Using Multi-Modal Network Models to Visualize and Understand How Players Learn a Mechanic in a Problem-Solving Game

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ABSTRACT: The incipient work in this poster aims to extend work on multi-modal learning analytics by exploring how blending think-aloud, eye gaze, and log data in network models informs how players learn a game mechanic. Preliminary models demonstrate differing patterns between players who have learned and have not yet learned the mechanic.

Keywords: Multi-modal learning analytics, network models, game-based learning, eye gaze.

1. INTRODUCTION

Video games are playful contexts that fuel learning through problem-solving (Gee, 2005) and provide traces of action for multi-modal learning analytics research (MMLA) (Emerson et al., 2020). By incorporating evidence from multiple data streams, MMLA offers an opportunity to understand deeper how problem-solving actions shape learning. Here, we use eye-gaze, log, and think-aloud data in multi-modal network models to understand how players learn a central game mechanic through problem-solving moves, such as noticing deviations from preference and searching for causal explanations. In doing so, we intend to contribute to the work on MMLA by answering the following question: *How do eye gaze and game actions provide markers of learning through problem-solving in a puzzle-based video game*?

2. METHOD AND DATA

We studied learning in the game *Baba is You* (Teikari, 2019). The physics of Baba is You are altered by moving text blocks. Figure 1a shows that players start as the white character (Baba) enclosed in the wall with the text WALL-IS-STOP. To win the level, the player must move Baba to push either the WALL, IS, or STOP text to “break” the rule. The player then could move through the wall and combine text to form the rule FLAG-IS-WIN. The player wins when they move Baba over the flag object. This work focuses on how players learn the STOP mechanic—that is, how players realize that impassable objects are caused by the WALL-IS-STOP (level 1) and FLAG-IS-STOP (level 2) rules.

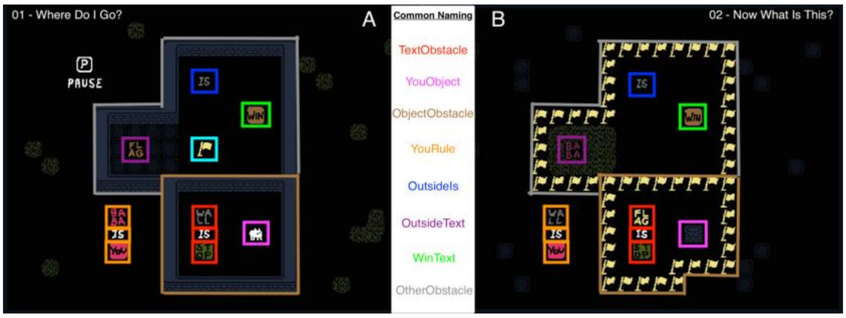

Figure 1: The Levels used to investigate learning the STOP mechanic. Objects with similar purposes across levels are marked with the same color and labeled to facilitate cross-level comparisons.

Data from 10 of the 18 recruited undergraduates are considered here due to attrition and equipment failure. In each of the two one-hour sessions, an Eye Link II eye tracker (SR Research) was calibrated, and students played while thinking aloud. We segmented the data streams to include moments players were trapped inside the initial wall/flag enclosure. This resulted in 27 cases across ten players on the first level and 32 cases on the second level. Trans-Modal Analysis (TMA)[1] was used to analyze the data. TMA is a novel extension of Epistemic Network Analysis (Shaffer et al., 2016) and Ordered Network Analysis (Tan et al., 2022). Descriptions of the three data streams incorporated into the models are as follows. (1) The think-aloud data identified 6 of the 10 players as learning the STOP mechanic. For example, a player categorized as "learned" hit the wall and said, "Oh, I can't get through. Oh, it's because WALL-IS-STOP (*breaks the rule)*". When players learned the STOP mechanic on the first level, subsequent trapped instances were coded as learned. (2) The codes briefly outlined in Table 1 were extracted from the log data. (3) Eye gaze was recorded at 250 HZ. Fixations on the colored areas of interest in Figure 1 represent the codes in the models.

Table 1: Description of Log Data Codes

Code	Description	Example in Log File
Start or restart	Player enters the level or restarts it from the beginning.	event_start; input_restart_
Deviation	Player can't get YouObject through ObjectObstacle.	input_up_ input_up_
Rule Break	Player moves a text block away from TextObstacle.	event_rule_remove_12:13:wall is stop
Passed Boundary	Player moves YouObject passed the ObjectObstacle.	change_update_baba:10:10:1 input_up_

3. PRELIMINARY FINDINGS: TMA MODELS OF TWO LEVELS

Integrating the eye gaze codes in Figure 1 and the log data codes in Table 1 resulted in the TMA model in Figure 2. We limit our discussion to salient patterns (the thicker lines in the models) related to learning the STOP mechanic. Figure 2A compares learned versus not-yet-learned on level 1.

[1] "ECR: Trans-Modal Analysis (TMA): A Mathematical and Computational Framework for Equitable Assessment of Multimodal STEM Learning Processes," National Science Foundation Grant DRL-2201723. TMA is an approach to constructing network models of complex problem-solving that incorporate connections of learning behaviors across different modalities. TMA uses a Temporal Influence Function (TIF) for each modality of data to account for different functionalities of modes.

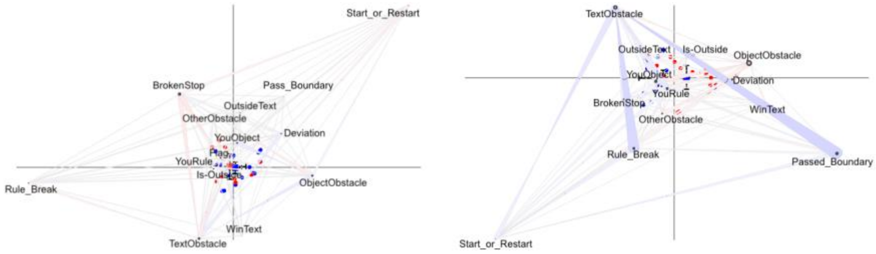

Figure 2: TMA models comparing groups on level 1 (left) and level 2 (right). Blue edges indicate patterns for the learned group and red edges indicate patterns for the not-yet-learned group.

It shows that looking from the TextObstacle to the ObjectObstacle and looking from the TextObstacle to experiencing the deviation is more common for the learned group. This indicates that the learned group interacts more with objects and text related to the STOP mechanic, as suggested by this group experiencing the deviation (i.e., hitting the wall) and searching for a cause (i.e., glancing at WALL-IS-STOP). Figure 2B compares learned versus not-yet-learned players on level 2. It shows that looking at TextObstacle and breaking the TextObstacle rule or passing the boundary is more common for the learned group. For the not-yet-learned group, looking at the ObjectObstacle and then experiencing the deviation is more common. Overall, players who learned the STOP mechanic on level 1 seemed to transfer this knowledge to a similar situation in level 2, and those who did not learn the mechanic on level 1 were looking at and engaging in similar actions as the learned group did on level 1.

4. DISCUSSION, LIMITATIONS, AND FUTURE DIRECTIONS

Two TMA models were used to compare players who learned and did not learn a game mechanic. On level 1, players who learned the mechanic made more connections between WALL-IS-STOP, the wall enclosure, and the deviation and transferred these experiences to FLAG-IS-STOP, the flag enclosure, and passing the boundary on level 2. These initial results make methodological contributions by using novel network models and could inform game designers to incorporate timely deviations. Apart from the small sample and limited level selection, some key limitations are that the TMA window size needs a stronger justification, and there were possibly too many variables to easily gauge connections. Next steps include devising data-driven methods for determining window size and extending the analyses to different levels.

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