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ORIGINAL RESEARCH

Learning Anatomical Structures: a Reinforcement-Based Learning Approach

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Abstract Given the reduced formal instruction time for many of the basic sciences within medical curricula, educators are searching for instructional methods that ensure students have the necessary foundational knowledge. The objective of this study was to design an anatomical structure identification reinforcement learning task for participants with minimal prior neuroanatomical knowledge. We predicted that the provision of immediate feedback would activate reinforcement learning mechanisms within the brain thus enhancing knowledge acquisition in novice learners such that performance accuracy (correct identification of neuroanatomical structures) improves from approximately 50 % (guessing) to 90 % by task completion. Ten participants learned to identify 10 neuroanatomical structures shown using two-dimensional (2D) coronal brain images over the course of 320 trials (20 trials per experiment block with 16 blocks total). An analysis of behavioural learning curves demonstrated the progression of learning, and each participant achieved a 90–100 % accuracy by block 13 (260 trials) for each of the 10 structures. The total task duration was approximately 30–35 min with all participants reaching proficiency by 25–30 min. Importantly, there was a significant increase in performance on a post-task knowledge identification test. Our results highlight the key role of reinforcement learning approaches to establishing foundational knowledge in the pre-clinical sciences, specifically anatomy, in a time-efficient manner. Further, progression of learning can be assessed through examination of learning curves. Designing effective pre-class exercises that make use of reinforcement learning theory as a means to promote learning may be an effective method to build base knowledge prior to classroom interactions in anatomy education.

Keywords Reinforcement-based learning · Anatomy education · Learning curves · Medical education

Introduction

Learning the basic sciences, specifically anatomy, is a fundamental building block relevant to successful practice in all health professional specialties [1]. A well-developed ability to correctly identify anatomical structures from different views and to interpret spatial relationships amongst these structures is a key competency for health professionals [2, 3]. Steady decreases in teaching/contact time in anatomy courses within the medical curricula over the last three decades require that educators identify how best to support development of this competency using time-efficient methods [1, 3, 4].

In order to make effective use of formal classroom time, pre-class exercises need to be carefully designed to match the learning objectives of the subsequent classroom session. For example, two essential elements of anatomy education are learning the vast number of terms used to refer to structures,

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for instance the subcortical neuroanatomical structures that form the basal ganglia, and being able to situate these structures on images or specimens. If students were able to effectively learn this information before scheduled class time using digital representations of anatomy, an instructor would have greater time available to focus on the development, function and interactions of these structures in the limited time available for classroom interaction.

Reinforcement learning is the process of providing immediate feedback on performance (either answers to a question or to a performed skill) to modify subsequent choices and actions with the goal of maximizing future performance [5]. The provision of immediate feedback on a recognition-based test has been shown to enhance the magnitude of performance on a subsequent test to a greater extent than just studying the material alone [6]. Providing independent, time-efficient, preclass exercises (preferably online) that successfully build a learner's knowledge through reinforcement mechanisms could promote improvements in student knowledge retention in anatomy education.

The purpose of this study was to design and quantitatively assess an educational intervention that improves novice learners' ability to identify and spatially situate anatomical structures. This contribution outlines a research paradigm that will form the foundation of future work to produce pedagogically sound learning tools for medical education given reduced teaching time in the basic sciences. Specifically, we created an experimental reinforcement learning task targeting neuroanatomical structure identification in cross section in order to determine the parameters necessary to develop sound teaching and learning tasks. The task was designed to yield a behavioural learning curve in which novice participants achieved a 90 % response accuracy over the span of the learning exercise. We tested the hypothesis that the provision of immediate feedback would activate reinforcement learning mechanisms, thus ensuring enhanced knowledge acquisition in novice learners. We predicted that this methodology will improve performance accuracy (correct identification of neuroanatomical structures) from approximately 50 % (guessing) to approximately 90 % through completion of this task.

Materials and Methods

Participants

Participants were recruited from health-related programmes at the University of Calgary, Canada (n=10; programmes represented include Bachelor of Health Sciences and Graduate Sciences Education). Participation was voluntary and consent was obtained. Participants were selected from learners likely to have minimal neuroanatomical knowledge. This was confirmed by a preliminary identification test related to information to be learned during the experimental task. Participants were excluded from the study if they failed to pass basic visual acuity tests (corrective lenses or glasses permitted) or if performance on the preliminary identification test exceeded 75 % accuracy.

Experimental Task

Participants were seated comfortably in front of a 17″ ASUS laptop computer and given a standard USB gamepad to respond to questions during the task. The experimental task framework was adapted from the task designed by Krigolson et al. [7]. The task was presented on the computer screen using a customized MATLAB (Release 2013a, The MathWorks, Inc., Natrick, MA) script in conjunction with Psychophysics Toolbox extensions [8, 9].

A feedback-driven trial-and-error shaping process was used to teach participants to identify 10 neuroanatomical structures. Neuroanatomical structures were represented using two-dimensional (2D) brain images in coronal view generated using MRIcroGL software [10] with arrows added to indicate the structure of interest. For each structure, three distractor (incorrect) labels were also generated in addition to the correct label. Representations using the correct image/label pairing were shown to the participant for 50 % of the questions while the other questions used a distractor label for the structure that was randomly generated from the three distractors for each structure. The parameters of the experimental task, determined using pilot data collection, consisted of 16 trial blocks, where each block consisted of 20 trials for a total of 320 trials per individual. The sampling frame, therefore, is within individual across trials; meaning the effective sample size is 320 trials rather than 10 participants.

The trial protocol consisted of the following stages (Fig. 1): participants viewed a fixation cross (500 ms); a neuroanatomical image appeared on the computer screen with an arrow indicating a structure (1500 ms); a label appeared that either correctly or incorrectly (50 % chance for each) identified the indicated structure, and participants were required to respond, whether they thought the image/label pairing was correct or incorrect (maximum time allowed 2000 ms). Participants were then provided feedback in the form of an "✖" or a "✔" 700 ms following response indicating accuracy (1000 ms). If participants exceeded the maximal allowed response time (2000 ms) on a trial, this information was indicated in the form of an "!" in place of accuracy feedback. Response accuracy and response time for each trial was collected. Each trial was approximately 5 s in duration. Following each block (20 trials), participants were provided a rest period. Participants then advanced to the next block when ready.

Upon completion of the experimental task (16 trial blocks), participants were re-examined using the identification test to determine if performance on neuroanatomical structure identification was improved as a result of the task.

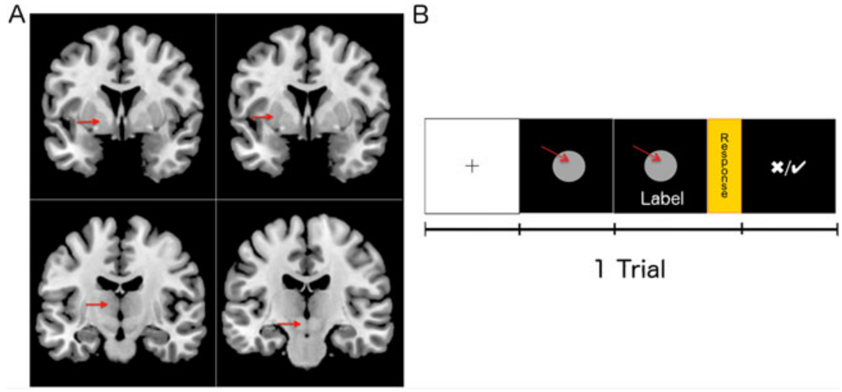

Fig. 1 **a** Example items of the neuroanatomical images with *arrows* indicating structures of interest. **b** Generalized experimental design of a trial. Each trial is approximately 5 s in duration and 20 trials form a block

Behavioural Analysis

Behavioural learning curves were generated for each participant, using the mean response accuracy and mean response times for each experimental block. Repeated measures analysis of variance (RMANOVA) was used to compare performance and response times across the 16 blocks. Bonferroni post hoc analyses were performed to identify specific between performance/time differences, if present in the RMANOVA. A paired samples t test was used to compare performance on the structure identification pre-post test. All analyses assumed an alpha level of .05.

This study was approved by the Conjoint Health Research Ethics Board at the University of Calgary (Ethics ID: REB14-088).

Results

Ten participants were recruited to participate in the study; no participants were excluded based on the exclusion criteria. Each individual completed a pre-test of neuroanatomical knowledge, 320 trials of the experimental task and a post-task identification test.

For analysis purposes for trials where participants were too slow at responding to questions (16.88 % of total trials), it was assumed that the participant would have answered incorrectly and the maximum allowed time for a response (2000 ms) was used as a reaction time.

Accuracy

The mean score on the pre-test of neuroanatomical knowledge was 4.00 % (SD=9.66; range was 0–30 %). When asked, all responded that they recognized the names of structures when mentioned by the researchers but that they had minimal knowledge of the function and location of these neuroanatomical structures. Following completion of the task, performance on the post-task identification test was 94.00 % (SD=9.94; range was 75–100 %). There was a significant increase in performance on the post-task identification test (M=90.00 %, 95 % CI [81.57, 98.43], $t(9)=24.15$, $p<.001$).

Behavioural learning curves showed that learning does occur over the course of 16 trial blocks (Fig. 2). There was a significant effect of block number on structure identification performance, $F(15, 135)=27.18$, $p<.001$, partial eta squared=0.75. Participation in the experimental task had a significant effect on structure identification performance as the task progressed and demonstrated a large effect size. Specifically, test performance significantly improved from the first to the fourth block and consistently exceeded the 90 % pre-established performance standard in block 13 (260 trials). Generally, the mean accuracy was higher on correctly matched image/label pairings (M=88.16 %, SD=13.94) compared to incorrect pairings (M=83.75 %, SD=14.39) throughout the task (M=4.41 %, 95 % CI [2.09, 6.73], $t(15)=4.05$, $p<.001$) (Fig. 3).

Duration

There was a significant effect of block number on response time, $F(15, 2985)=72.22$, $p<.001$, partial eta squared=0.27. Over the course of the experiment, participant response time decreased and demonstrated a large effect size. Specifically, the mean response time significantly improved between the first block (M=1345 ms, SD=386 ms) and the second block (M=1141 ms, SD=284 ms); response time plateaued in the last four blocks as response time did not differ significantly from the last block (M=686 ms, SD=283 ms) (Fig. 4).

The total duration of the experiment was approximately 30–35 min, and all participants reached proficiency by 25–30 min, for all 10 structures being tested.

Discussion

The goal of this pilot study was to design a reinforcement learning task that improves novice ability to identify and localize neuroanatomical structures in brain images displayed in 2D cross section. The reinforcement learning theory informed

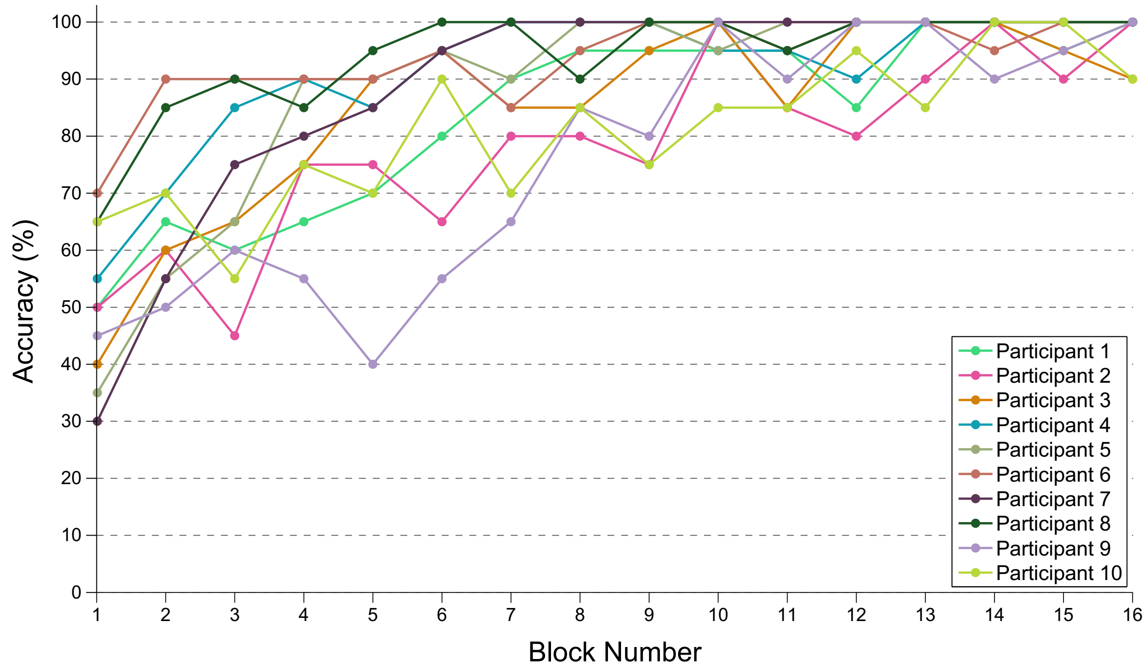

Fig. 2 Changes in accuracy performance during the course of the experiment for each participant. Performance is a percentage score of correctly answered questions out of 20 trials for each block. The experimental task consisted of 16 blocks (320 trials)

the design of our task, where learners received immediate positive and negative feedback based on performance accuracy. As predicted, participants in this study were able to use feedback in order to adapt their behaviour to maximize performance. Specifically, participants were able to achieve a 90 % (±1 SD) accuracy in block 13 (260 trials) of the experiment with response times on each trial decreasing throughout the experiment. Importantly, the task led to significant improvement on a subsequent post-task knowledge identification test. Finally, given that our task is highly time efficient (total task completion time is 30–35 min), it is well suited as an independent pre-meeting/class exercise to

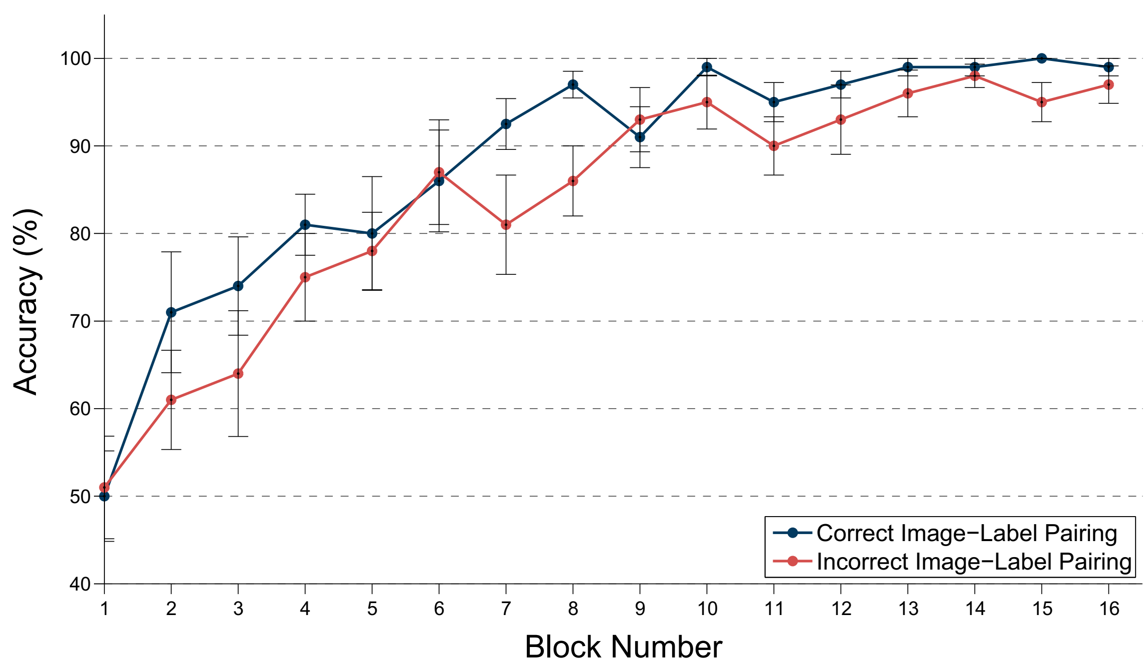

Fig. 3 Comparison of accuracy performance (mean score of 10 participants±SEM) on trials using correctly versus incorrectly labeled neuroanatomical images

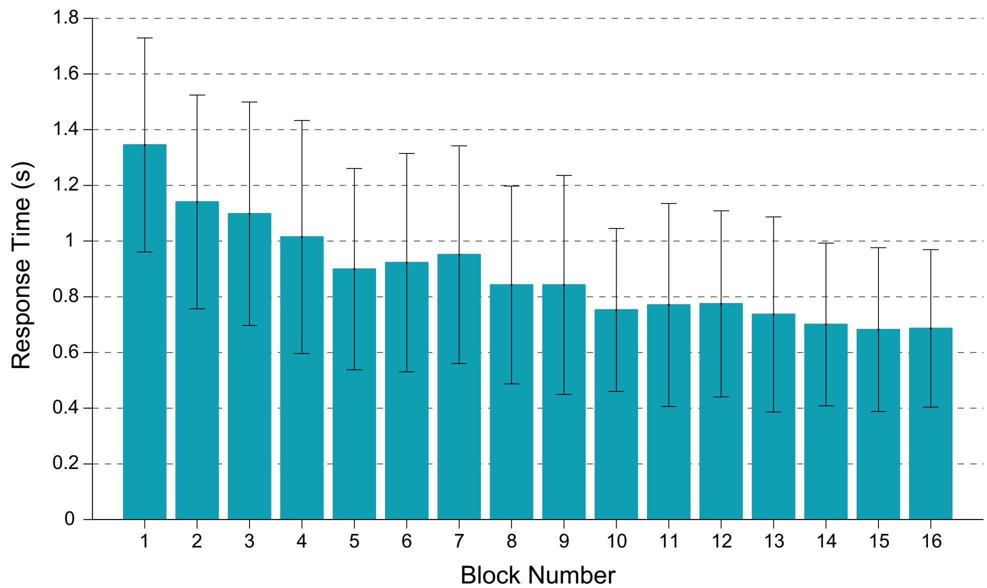

Fig. 4 Response time (mean± SD) for a trial during each block of the experiment

augment the time-limited environment in anatomy teaching and learning. Together, our results suggest that a pre-class exercise task that makes use of reinforcement learning theory as a means to promote learning of neuroanatomical structure identification may be an effective method to build base knowledge prior to classroom interactions.

At an individual level, all participants eventually achieved proficiency in our experimental learning task; however, each participant had a unique learning curve associated with their task performance (Fig. 2). When reviewing these data, instructors should be mindful of the contributing factors to each learner's progression in performance when designing subsequent classroom learning. As predicted, our novice participants' initial performance rating on this task was akin to guessing since the group response accuracy on block 1 was 50.5 % (SD=13.4 %; ranged between 30 and 70 %). The elevated variance in early performance ratings suggests that participants have varying levels of success associated with initial random chance guessing of correct answers. Instructors should be aware that performance in this task could be deterministic, meaning that initial accuracy in guessing answers determines the type of feedback a learner receives to modify future behaviour. If a learner answers incorrectly, the only information they receive is that their response was incorrect and they will have to wait for future trials for the opportunity to "find" the correct structure/label pairing amongst the remaining three pairings. This means that those participants with early success in guessing correct structure identification resulting in positive feedback reinforcement may experience an earlier shift in the nature of feedback usage from informative to evaluative function, leading to earlier proficiency in the task. Rather than focusing on early absolute performance on the task, instructors should focus on a learner's progression in the task and reliability of high performance in the later stages of the task to gauge true performance.

The variability in the general shape of individual learning curves may also illustrate the influence of factors external to experimental conditions that are contributing to a participant's performance. These external factors may confound learner performance projected by learning curves in this task and limit the reliability of conclusions drawn in this study. For example, participants 9 and 10 voluntarily mentioned feelings of general fatigue and sleep deprivation. Numerous studies indicate that high levels of fatigue negatively influence the capacity of executive cognitive functions necessary in new learning of cognitive-based tasks such as this task [11, 12]. Unlike some participant curves that show a general steady improvement in performance, the learning curves of participants 9 and 10 are quite variable in both positive and negative directions from block to block of the experiment. This finding could be related to these participants' level of fatigue. Since this information was voluntarily offered by these participants, it is not known if other participants with variable learning curves were also experiencing fatigue. This information will be gathered by questionnaire in future studies to determine if a significant correlation exists between performance and fatigue that needs to be accounted for when evaluating individual learning curves.

In conclusion, the present study reveals that a task designed using the reinforcement learning theory is a time-economical means to improve novice learner ability to successfully identify neuroanatomical structures. Future research will determine if building base neuroanatomical knowledge using this specific type of task as a pre-meeting/class exercise prior to an instructor-led session significantly improves short- and long-term retention and application to clinical scenarios. While 2D representation remains the prevalent approach, the proliferation of 3D tools for teaching suggests the application of approaches such as the one described here to a 3D paradigm. Tasks designed to teach other anatomical concepts will also need to be tested to ensure the success of this approach is not limited to neuroanatomical teaching and learning.

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Conflict of Interest The authors declare that they have no competing interests. The authors alone are responsible for the content and writing of this article.

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