Successful Use of a Novel Artificial Neural Network to Computationally Model Cognitive Processes in High School Students Learning Science

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Abstract

The purpose of this paper is to outline the creation of a computational model making use of an underlying processing element in the form of an artificial neural network (ANN). Within the study, the ANN models multiple conservation tasks as inputs from video game play during a high school science content learning game. This model is based upon the identification of cognitive attributes and integration of two advanced psychological and educational measurement theories. Using the approach of cognitive diagnostics, and item response theory (IRT) data was examined for computational suitability. Once initial task response patterns are identified via IRT; the patterns are developed and presented to an artificial neural network (ANN) as probabilistic test data. Using the ANN derived Student Task and Cognition Model (STAC-M); the study author simulated a cognitive retraining intervention using 100,000 modeled students in science classrooms. Results of the simulation suggest that it is possible to increase levels of student success as measured through positive changes in underlying cognitive measures using a targeted cognitive attribute approach. The use of computational modeling in this educational context provides a means to develop future science education research and is a means to test current educational theory.

Keywords: Artificial Neural Networks, Computational Modeling, Cognition, Science Education, Critical Thinking

Introduction

This paper presents a computational model of cognition and a computational experiment related to student learning in the sciences. This model based on the identification or cognitive attributes and integration of two advanced psychometric and educational measurement theories, cognitive diagnostics, and item response theory (IRT). The integration of these two psychometric theories act in the identification of cognitive attributes and probabilities of success related to each of the student science tasks. The proposed model developed by the author is the Student Task and Cognition Model (STAC-M). This model represents the convergence of two important goals within education. First, to create levels of understanding related to the complex interactions between the student and science-classroom learning tasks as a system (i.e. understanding the process of learning) and second the development of a computationally powerful model of student cognition that can "learn" to perform complex science-based tasks using artificial intelligence (i.e. develop the products of learning). Such complex tasks require learning and development of relationships between the inputs, data processing, and outputs. Each individual task in the educational environment requires the assignment of probabilities related to each student's cognitive processing outcomes.

This model (STAC-M) illustrates the role of cognitive attributes as they interact to solve problems employing a flexible analysis system with adaptations related to cognitive activation and stimulus presentations. Mechanisms of action provide ways to incorporate novel information within the system while incorporating prior student knowledge using Bayesian Statistical Models [1]. Lamb, 2013 trained the computational models using a version of pedagogy thought to successfully assist science students in the completion of tasks via detailed virtual environments [2, 3]. At the cognitive system level, this computational model of student learning builds on the existing work helping to understand the mechanisms of cognitive processing [4]. This model framework is developed from the context of connectivity with emergent properties arising from the interconnection of processing unit [5].

Connectivist Computational Models

As an example of how this model is expected to behave this example is drawn from analogous manifestations in biological frameworks to illustrate parallels. Within the biological connectivist framework, cognition is a product of neurological connections of interconnecting neurons processing sensory and memory information [6]. The emergent properties of the interconnections of processes of the brain, as the students interact with the virtual environment produce the behaviors and outcomes we see in education (i.e. the products of education) [7]. Within these interactions, the modularity of the ANN nodes allows the researcher to dedicate processing systems and engage in information transformation using selected processing components known as cognitive attributes [8, 9]. A cognitive attribute is the lowest level system of cognition retaining its individual systemic function. Within the STAC-M model the individual ANN nodes represent the cognitive attributes associated with cognitive systems. It is in this processing of information that mechanisms trigger quantified component parts of fixed behaviors when suitable antecedent stimulations are present [10]. Control of complex cognition related to learning and ultimately problem solving for conservation tasks is computationally and symbolically addressed via the nodes and connections associated with Artificial Neural Networks (ANNs).

The interconnection of biological cognitive systems modeled using the ANN occurs within the physical potentiation of neurons at the functional level [11]. The sequential firing and potentiation of neuron activations allows the functional properties associated with cognition to occur [12]. Within biological systems, neurons serve multiple purposes, however generally they can be classified as signal propagation for the computational (information processing) components. Examination of ANNs as a computational engine for the model is essential to understanding the connectionist framework and the outputs of the ANN. It is the computational and propagation functions acting in concert that produce the emergent properties associated with ANNs and biological neural networks making the ANN suitable for cognitive modeling purpose.

Purpose, Research Question and Hypothesis

The purpose of this study is to verify the validity and functionality of the STAC-M computational model. Verification of the functionality and validity of the STAC-M allows for the exploration of the complex cognition and behaviors arising as high school students solve learning tasks presented in a virtual environment. The research question associated with this hypothesis are:

> Research Question: Does the use of an ANN as the computational component of a cognitive model of student learning allow valid and functional analysis and modeling of complex systemic processes seen within the classroom setting as student engage in learning science?

Consideration of the research questions resulted in the following hypotheses:

> Hypothesis: The central hypothesis in this study is that neural mechanisms that support student learning and support adaptive control of behavior in the classroom are sufficiently modeled through application of Artificial Neural Networks, Item Response Theory and Cognitive Diagnostic Assessment.

Materials and Methods

The implementation of the computational model included the addition of learning algorithms to promote flexibility in the classification of cognitive processes. What follows is a discussion of underlying architecture of the STAC-M and the validity and functionality.

Generalized Description of an Artificial Neural Network

The artificial neural network (ANN) used in this study acts as the computational and processing element of the STAC-M model of human cognitive action in learning. This computational model is based upon the interaction of several interconnected processing elements arrayed in a non-linear fashion using Bayesian Statistical functions. The connection of the input to the output occurs through potentiation between the nodes which act as weights [13]. Within the connectionist, theoretical framework a key feature of the ANN is the connections and emergent properties between the processing elements [14]. However, like human cognitive processes, the elements detailing the input-output relationships in the ANN are not fully identified or researchers could model these connections directly via regression or more traditional analytical methods [15]. Artificial neural network architecture allows analysis and modeling of complex cognitive constructs related to learning in the classroom [16].

The ability to process non-linear complexity arises from the interconnection of the nodes and systems of nodes makes the ANN more appropriate for cognitive model development [17]. The ANN and derived models approximate the architecture and relationships of the parallel, non-linear processing found in biological based cognitive processing systems (18). When modeling cognitive systems and processes, ANNs are often used in three modes: (1) as a model of biological neurological systems and intelligence, (2) real-time, adaptive, signal processors, and (3) as a data analytical method.

Generalization of this model reduces the underlying ANN functions and algorithms to pattern recognition and classification algorithms. This occurs via the addition of cognitive diagnostic assessments and IRT measurements. When using the ANN as the underlying computational element of cognitive processing the authors represents the patterns of the activations from the IRT and Cognitive Diagnostic measurements in terms of numerical probabilities assigned to the hidden nodes within the computational model [19, 20].

Developers of Artificial Neural Networks designate nodes using one of three descriptions. The designations are simply a way of designating the manner in which the information processes. The designations are input nodes (memory and sensory stimulus), output nodes (outcomes i.e. task completion), and hidden nodes (computational nodes i.e. cognitive attributes) [21]. The nodes in an ANN link using connections between input nodes, hidden nodes, and output nodes propagating multivariate functions. This multivariate function provides the probabilistic outcomes derived from IRT and cognitive diagnostics for the propagation of task completion probabilities across the nodes [22]. The ANN accomplishes the actual transformations of the probabilistic estimates via a learning algorithm using forward feed networks. The use of a forward feed propagation networks makes the computational model more flexible using the ratio differences between the expected and actual output [23]. Using weighting adjustments of the nodes, it is possible to standardize the output of the maximum propagation weight to 1.00 creating a more probabilistic interpretation based on Bayesian estimates. This adaptive ability allows for flexibility within this type of model not seen in computational or other modeling techniques.

The movement from a narrow view of ANNs as an information-transmitting program to a cognitive information processor involves the inclusion of probabilistic assumptions. The development of probabilistic assumptions for the ANN in this study derives from the two-parameter item response theory (2PLM IRT) established from student behavioral outcomes reduced to a bivariate description of success (1) or failure (0). Item response theory is a psychometric theory established as a means to examine responses and characterize the probability of success and failure probability measurement. The ANN makes use of the probabilities from IRT as an input, while the output nodes are recast as resulting task completions. It is through this bridging to psychometric and ANNS via IRT and Cognitive Diagnostics Assessment (CDA) that links the ANN and learning within the classroom. The linkages help to visualize the hierarchical relationships between the attributes. It is in this light that the ANN offers answers to a complex array of problems through its intricate statistical modeling.

Data Description

The unit of analysis for this study is the participant's actions (i.e. behavior) towards task completion these behaviors resulted in n=158,000 data points for analysis by the ANN and computational model development. The target population in the study (n=645) consisted of students enrolled in traditional high school science programs in the mid-Atlantic region of the United States. Criteria for selecting subjects included: (1) taking their current science class for the first time and (2) taking the course as a member of a class and not in an online or virtual capacity. This study used a proportionate stratified sampling approach of science students to generate the computer log data later developed via psychometric analysis for presentation to the ANN. The sample size of each stratum was proportionate to the population size within the school district of interest. This particular sampling technique provides greater precision when compared with a simple random sample. This approach allows for a smaller sample size, and increases the probability of inclusion of specific subgroups within the sample. This allows for a more balanced and representative model. Stratum parameters for the sample were grade, gender, and science class level. Due to the sequential analysis of this study, selection of results within each phase results in aggregation of group results to reduce the number of dimensions for analysis [24, 25, 26].

Tasks

It is not computationally possible to model all cognitive processing types, due to lack of sufficient computational processing power. The selected tasks in this study reflect some of the complexity of the classroom related to student learning, cognitive processing, and provide generalizable results related to cognitive systems using an artificial intelligent model trained using data from a science based virtual environment.

The tasks presented to the ANN are modifications of the Piagetian conservation tasks [27, 28, 29, 30]. The specific tasks used in this study were the Piagetian; (1) Volume Conservation Task, (2) Mass Conservation Task, (3) Liquid Conservation Task, and (4) Number Conservation Task see Table 1. A panel of experts validated identification of the underlying cognitive attributes related to the tasks. The theoretical attributes were then assigned to the tasks, and response patterns related to the students were randomly assigned to the model training set or test set. Encoding of the attributes' parameters occurred via a Q-matrix. The Q-matrix is a tool used to characterize cognitive attributes identified when using cognitive diagnostic assessment and, individual task completion probabilities.

Table 1. Population parameters and psychometric descriptions of each task presented to the ANN.

Task Description	Discrimination (a)	Difficulty (b)	π_i	var (e_i)	var (τ_i)	ρ_{ii}
Volume Conservation	0.78	1.98	.17	.12	.03	.64
Liquid Conservation	0.96	1.01	.35	.08	.04	.57
Number Conservation	0.36	0.45	.45	.08	.07	.53
Mass Conservation	0.56	0.63	.33	.08	.06	.50

Note. *P*i = 0.366, VAR (*e*) =4.212, VAR (τ) =51.051, P=0.95

Within the virtual game environment, students were provided with tasks similar to the conservation tasks presented to the ANN. The major underlying concepts analyzed are the student's underlying cognitive processes related to student understandings of physical properties such as how volume is conserved. The conservations tasks in this study are typically mastered between the ages of 5 and 10, with the volume conservation task being the most difficult to master. Specifically, the volume conservation task is mastered last and mastery usually occurs between the ages of 8 and 10. By adjusting the context of the conservation task from an observational task to an interactive task which include important concepts such as density and its underlying variables, the author was able to build a practical computational model of human cognition related to the prediction of behavior.

Analysis and Modeling

Probabilistic estimates were calculated using a 2PLM IRT model and assigned to an attribute mastery matrix (tasks, attributes, and completion probabilities) and further developed around the sample characteristics into a Q-matrix. The use of the IRT model and cognitive diagnostics helped to develop the data in to a predictive computational model of individual subject cognitive processes for input as the training data for the ANN [31]. From the study sample IRT probabilities for the general population were estimated using the IRT True-Score Method [32, 33]. Based upon the results of the IRT True-Score parameterization, task probabilities for the population are the probabilities assigned to cognitive attributes using a population estimation within the Q-matrix.

The population estimation of the Q-matrix probabilities was further refined through application of the artificial neural network potentiation weightings across the nodes as taken from the sample probabilities. ANN node coding was assigned using one input node per task actions; flagging the node via a "0" or "1" indicating the presence or absence of the cognitive attribute represented in the node. This type of coding provides a simpler model allowing the ANN to learn the training data more efficiently. Folding all values of the IRT parameter outputs into one node is a way to represent and account for student prior knowledge estimates. Accounting for prior knowledge within the ANN model is a key feature of Bayesian models that is not present in IRT models.

Coding input data using IRT and CDA (i.e. tasks and attributes) in this manner provide a large number of examples of cognitive processing of science-based tasks that preserve the individual characteristics of the tasks. Due to a larger number of coded tasks, the ANN model becomes more flexible and generalizable as the number of parameters increases. The generalizability in the processing components of the ANNs allow the use of the computational model for both predictive aspects in science education and novel task presentations. The flexibility also reduces the likelihood that review bias may occur when assigning cognitive attributes to the Q-matrix. Training of the artificial neural network used a random 1/2 *N* split data approach. Node weights initially consisted of limited values within the range of -2/Ω, 2/Ω for each of the neurons in the ANN model. Range limitations ensure the propagations potentials do not become too large and select for one dominating cognitive attribute. After initialization of the network using the random weighting approach, the network was trained by providing a number of examples from one half of the total training set (K-fold). The use of hold-out validation also allows the ANN to act as a true control group for this study. The resultant weights represent the strength of cognitive attribute use as the signal moves from node to node within the network. For clarity, the study has standardized ANN weights to 1.00, with each subsequent weighting value developed from the standardized value allowing for increased interpretability and estimation.

Results quantified via the Q-matrix act as the input to the artificial neural network in the form of training data to establish the cognitive attribute hierarchy, propagation weightings, and aid in model fit. Post development of the correctly fitting ANN, initial weightings associated with the data were recorded and an adjustment of .07 or 7% increase to weightings corresponding to the critical thinking nodes were made. This increase in critical thinking simulates an educational critical thinking intervention within the classroom using an attribute retraining approach. This step essentially allows educational researchers to test novel curriculum and interventions using simulations to ascertain potential outcomes. Reliability of measures related to cognitive attributes was established using the Latent Trait Reliability Method [33]. Within the framework for latent variable modeling, score reliability is the ratio of the true-score variance to the observed variance [33].

Results and Discussion

Results illustrated in Table 1 are the estimated population parameters for the tested tasks (i.e. Piagetian Tasks). Table 1 displays the population proportion of correct responses on item i (π), the population estimate of the item error variance σ2 (ei), the population estimate of the item true variance σ2 (τi), and the population estimate of item reliability ρii. Review of Table 1 provides overall descriptive statistics for the combined tasks. The test population reliability parameter is high (ρ_{xx} =0.95). However, the overall difficulty of the test was moderate with 36.6% of the population correctly completing all tasks. Of the total items included in the final analysis, volume conservation was the most difficult while number conservation task is the easiest task to complete. Items, showing difficultly over +/- 2 on Table 1 would have resulted in removal due to poor model fit. The volume conservation task is the most reliable at ρ_{ii} = .64 while the mass conservation task is the least reliable ρ_{ii} = .50. It is important to note these data represent the properties of tasks prior to the simulated curricular intervention.

Fit statistics for the 2PLM model suggest adequate model fit for the data (X^2=1.70, *df*=1, *p*=0.19). Comparison of 2PLM model fit statistics and one-parameter logistic item response model (1PLM) fit statistics suggest that the 2PLM model was more appropriate, as 1PLM model fit statistics resulted in a significant chi-square test value. The authors did not consider a three-parameter logistic item response model (3PLM) as the items are representative of tasks and guessing was not a feasible option.

Estimation of reliability for the measured constructs used the Latent Trait Reliability Method (LTRM). LTRM provides superior estimation of internal reliability as it does not rely upon the assumptions associated with more commonly used reliability methods [34]. The reliability of the measured constructs is estimated at REL = 0.73, CI 5% (0.71-0.80), SEM 2.10, CI 5% (2.07- 2.47). The computed level of reliability is adequate for this type of measure. Analysis of reviewer agreement of relevance suggests a task-attribute validity coefficient of 0.75 this is adequate for an exploratory study.

A discrete latent attribute model was used to develop an understanding of the place of each cognitive attribute within the current model. This model allows for the examination of relative cognitive weighting --via artificial neural network propagation weights-- and for inferences about the hierarchical position of the cognitive attributes of the subjects. Within the model, the latent variables conceptualize as a vector of *0s* and *1s* for each subject. Zero indicates the absence of the trait and *1* indicates the presence of the trait. Table 2 illustrates the hypothetical attributes needed to complete the corresponding tasks. More specifically to describe the model one can draw upon a similar model developed by Tatsuka (1995), where *N* examinees and *J* binary task performances variables combine. A fixed set of *K* cognitive attributes are involved in performing the tasks. Thus, one can understand model parameters in the terms below:

X_{ij} = 1 or 0, indicating whether examinee *i* performed task *j* correctly;

Q_{jk} = 1 or 0 indicating whether attribute *k* is relevant to task *j*; and

α_{ik} = 1 or 0, indicating whether examinee *i* possesses attribute *k*.

Analysis of the Q-matrix assists with the standardization of the outputs by fixing term Q_{jk} to one, prior to insertion into the matrix. The underlying thinking for fixing term Q_{jk} equal to one is similar to the logic associated with the Linear Logistic Test Model (LLTM). It is important to understand the objective is to infer about the latent cognitive attributes developed via the artificial neural network model weightings and fixing the terms to one eases the interpretation. This is not to suggest traits that the examinees do or do not possess but to aggregate the attributes along with suitable tasks to measure them. The matrices are developed out of statistical estimations associated with task response parameters under a 2PLM. Table 2 also displays the odds of successful completion of the task along with the contribution of each attribute to overall task completion. The existence of residual unaccounted for variance is suggestive of the need to include additional attributes in the model.

Table 2. Probability of task success and the contribution to that success to each cognitive attribute (Q-Matrix).

Task	Proportion of Success	Cognitive Attribute 1	Contribution to p_i	Cognitive Attribute 2	Contribution to p_i	Cognitive Attribute 3	Contribution to p_i
Volume Conservation	.37	Parity Judgment	.03	Critical Thinking	.48	Retrieval	.13

Liquid Conservation	.49	Parity Judgment	.09	Critical Thinking	.23	Retrieval	.11
Number Conservation	.53	Parity Judgment	.01	Critical Thinking	.13	Retrieval	.04
Mass Conservation	.48	Parity Judgment	.07	Critical Thinking	.21	Retrieval	.09

Artificial Neural Network

The artificial neural network was developed to describe the latent interconnection between the cognitive attributes and successful task completion that arise from a series of interconnected nodes (neurons). The neurons develop from three distinct layers in the ANN architecture- input, hidden, and output. The input layer provided no computational function but distribute stimulus into the neural network. For the purposes of this model, the task probabilities developed from the application of the 2PLM IRT model and the cognitive diagnostics act as the input. The hidden layer represents the cognitive attributes assigned to process the tasks and the output layer consists of the task success and failure probabilities.

The ANN used within the portion of the study was designed using *Rx64 3.0.2 Artificial Neural Network Package*. Training of the artificial neural network used a random K-fold 1/2 N data validation approach similar to the validation method for cross validations of data structures with large data sets. The authors made use of a backpropagation training algorithm. Link weights initially consist of randomly weighted values. Post initialization of the network using the random weighting approach, the network was then trained by providing (the ANN) a number of examples from the data set N = 77,120. The data points provided examples of how the ANN is to behave and respond to the conservation tasks. This sets the conditions for the computational experiment with the curriculum by establishing the base line behaviors and cognition activation patterns. Setting nodes to zero propagation also allows a comparison to be made with and with the presence of cognitive attributes.

Review of the results of the trained ANN with calibration suggests an accurate behavioral predictor of subject success based on the cognitive attributes supplied. The forward feed model training set shows a .82 and .64 r^2 for the prediction of correctly completing the tasks and incorrectly completing the task respectively. These r^2 values suggest that the ANN model accounts for 82% and 84% of the variance around the sigmoid function used to develop the outputs. The generalized r^2 (.82) for the forward feed model provides for the aggregation of the predictive ability of the network across the multiple output nodes of *correct* and *incorrect*. By comparison the r^2 values for the feedback network illustrate lower model fit, 76% training and 64% variance accounting indicating poorer model fit. This resulted in the rejection of the feedback model.

The ANN output for the test set of data illustrates that the set is less able to predict the output states, i.e. *correct* or *incorrect* task completion ($\Delta\ r^2$=-0.18). Despite some loss in predictive power associated with the model, there is not a statistically significant difference in the r^2 values ($t(2)$ =1.55, p=0.250, α=0.05). Given the lack of significance for chi-square, the model adequately predicts subject outcomes modeling student cognitive approaches. When tested using the second set of data the model is able to account for 77% of the variance for *correct* outcomes and 69% of the *incorrect* outcomes. Examining the ΔRMSE (+0.03) term, there is a slight increase in the error term however this is not considered significant ($t(2)$ =1.32, p=0.29, α=0.05). Review of the correlation coefficient r=0.84 suggests there is a strong linear relationship between the models. In an effort to reduce misspecification errors, the author of this paper chose to include a penalty for overfit error at a rate of .05.

An Artificial neural network derives propagation weights from random assignment to the training or the test set data for each of the proposed attributes. The weights represent the strength of signal propagation as the signal moves from node to node within the network. For clarity, the study has standardized ANN weights to 1.00, with each subsequent weighting value developed from the standardized value allowing for increased interpretability under Bayesian estimation. The greatest increase in success is seen in the volume conservation task with a 10% increase. The least increase in success is seen in the number conservation task with only a 3% increase in success. This is presumed to be due to the contribution of critical thinking to each task.

Model Comparisons

Two ANNs were examined as a means to model the cognitive processing. The proposed models each have two outputs illustrating to have correctly solved or incorrectly solved the tasks. Thus, the task model is used with differences in the number and types of processing neurons to examine potential rival models. The authors compared a feed-forward network to the feedback network. The feed-forward network is a non-recurrent network in which the signal transmission moves in only one direction. The feed-forward network is in contrast to a feedback network in which all possible combinations of neurons are examined and recursion occurs. A network of this type is allowed to continue until it reaches equilibrium. Model comparisons suggest that the forward feed model best fits the data Table 3 and 4.

Table 3. *Neural Network Output (Training Set, 0.5 Holdback Validations)*

Neural Network	Correct	Incorrect
R-square	0.84	0.73
RMSE	0.19	0.11
Mean Abs Error	0.12	0.08
Generalized R-Square	0.82	

Table 4. *Neural Network Output (Test Set, 0.5 Holdback Validations)*

Neural Network	Correct	Incorrect	Average Change from Training
R-square	0.79	0.63	-0.05
RMSE	0.20	0.23	+0.01
Mean Abs Error	0.13	0.17	+0.01
Generalized R-Square	0.64		
Correlation Coefficient:	0.84		

Discussion

The primary purpose of this study was to develop a computational model of student learning and model the complex dynamic systems within the science classroom. A secondary purpose of this study is to examine the effects of cognition-based interventions designed to train critical thinking in a science classroom. The results illustrate the development of a suitable ANN model of student cognition relating to science learning, which provides usable data for educational researchers. The computational model provides a view of the complexities associated with the processes of learning in the science classroom. Emergent factors developed from the psychometric analysis of the four tasks using cognitive diagnostics suggests that critical thinking is a key component in each of the tasks providing the greatest contribution to task completion. The analysis of the ANN weightings suggesting this hierarchical relationship, future STAC-M models of cognitive attributes might insert this gating mechanism to test this data channel view of cognition. Data channels can be modulated via propagate non-propagate firing of the hidden layers in a multi-layered ANN. This will create differentiated patterns of activation with the most successful pathways achieving the highest levels of task success. Table 6 illustrates the changes due to intervention.

Table 5. ANN changes in success due to the curricular intervention.

Task	Critical Thinking Contribution (Pre-intervention)	Critical Thinking Contribution (Post-intervention)	Change in Success
Volume Conservation	.48	.55	+.10
Liquid Conservation	.23	.30	+.06
Number Conservation	.13	.20	+.03
Mass Conservation	.21	.28	+.05

Note: Each task was simulated 100,000 times representing an intervention study of n=100,000.

Modulation of attributes using the ANN nodes may allow researchers to manipulate variables to understand individual differences at a deeper level as governed by psychological mechanisms. Recruitment of additional processing centers via this gated mechanism allows for an increase in the number of data channels and increasing processing power when individuals are presented with difficult problems. This can lead to an assumption within computational modeling that simply adding neurons to the hidden layer will create greater model fit. However, this assumption become problematic with as one increases computational components associated with STAC-M this can lead to overfit errors. The additions of the correct number of computational neurons related to processing also supports the link between affect, cognition, and behavior as portions of the striatum (represented in the STAC-M as a critical thinking system of neurons) are associated with motivation and behavior in addition to critical thinking and related attributes.

The computational cognitive model in the form of an ANN assists in obtaining information related to science-based curriculum and offers additional data related to student learning. The STAC-M exhibits good data fit and approximates human learning related to completion of science related conservation tasks. The STAC-M provides a means to establish the linkage between cognition, affect, and behavior. Given the complexity and limited (though important) contribution of critical thinking to science tasks we should not expect that one method of intervention as suggested here will prove sufficient for developing each component. While it is possible to teach critical thinking as an isolated skill, it seems best developed when connected to specific domains of knowledge. Using the STAC-M, researchers can generate comparisons not otherwise possible due to concerns related to access, funding, and other impediments to experimental research.

Conclusions

The computational model and ANN demonstrates the powerful learning abilities associated with complex and dynamic systems. The ANN tested on four tasks with simulated curriculum illustrates excellent results and provides for use as a means to analyze and test curricula prior to implementation within the schools. The STAC-M computational model assists in the conceptualization of the complex components of attribution retraining via curricular intervention in learning. This model also allows for analysis of transfer effects between science-based tasks, by converting tasks within science to the common currency of cognitive attributes and giving researchers tools to compare directly those outcomes. Similarly, derived models of cognition may allow for increased use of models to test curricular ideas prior to implementation within the classroom not reliant on the current paradigm of single outcome measures of content knowledge, and accessing underlying cognition.

Models such at STAC-M allow for testing of tens of thousands of students with little cost in time and resources and provide a means to probe more deeply.

Data Availability (excluding Review articles)

Research requesting the data or access to the developed model should contact the corresponding author Richard Lamb at rllamb@buffalo.edu. Due to the sensitive nature of educational data used for this study, the data will be provided in an aggregated deidentified form.

Conflicts of Interest

The author has no conflict of interest to declare.

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