Teaching Students About Variation and Covariation: What Do We Know, and What Do We Need to Find Out?

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Overview

The purpose of this project is to gather, analyze, and synthesize educational research published from 1988 to the present that investigated different approaches to supporting students in learning about variation and covariation. The findings of this study should inform the mathematics and science education community about how to approach new instructional programs for teachers and students.

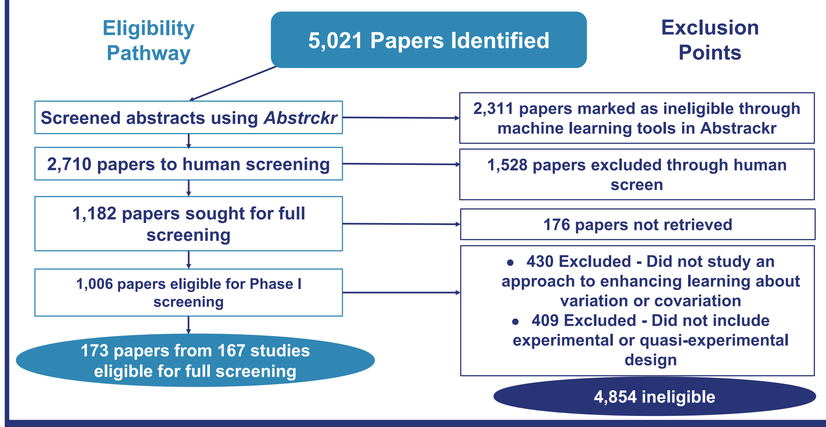
The project has been split into three phases:

Phase 1 – Full-text screening for eligibility in the synthesis study

Phase 2 – Coding eligible papers based on approaches and features

Phase 3 – Analyses are ongoing, including using MetaForest to identify meaningful moderators (reported her) and a meta-regression to identify and quantify the impact of explanatory variables.

Eligibility Screening



Identifying Moderators

Approaches

1. Open coded approaches into 48 categories.
2. Reduced into 16 categories of approaches based on meaningful overlaps (for instance simulation and interactive).
3. Further reduced into 11 approaches so that approaches had a viable number of studies for meta-analysis eligible for meta-analysis.
   - Argumentation / Explanation
   - Collaboration
   - Conceptual Change
   - Didactic
   - E-Learning / LMS / Online
   - Inquiry
   - Simulation / Interactive
   - Situated Learning
   - Using Data
   - Visualizations

Study Features

Selected based on findings from previous meta-analyses.

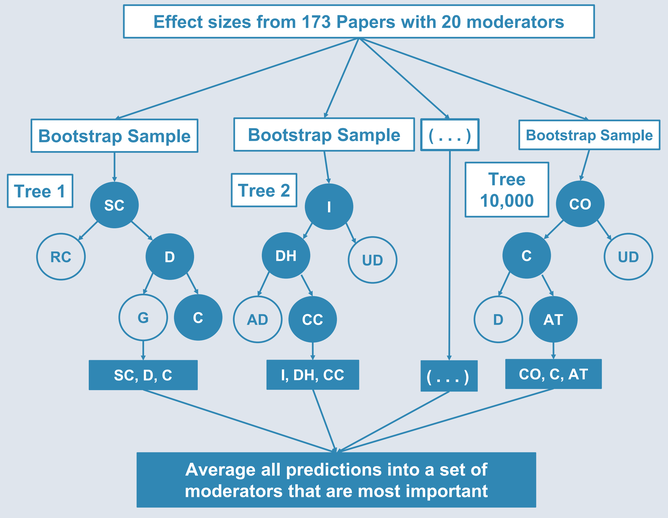
- Alternate Focal Treatment
- Assessment Developer
- Country of Study
- Discipline Focus
- Duration in Hours
- Extended Duration (weeks)
- Grade Band
- Hours Per Week
- RCT
- Emphasis on Variation and/or Covariation in Assessment

MetaForest: Identifying Meaningful Moderators

Decision Trees are machine learning algorithms that iteratively split data based on features to create a tree-like model. The splits are determined by selecting random moderators to maximize group homogeneity until a stopping criterion is met.

Random Forests create tree models by randomly selecting a subset of the data (called a **bootstrap sample**), then building the decision trees based on these subsets. The random forest algorithm repeats this process 10,000 times and averages the predictions of all tree models.

MetaForest averages many **Random Forests** which average many **Decision Trees.** We are using decision trees to determine which moderators best predict effect sizes.



MetaForest is an adaptation of the random forests algorithm for meta-analysis that is used to identify the most relevant moderators.

MetaForest Part 1:

1. Run a Random Forest model with all moderators and 10,000 trees.
2. Drop the moderator with the most negative variable importance and re-run the analysis.
3. Repeat this process until only moderators with a positive moderator importance are left, or no moderators are left.

MetaForest Part 2: Retain moderators that were included in at least 50% of the random forest models.

Van Lissa, C. J. (2018). Metaforest: exploring heterogeneity in meta-analysis using random forests (version 0.1.3) [R-package].
Van Lissa, C. J., Van De Schoot, R., & Miočević, M. (2020). Small sample meta-analyses: Exploring heterogeneity using MetaForest.

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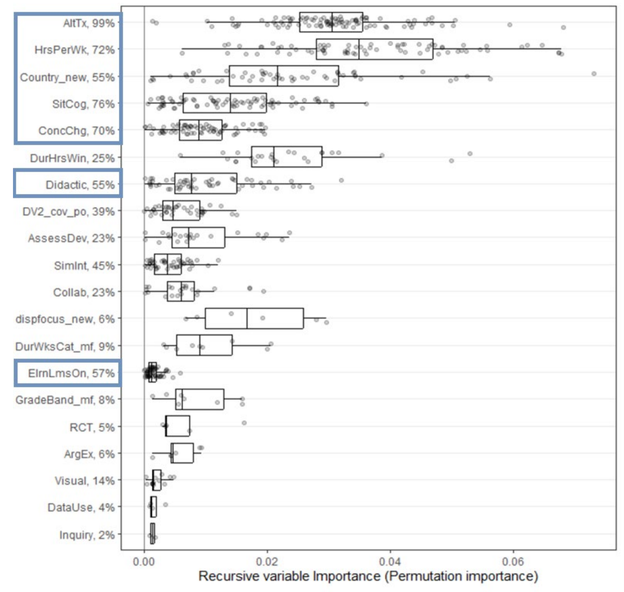
Findings

To determine the most important moderators, we ran 100 replications of MetaForest models. In the figure below, each dot represents the **variable importance** value from one random forest. The y-axis percentage indicates the number of MetaForest model iterations in which the moderator was considered important. Moderators should be considered for further analysis if they were included in at least 50% of the iterations. Of 20 moderators we retained 7, shown in blue boxes below.

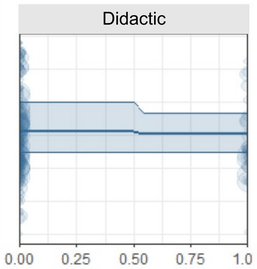
Variable importance refers to the measure of the relative importance or impact of different variables or features in a predictive model.

A moderator is considered "important" if the variable results in a significant decrease in model performance when its values are randomly shuffled or permutated.



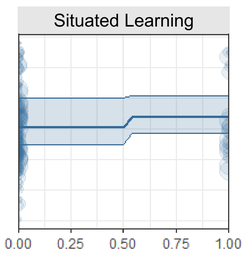
Implications

Of the seven retained moderators four were instructional approaches. This highlights their importance in contributing to the model's predictive performance. Two are described below and have accompanying partial dependance plots which show the relationship the moderator and the effect sizes for all the studies while holding all other variables constant.



Didactic - Emphasis is on presentation of ideas to students in a clear and comprehensive way. Laboratory activities, if present, are used to verify relationships.

Situated Learning - Situating mathematical learning or statistical learning in contexts important to the learner and/or emphasizing real world connections that are important to the learners when considering mathematical concepts.



Next Steps

We will conduct a meta-regression on the same dataset to identify and quantify the impact of covariates on the overall effect from all the included studies.