This research was supported by the NSF Research Experiences for Undergraduates (REU) funding.

Next Generation Science Standards (NGSS) require all students to engage in science practices to deepen their understanding of science (NGSS Lead States 2013). However, linguistically diverse students, particularly those from low-income families, often attend public schools that have limited resources or limited access to such practices.

Advances in technologies provide tools to automatically capture and analyze students’ interaction while engaging in science practices. Such data can be used to create an adaptive learning environment with personalized feedback.

• Current understanding of how students interact with science visualizations due to their varying knowledge levels is limited, thus making it challenging to create personalized feedback.

• Current methods of processing interaction data, such as transition matrices (Mavrikis 2015) and multi-modal directed graphs (Vovides & Inman 2016), are inflexible and hard to incorporate in newly developed visualizations.

Research Question
How does a new computational method capture different interaction patterns between students with varying knowledge levels?

Methods & Data
This study, which is part of a larger study, involved 80 eighth grade students from two low-income, linguistically diverse middle schools.

• English Language Learners (ELLs) and non-ELLs in each class were paired to complete the provided inquiry units for 2 weeks.

• Students’ interactions with two simulations were automatically logged.

This study explored the differences in interaction data based on students’ performance in prediction and reflection activities. In particular, this study focused on the interaction patterns captured by a new computational method, which uses numerical encoding and Levenshtein edit distance to encode and compare student interaction data.

Study Overview

Interactive Simulations
Properties of Matter

This simulation allows students to visualize the relationships between thermal energy, kinetic energy, molecular movement, and the space between molecules during phase changes.

Chemical Reactions

This simulation allows students to visualize how the relationships between thermal energy, molecular movement, and bond breaking/forming affect the rate of chemical reactions.

Data Collection Process

Students' pairs' interactions sampled in simulations. Students' responses scored.

Students' log data are assigned response scores.

Quantitative analysis of students' interactions.

Qualitative analysis of students' interaction patterns.

Steps 2 & 3: Preparing Interaction Data

Chemical Reactions

Visualizations recorded interactions (e.g., button clicks).

Reflection: Record drop-down and short answer responses.

Students' interactions are assigned an integer value.

Conversion of interactions into strings that contain the list of integers.

Comparing strings using Levenshtein edit distance algorithm

Step 4: Levenshtein Edit Distance

Edit distance is a measure similarity between two strings. Lower edit distances indicate higher similarity. For example:

• It takes 6 edits to transform INTENTION into EXECUTION
• The edit distance is therefore 6
• The edit distance of this string can be compared to another for similarity

Qualitative Data Analysis

• Students’ pairs’ average Levenshtein distances within each score group was compared.

• ANOVA showed statistically significant differences between mean edit distances of the score groups (p < .05).

• The results suggest that this new computational method shows promise for comparing interaction data as differences in interaction patterns were found between the score groups.

Qualitative Analysis of Representative Individuals

• Using the numerical encoding performed previously for the computational method, graphs were made to visually compare interaction patterns.

• Each interaction is plotted along the time progression of the X-axis against the assigned integer for the interaction on the Y-axis.

• Students who scored low on reflection questions often had chaotic interactions that seemingly random peaks and very little repetition.

• Students who scored highly on the reflection questions had more defined, repetitive peaks in their interaction patterns.

• For example, the representative individuals with illustrated interaction patterns contain many peaks and troughs, indicating the student viewed the same information multiple times.

• However, score groups that scored low on the reflection questions were found to contain dissimilar patterns and had more chaotic interactions with the visualization.

Conclusions & Future Research

Conclusions

• The new computational method was flexible and easy to implement.

• The interaction data results suggest that students with different levels of knowledge have identically different interaction patterns while they engage in science practices using dynamic visualizations.

• By better understanding student interaction patterns and their ability to predict a high or low reflection score, visualizations can be adapted to guide students towards productive interaction techniques.

• Personalized learning environments can be automated to provide individual feedback, thus further accommodating each student’s learning needs.

References

