Validating Game-based Measures of Implicit Science Learning

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ABSTRACT
Building on prior work visualizing player behavior using interaction networks [1], we examined whether measures of implicit science learning collected during gameplay were significantly related to changes in external pre-post assessments of the same constructs. As part of a national implementation study, we collected data from 329 high school students playing an optics puzzle game, *Quantum Spectre*, and modeled their gameplay as an interaction network, examining errors hypothesized to be related to a lack of implicit understanding of the science concepts embedded in the game. Hierarchical linear modeling (HLM) showed a negative relationship between the science errors identified during gameplay and implicit science learning. These results suggest *Quantum Spectre* gameplay behaviors are valid assessments of implicit science learning. Implications for how gameplay data might inform classroom teaching in-game scaffolding is discussed.

Keywords
Game-based learning, Interaction Networks, Implicit Science Learning, Hierarchical linear modeling

1. INTRODUCTION
As digital games become increasingly prevalent in today's society and are played by the majority of youth of all demographics [2], it behooves us to study how the energy and passion invested in gaming can be harnessed for productive purposes. Game-based learning interests education researchers and learning scientists because digital games uniquely engage learners and because their data logs can serve as input for innovative learning assessments [3]. Data logs generated through gameplay can be used to study players' in-game activity [4] and how game-based learning can be leveraged for classroom learning. Research shows that elements of gameplay can invoke complex thinking such as scientific inquiry [5] and may foster learning-related skills such as creativity and persistence [4].

This work examines complex behaviors of students solving optics puzzles in the educational game *Quantum Spectre,* using interaction networks. An *Interaction Network* is a complex network representation of all observed player-game interactions for a given problem or task in a game or tutoring system [6]. Regions of the network can be discovered by applying network clustering methods. These regions correspond to high-level student approaches to problems [7]. In this work, we used Interaction Networks as visualizations to analyze *Quantum Spectre* gameplay data and automated the coding of game states that correspond to incorrect applications of the game's core science concepts. Three types of errors were coded: two science errors (placement and rotation) and puzzle errors.

This paper reports HLM analyses that relate those coded game states to implicit science learning measured by external pre/post assessments. The analyses examine how game-based learning is a function of *what players do* in the game, not simply duration of gameplay or highest level reached. This information is useful for building an adaptive version of the game to scaffold players' implicit science learning and for informing teachers about important aspects of student competency.

2. IMPLICIT SCIENCE LEARNING
Polanyi argued that implicit knowledge (also called tacit knowledge) is foundational and a required element of explicit learning [8]. Implicit understandings are embodied and enacted through our interactions with the world around us, but may not yet be formalized or expressed verbally or textually. Vygotsky described similar abilities and understandings a learner brings to a learning situation that can be scaffolded by a teacher, environment, and tools [9]. Implicit misunderstandings (often called misconceptions) may get in the way of a learner's conceptual development [10, 11], particularly in the area of basic physics, such as Newton's Laws of Motion. The work of diSessa distinguishes between the intuitive knowledge that novices hold—a book will not fall through a table or a glowing filament is hot—from an expert understanding of these phenomena, explaining that while learners' behaviors may be guided by implicit understandings, the learner is not necessarily ready to express the related formalisms or question the ideas in a deeper sense [12].

Games promise to reveal implicit learning because they can be (a) "sticky"—meaning they encourage players to dwell in the phenomena and (b) they leave a digital trail that reveals the patterns the players used in their learning process. Several researchers have used educational data mining techniques within an Evidence-Centered Design framework to develop stealth assessments that discern evidence of learning from the vast amount of click data generated by online science games such as *SimCityEDU* [13], *Physics Playground* [14], and *Surge* [15].

As players "level up" in a game, they typically deal with the mechanics in increasingly complex applications, building implicit knowledge about the underlying system. Because games allow players to fail, repeat, revise, and try again—recording what players do in the process—games may be powerful formative assessments of learning, and the strategies players build. The methods players use to tackle new challenges may demonstrate conceptual understanding that the learner may not express in other ways and that may not be measured by current external learning assessments [4, 16]. Careful alignment of game mechanics with learning and assessment mechanics [17] may reveal implicit learning and empower teachers and learners to help bridge game-based knowledge to other forms of learning.

In a classroom, teachers may be able to build on implicit game-based learning if they have the right information and tools to support students at key moments in the learning process. That may consist of real-time information, provided during class to know who is struggling and needs attention, or more reflective information after school to help plan lessons for the next day based on class gameplay [18]. Post-game debriefing and discussions connecting gameplay with classroom learning help students apply and transfer learning that takes place in games [19]. To exploit learning that happens in games, teachers need to build bridges between the students' "aha" moments while playing [20] and the content being covered in the classroom.

3. QUANTUM SPECTRE

To examine implicit science game-based learning, we studied high school students playing a Physics-oriented game called *Quantum Spectre. Quantum Spectre* is a puzzle-style game, designed for play in browsers and on tablets (Figure 1).

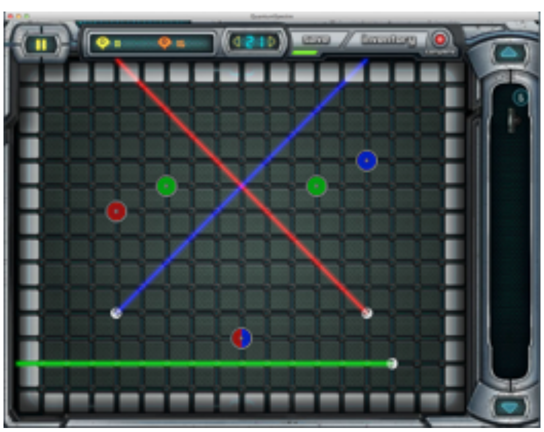

Figure 1: *Quantum Spectre* Puzzle 21. Players must direct the laser beams to the matching colored targets using movable mirrors and other optical devices, selected from the inventory on the right.

Players use optical devices, such as lenses and mirrors, to guide colored laser beams to matching targets. The lenses and mirrors can be flat, convex, or concave and single or double-sided. All devices produce scientifically accurate results when interacting with the laser beams. When the laser beams in a puzzle reach the matching colored targets, the puzzle is solved (i.e., goal state is reached) and the player is scored on the number of moves used. The player earns three stars if the puzzle has been solved in the optimal number of moves, two stars for a low number of extra moves, and one star for simply solving the puzzle. Regardless of their score, players can proceed onto the next level, but players can repeat earlier levels at any time to improve their performance.

The game is divided into 6 zones with 30 puzzles in each zone. In Zone 1 of *Quantum Spectre*, the puzzles focus on 2 key concepts:

- The **Law of Reflection**, or Angle of Incidence equals Angle of Reflection—When reflecting off of a smooth surface, the path of a ray of light (such as a laser beam) will make the same angle with the surface (relative to the normal) upon exit as it makes upon entry.
- **Slope**—Players can use the squares on the game grid and calculate the slope (rise over run) to figure out and/or predict the paths of laser beams and where to place items.

This study focuses on data from Puzzles 14-23 in Zone 1 of the game. At this point in gameplay, players have presumably mastered the game mechanic, and mastery of the puzzles typically requires an understanding of Slope and the Law of Reflection. Table 1 provides an overview of Puzzles 14-23. The number of goal states reflects the number of unique solutions (position-rotation combinations) for each puzzle.

Table 1: *Quantum Spectre* Puzzles 14-23

Game Level	# Mirrors	# Targets	# Optimal Moves	# Goal States
14	1	1	2	1
15	2	1	4	5
16	2	1	3	8
17	2	2	4	1
18	2	2	4	6
19	4	4	7	4
20	6	3	12	42
21	6	5	11	6
22	3	1	6	1
23	4	2	8	3

4. CLASSIFYING GAMEPLAY BEHAVIORS USING INTERACTION NETWORKS

To simplify the vast number of puzzle solution paths into a manageable group we could study, we used a method called Interaction Networks (INs). INs use a complex network data structure to represent players' solutions as traces of game states and actions, with additional information such as edge labels (e.g., labels of player actions). This process involved 4 key steps [1]: creating a full IN for each puzzle, clustering player actions using laser shapes, classifying clusters for evidence of implicit science understanding, and automating coding of player actions.

4.1 Create Full Interaction Network

To construct an IN, we collected the set of all solution attempts for that puzzle. Each interaction is defined as Initial State, Action, and Resulting State, from the start of the puzzle until the player solves the puzzle or exits the system. A sample trace is shown in Figure 2. Player actions are represented as edges in the network.

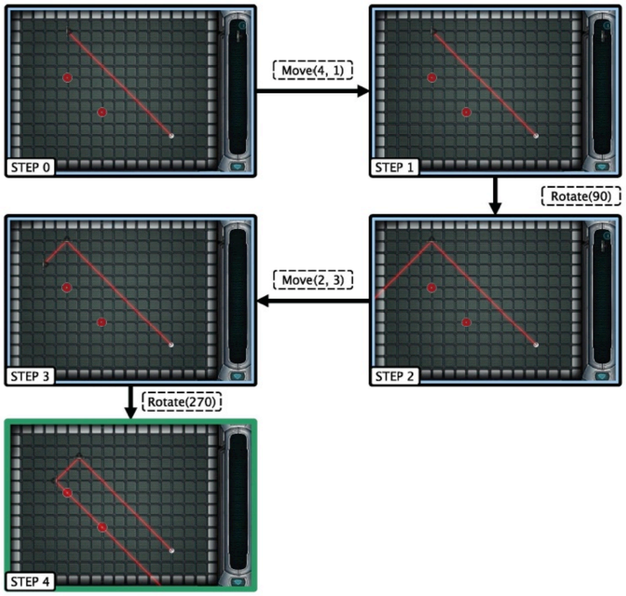

Figure 2: Sample trace of player actions in *Quantum Spectre* Puzzle 18 of Zone 1

Table 2 describes the complexity of the full interaction networks for Puzzles 14-23 for the full sample of students playing the game. The full IN of every state and every action taken was large, complex, and difficult to interpret in terms of player understanding.

Table 2: Interaction Networks in Puzzles 14-23

Game Level	# Players	Total # Moves	# Network Edges	# Unique States	# Laser Shapes
14	479	3003	462	164	5
15	473	3866	1009	484	10
16	462	3218	761	446	12
17	454	10878	1899	1067	21
18	439	10314	3458	1800	22
19	416	15389	7093	4550	330
20	384	10778	4947	2391	264
21	349	23080	13919	6261	696
22	282	3697	1500	1017	146
23	271	10529	6154	4138	364

4.2 Cluster States by Laser Shapes

Most puzzles have states in which different configurations of objects result in similar output. These states could be considered equivalent since they show the same player proficiencies or errors, but a simple state representation would consider them as different states. In previous work using INs for games, it has been helpful to consider the output of a state as well as the position/orientation of objects in that state [7]. To group these equivalent states, we took a similar approach, using "laser shape" as part of our state representation to create Approach Maps. Approach Maps are a visual summary of the information contained in the interaction network [7]. This reduction is created by grouping similar states together based on how often students co-visit the states during their solution attempts. Here, the approach map consists of a list of targets hit by a laser of the appropriate color and a list of angles taken by that laser. This allows game states that represent similar errors to be effectively grouped together, as shown in Figure 3.

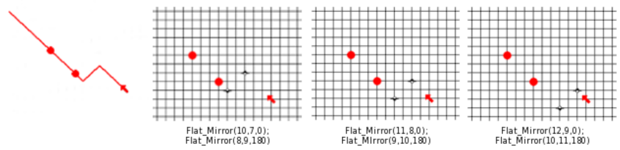

Figure 3: Using laser shape to group similar game states in Puzzle 18.

This approach preserves the relevant properties of a board state while ignoring distance traveled, which is not relevant to the game state.

4.3 Classify Player Actions for Implicit Science Understanding

A *Quantum Spectre* game designer who has a science education background, worked with a researcher to classify each laser shape into one of three categories:

1) *Correct move*—placement and rotation of the mirror are consistent with an eventual goal state
2) *Placement errors*—placement of the mirror in a location that does not match a goal state—may indicate a lack of understanding of slope.
3) *Rotation errors*—rotation of a mirror to an angle that does not match a goal state—may indicate a lack of understanding of the Law of Reflection.

As described elsewhere [1] using a subset of these data, the game designer and researcher also identified placements that were not consistent with a goal state but were more indicative of a lack of grasp of the puzzle mechanic than of a lack of science understanding. We labeled these *Puzzle errors*. For example, in puzzle shown in Figure 2, a correct solution requires players to use the two available mirrors to direct the laser through the two targets simultaneously. In Figure 4, player actions are consistent with someone who understands slope (i.e., they placed the mirror on the path of the laser) and the Law of Reflection (i.e., they rotated the mirror to reflect the mirror through the target). However, their actions are not going to let them solve this puzzle.

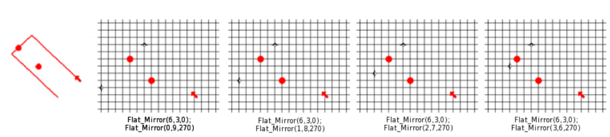

Figure 4: Sample Puzzle Errors in Puzzle 18.

4.4 Automated Coding of Individual Player Behaviors

Once all laser shapes had been coded and puzzle error placements identified, we automated the coding of individual player behaviors. Every player behavior was classified as a Placement Error, Rotation Error, or Puzzle Error (0=Not Present; 1=Present). These are mutually exclusive player behaviors. Player actions with none of these errors were classified as Correct. Figure 5 shows the distribution of player behaviors across each puzzle.

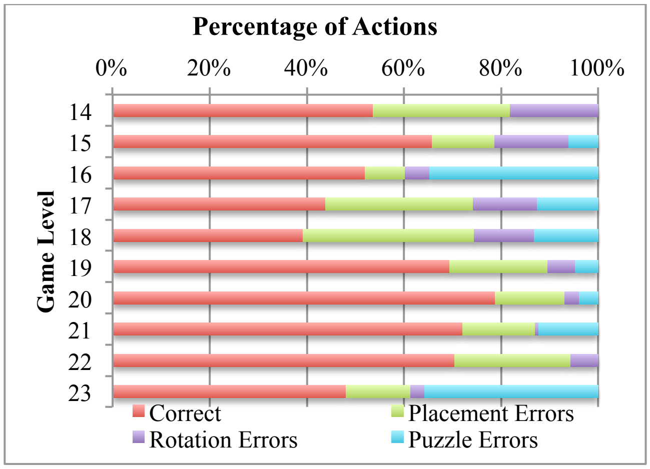

Figure 5: Error rates by puzzle level

The percentage of correct moves ranged from 39% in Level 18 to 79% in Level 20. Placement error rates range from 8% (Level 16) to 35% (Level 18). Rotation error rates were most common in earlier puzzles, 35% in Level 14 to 1% in Level 21. In two puzzles, Levels 14 and 22, no puzzle errors were possible. Puzzle errors in the remaining puzzles ranged from 4% (Level 20) to 36% (Level 23).

5. RESEARCH QUESTIONS & HYPOTHESES

In this paper, we examine the ways in which the extent of players' puzzle and science errors are related to changes in their performance on a pre-post assessment of slope and the Law of Reflection. We anticipated a negative relationship between placement errors, rotation errors, and pre-post assessment results—that is players who are demonstrating a lack of understanding of the science concepts in their gameplay will have smaller gains than players whose gameplay is consistent with an implicit understanding of slope and the Law of Reflection. Our anticipated relationship between puzzle errors and pre-post assessment results was less clear. It could be that puzzle errors interfere with their implicit learning of the science content. It could also be players who understand the science content are just as likely to make puzzle errors as players without that understanding, so there may be no relationship between the number of puzzle errors and pre-post assessment results.

6. METHODS

Teachers were assigned to one of three groups as part of a national *Quantum Spectre* implementation study. In Bridge classrooms, teachers encouraged students to play the game outside of class and used examples from the game as part of their science instruction. In Game Only classrooms, teachers encouraged students to play the game but provide no game examples during their science instruction. In Control classrooms, teachers and students did their normal science instruction with their students not knowing about the game. This paper reports gameplay data from the 329 students in 29 classes (14 Bridge and 15 Game Only) that participated in the implementation study during the 2013-14 and 2014-15 academic years.

6.1 Sample

Because this study focuses on Puzzles 14-23 in Zone 1 of the game, 79 students were excluded from these analyses because they did not attempt Puzzle 14 of the game. The final sample of 329 high school science students included 132 females, 162 students in Bridge classrooms, 281 students in non-Honors/AP classrooms, and 249 students in classrooms where more than 75 percent of the students participated in the study.

6.2 Measures

This study collected gameplay log data, as described above, as well as pre-post assessment and student/classroom characteristics,.

6.2.1 *Gameplay Metrics*

To allow for the fact that students (a) used varying numbers of moves to solve the puzzles and (b) not all students completed Levels 14-23; the percentage of the total number of moves (actions) that were correct, placement errors, rotation errors, and puzzle errors was calculated. The mean error rate across all students was 19% placement errors, 7% rotation errors, and 12% puzzle errors. We used standardized (z-scores) error rates.

The total amount of time each student played *Quantum Spectre* and the highest level reached were also recorded. Previous analyses showed Puzzle 21 to have a high dropout rate [21], we analyzed whether or not players completing Puzzle 21 had any relationship to changes in pre-post assessment results. Among this sample, there was no significant difference in the percentage of students in Bridge and Game Only classrooms that reached Puzzle 22 (X^2=3.53, 1 d.f., p=0.06). Given the non-normal distribution of the amount of time students played *Quantum Spectre*, we categorized students as having played less than 1 hour, or 1 hour or more. Forty-one percent of students played 1 hour or more, this proportion did not vary among students in Bridge and Game Only classrooms (X^2=3.23, 1.d.f., p=0.07).

6.2.2 *Students & Classroom Characteristics*

When completing the pre-assessment, students were asked to indicate their gender. We categorized class names (e.g., Honors Physics 101) obtained from teacher applications as being either Honors/AP classes or not. Seven of the 29 classes in this study were Honors/AP classes. Finally, we asked teachers the total number of students enrolled in each class. We calculated the percentage of the class with complete study information (e.g., complete consent/assent forms, pre-post assessments complete, and gameplay beyond Puzzle 1 in Zone 1). This ranged from 31 to 100 percent of each class, with the majority of classes (26) having more than half of the students participating.

6.2.3 *Assessments*

Science content experts developed assessment instruments and tested them in a series of think-aloud interviews with 10 high school students. Each assessment contained 12 (pre) and 13 (post) questions that required minimal formalisms to complete. The pre- and post-assessments each included 3 items related to focal length that are not included in these analyses. Figures 6 and 7 are sample items for slope and the Law of Reflection, respectively. In Figure 6, students are asked which point (A-D) a line drawn through the two black points would hit. The item in Figure 7 asks students which letter each laser would hit.

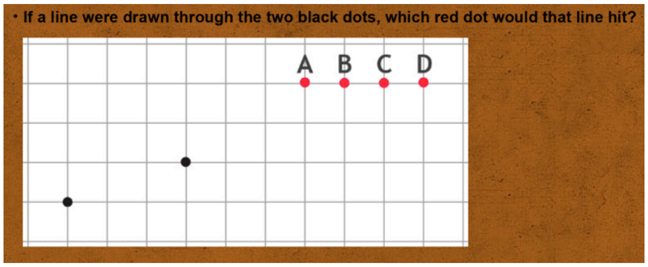

Figure 6: Sample Slope assessment item

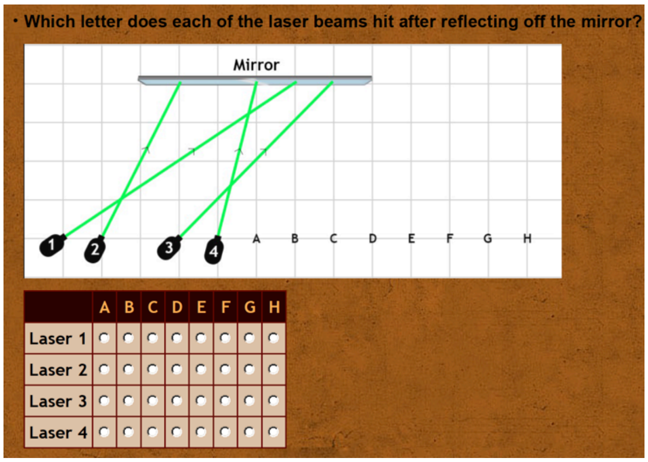

Figure 7: Sample Law of Reflection assessment item

These analyses are limited to the 9 pre and 10 post items focused on slope and the Law of Reflection. These pre- and post-assessment items had good internal consistency (Cronbach's alpha was 0.70 (pre) and 0.73 (post). To account for the different number of items, we used the percentage of items answered correctly in the analyses. Students answered an average of 53 percent of the pre assessment items and 59 percent of the post assessment items correctly. Students in Bridge classrooms, however, answered significantly fewer questions correctly on both the pre- and post-assessment than students in Game Only classrooms ($F=19.2$, 1, 132 d.f., $p<0.01$). On average, students in Bridge classrooms answered 48 percent of the pre-assessment and 55 percent of the post-assessment items. In contract, students in Game Only classrooms answered 58 percent of the pre assessment items and 63 percent of the post assessment items correctly.

7. RESULTS

Using the SPSS MIXED linear models procedure, HLM analyses began with an unconditional 3-level model with students, classrooms, and teachers using Restricted Maximum Likelihood (REML) and unstructured covariances. In the 3-level model, seven percent of the variation was at the teacher level. Triple that proportion of the overall variation was attributable to the classroom level. A 2-level unconditional model with students nested within classrooms was estimated. In that model, a statistically significant 34 percent of the variance in the post-assessment was attributable to classroom level variation.

Sets of covariates were added to the unconditional HLM model in this order:

Set 1. Pre-assessment score (standardized)

Set 2. Study Group (Bridge or Game Only)

Set 3. Student gender (1=Female)

Set 4. Classroom Level Characteristics: Whether or not they were enrolled in class in which more than half of the students completed the study (1=Yes); whether or not they were enrolled in an AP/Honors science class (1=Yes)

Set 5. In-game measures of implicit understanding—% Placement Errors, % Rotation Errors, and % Puzzle Errors (all standardized)

Set 6. Gameplay duration (>1 hour vs. not) and highest level reached (Level 22 vs. not)

Only statistically significant covariates were retained in the HLM model presented in this paper. Sets 3, 4, and 6 had no significant results, meaning student gender, Honors/AP status, gameplay duration and highest level reached were not significantly related to changes in pre-post assessment scores.

The model with the in-game measures of implicit understanding of slope and the Law of Reflection were a significantly better fit than the model without those measures (X^2 (3 df, N=317), 6.76, $p<0.10$). The best-fitting HLM model, which accounts for 33 percent of the variation at the classroom level, is presented in Table 3. Overall, after accounting for students' performance on the pre-assessment, students who exhibited more Placement and Rotation errors while playing the game performed more poorly on the post than students with lower science error rates.

Table 3: Best-fitting HLM model

Parameter	Est.	Std Err	df	Sig.	95% Confidence Interval Lower	95% Confidence Interval Upper
Intercept	0.10	0.12	24	0.43	-0.15	0.35
Pre-Assessment[1]	0.35	0.05	320	0.00	0.26	0.45
Bridge (vs. Game Only)	-0.17	0.17	25	0.33	-0.52	0.18
%Placement Errors[1]	-0.08	0.05	304	0.09	-0.17	0.01
%Rotation Errors[1]	-0.17	0.05	320	0.00	-0.26	-0.07
%Puzzle Errors[1]	0.00	0.04	310	0.93	-0.09	0.08

[1]Standardized

The intercept coefficient represents the estimated outcome for male students who scored at the mean level of the pre-assessment, were in the Game Only group, were not in a Honors/AP class, and had mean levels of Placement and Rotation Errors. These students would score 0.07 standard deviations below the mean post-assessment score. The Pre-Assessment coefficient reflects the change in number of standard deviations of the post-assessment for every increase of 1 standard deviation on the pre-assessment. For every standard deviation increase on the pre-assessment, students would be expected to score 0.35 standard deviations higher on the post-assessment. Students in Bridge classes scored 0.17 standard deviations lower on the post–assessment than students in Game Only classes—a non-significant difference. There was no significant difference between Bridge and Game Only groups in their pre-post gains. This may be because Game

Only classroom instruction provided lab experiences with lasers that mirrored what Bridge classrooms did with *Quantum Spectre*, providing comparable experiences and similar gains.

Students whose placement or rotation error rate was one standard deviation above the mean, however, had post-assessment scores 0.08 and 0.17 standard deviations below the mean, respectively. There was no impact of puzzle errors. Interactions between study group (Bridge vs. Game Only) and gameplay errors were examined but none significantly improved the fit of the HLM model, suggesting the impact of these errors was the same across study groups.

8. DISCUSSION & IMPLICATIONS

Hierarchical linear modeling suggest a direct negative relationship between science-related gameplay errors and implicit science learning—players making errors consistent with a lack of implicit science understanding performed worse than players not making as many of those errors. Educators can use this information as a real-time, or reflective, formative assessment tool. This could be very useful in a class where students are playing a learning game, individually or in groups, while the teacher has an app that alerts them to which students are struggling and may need attention. A more comprehensive dashboard they can use after class might show them overall progress of their class and trends that inform how the next lessons are planned. Teachers might also use a dashboard to monitor their students' game-based learning as they play at home or with friends outside of class. The ability to validly infer implicit science learning from the digital records of game activity makes this all possible.

9. ACKNOWLEDGMENTS

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