulate such interactions also in the context of a more open and self-directed scheduling (e.g., forming new concepts of a zoological taxonomy) should fit the development of a service well, which assists a self-determined cycling between old and new items.

With respect to RQ2, the study outcomes harmonize well with the search-as-learning literature (e.g., [11, 17, 39]). This line of research assumes a student's evolving knowledge structure to mediate a coupling between learning and searching. Starting off with a well-established model of learning (connectionist account of WMC), we accordingly show that it does not take much, namely a 1-parameter extension, to turn such a model into an 'autonomous agent' making its own study choices in a student-like manner (diagrams a and b in Figure 3). The extension is derived from the region-of-proximal-learning framework (e.g., [25]) and predicts an increasing tendency to perseverate on frequently studied but yet not mastered items. Finding this prediction to be born out in the empirical data and additionally, finding its algorithmic implementation to result in accurate model predictions, lends evidence to the cognitive-psychological reality of the suggested model extension. Though leaving room for refinements, we believe that this simple formalism can be read as pointing towards a valid way of how to integrate meta-cognitive and more fundamental learning processes into a single cognitive-computational account of self-directed learning. Our future work will therefore examine its validity in more detail. For instance, one goal will be to also look at semantic search patterns (e.g., switching between particular types of categories) and include them as additional benchmark effects. This will also increase the number of data points used to evaluate the model fit. In the light of its complexity, we recognize the need for a continued investigation of whether the model describes "true generating processes" without fitting noise (e.g., [10]). At the same time, we do not think that our results suffer from over-fitting. First, the simulated curves capture the general trends of the empirical curves but do not make a perfect fit to single data points. Second, the results on RQ3 show a strongly simplified variant to account for individual data as well.

Hence, regarding this last and more exploratory research question, the results suggest the model's applicability for individual learning analytics. By running an efficient estimation technique (*Simplex*), a simplified model variant can be fitted to almost all of the students' learning curves. It thus seems possible to estimate aspects of a student's mental capacity (e.g., control of interference) by performing a model-based analysis of their learning traces. That way, the paper also contributes to research on moment-to-moment student models for self-directed learning scenarios (e.g., [26]).

At the same time, our results uncover several limitations when applying the current model version to individual learning analytics: while having validated the cognitive meaning of parameter τ (inhibitory control during retrieval) in form of a significant (though rather weak) correlation with an external criterion (*Ospan*), we have yet not observed such a relationship for parameter ρ (rate of removing interfering and erroneous associations). We mainly attribute this finding to the different levels of specificity at which τ and ρ on the one hand and the Ospan score on the other index aspects of WMC. We assume that future studies, drawing on more specific external criteria (e.g., separate tasks on different executive control functions), will increase the correlation with τ and clarify the cognitive meaning of parameter ρ.

Viewed from a wider perspective, the main contribution of the present paper is the conceptualization of a student model that relates concept formation to individual WM abilities. We believe that this can set the stage for making conventional scaffolding principles more dynamic, e.g., by trading off typical drill-and-practice features (e.g., frequency and recency of learning trials) with cognitive capabilities. For instance, given a particular learning history and particular estimates of interference control, a student could be hinted to a learning object, which is either similar or dissimilar to already mastered objects. While the similarity-based strategy would aim to trigger processes of generalization (over objects with overlapping features), the purpose of the dissimilarity-based strategy were to keep interference low.

Theory-guided scaffolding ideas such as these should facilitate concept formation, which we regard as the basis of all learning and as cutting across different domains and learning design characteristics. This also points to our future work where we will examine how robust the present findings and conclusions are. Specifically, we are planning studies that will test the model in different STEM domains (e.g., physics) under more natural conditions. For instance, one of them will draw on the Robomath approach (e.g., [21]), in which students search and manipulate physical dimensions, such as space and time, with the help of educational robots. In so doing, the act of forming abstract concepts, such as velocity, is situated in learning experiences comprising richer interactions between students' cognitive mechanisms and sensory-motor systems [6]. This will provide a challenging testbed for examining the ecological validity of the present model and scaffolding ideas built upon it.

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