**"Input Modality Evaluation for Concept Building Software"**

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## Introduction

Past research into how people learn suggests there are individual differences in how people acquire certain concepts (DeLosh et al., 1997; McDaniel et al., 2014), and that these differences can predict one's success in learning and STEM disciplines (McDaniel et al., 2022; Frey et al. 2017). This past work found one of the best predictors of learning is the concept-building task. The concept-building task is a computer-based task in which an individual is trained on learning a relationship between input and output pairs modelled by an underlying function. There are two main classifications of learners – *abstract learners* (individuals able to abstract the underlying function or rule that associates the input values to the output) and *exemplar learners* (individuals that that use rote information as a basis for predicting the relationship between the input and output values). However, in all studies which have used the concept building task, there are individuals dubbed *non-learners*, participants that cannot be identified as either exemplar or abstract learners. We suspect that this is at least in part due to the cognitive demands of the human-computer interaction required of the task as implemented.

## Methodology

Participants included 40 undergraduate students recruited from a small liberal arts college in the Southeast with results included from 34 of those participants. Participants were randomly assigned to use either a mouse or keyboard to complete the concept-building task.

In the keyboard condition, participants made their predictions by using the arrow keys: Up and Down arrow keys enabled participants navigate close to their prediction and the Left and Right arrow keys were used to fine tune the prediction. In the mouse condition, participants made their predictions by using their mouse cursor to click on part of the graph corresponding to their prediction. While using the computer software, participants were shown a bar graph labeled with the stimulus at a predetermined height (left, blue bar) as illustrated in Figure 1. They were also given a bar which they used to predict the response using either the keyboard or the mouse to mark their predicted response (middle, red bar which the participant moves up/down). Once they marked their predicted response on the red bar, they were shown a third bar indicating the height of the correct response (right, green bar). Participants were given four seconds to observe the third bar with the correct result and then the bars reset to their original state and a new trial began with a new stimulus level. This cycle continued for 260 trials. After the training blocks, participants were given a transfer block with 36 trials: 30 extrapolated (outside the training range) input data points and 6 interpolated (within the training range). Participants did not receive feedback (i.e., the green bar) on their predictions in the transfer block.

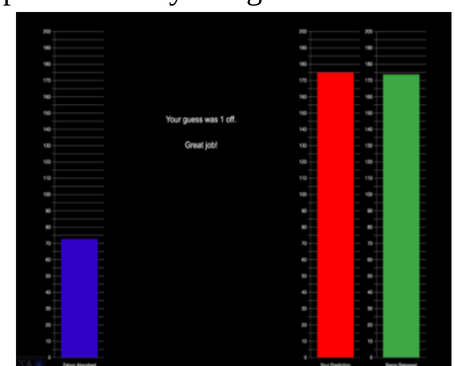

*Figure 1*

## Results and Discussion

We formulated and tested a set of hypotheses (each with its own distinct focus) to assess the effectiveness of our mouse-based input prototype of the concept-building software and explore the possible advantages of it compared to the currently used keyboard-based version. In this section, we will summarize the findings a, offering insights into the implications of our results for implementation of the alternative input modality for the concept-building software.

We found support for the equivalence in the proportion of different types of learners of our keyboard-based input prototype to the published data using a keyboard-based input. We also found support for the equivalence of our keyboard-based and mouse-based input prototypes in the proportion of learners classified as abstract and exemplar. The support for both of these was statistically weak probably due to our small sample size, impacting the strength of evidence provided by the Bayesian analyses d. Expanding the sample size in future studies may yield more robust and conclusive results.

We also evaluated the superiority of our mouse-based input prototype relative to the keyboard-based prototype on several HCI factors (time and accuracy; English et al., 1967) and its ability to avoid the non-learner classification from the published literature with varied results. The results indicated that there was no significant difference in the time taken to complete the task across both conditions. On the other hand, the results suggested that the mouse-based prototype was 'better' than the keyboard-based in terms of reducing the prevalence of individuals classified as non-learners, and the overall error when making predictions. The results also demonstrated that the mouse-based prototype was better in that participants got to learner criteria much faster than those in the keyboard-based prototype.

## Conclusion

Altogether, an analysis of our hypotheses and their corresponding results demonstrates a lean towards the mouse-based prototype being a better task than keyboard-based prototype. This has some implications. Firstly, it addresses the initial problem of the prevalent number of individuals classified as non-learners. Even considering our small sample size, we can make a plausible conclusion that the mouse-based prototype of the task would help reduce the number of non-learners for future use of the concept-building task. Secondly, it opens the door of enquiry for asking more about how input modality can affect one's performance in the concept building task. Thirdly, an improvement in the task would help in increasing the reliability and internal validity of the task, giving us leeway to explore questions like: do individual differences really exist? Or does learning occur in a continuum as opposed to discrete categorizations of learners?


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