Studying Implicit Science Learning in Digital Games

Elizabeth Rowe (elizabeth_rowe@terc.edu), Jodi Asbell-Clarke (jodi_asbell-clarke@terc.edu), Ryan Baker (baker2@exchange.tc.columbia.edu)

EdGE at TERC
2067 Massachusetts Ave.
Cambridge, MA 02140

Purpose of Study

EdGE and their partners are building and studying science-learning games that people choose to play in their free-choice time. In these games, the game mechanics provide accurate scientific models. We theorize that through playing the games, learners build implicit understandings of these scientific phenomena (Polanyi, 1966; Thomas & Brown, 2011). This poster reports on the first phase of the research in which we are identifying the strategic moves that emerge from our video observations of high school students playing the games. We use video analysis to identify strategies that emerge as players advance in the games. Then we use educational data mining (EDM) methods to relate the strategies to game log data that we collect from a much larger sample of players. We are also building upon those cognitive strategies to develop classroom activities that can bridge game-based learning with formal STEM learning.

Measuring Implicit Learning with *Impulse*

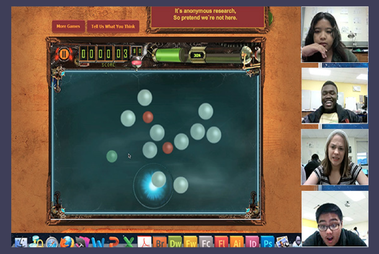
Design of Intervention

Impulse immerses players inside an N-body simulation with accurate gravitational interactions and elastic collisions. Players must navigate their particle (green) to a goal through ambient particles that will explode upon contact.

To succeed, players must predict the motion of the particles and interactions between particles, thus predicting the laws of Newtonian physics.

Screen captures of the game Impulse

Capturing the Videos



Screen Capture of Impulse with Multiple Camera Shots (for effect)

Data were collected from 69 high school students (29 female) from urban and suburban schools in the Northeastern United States. Players were recorded with Silverback, which captures players' onscreen game activities, and audio and video of their faces. Players were asked to "think aloud" or discuss the game with a partner.

Coding the Videos

Two researchers built a coding system for strategic moves. They trained a third researcher to code the 69 videos. Ten videos were double coded by two independent researchers and one of the coding system developers, achieving Cohen's Kappas ranging from 0.39 to 92. Kappas exceeded 0.70 for all codes related to implicit science learning.

Coding Scheme for Player Moves in Impulse

Float
The player particle was not acted upon for more than 1 second (κ = .759)

Direction
The direction the learner intended the player particle to move (κ = .778)

Target
Type of particle (player, other, both) the learner intended to move (κ = .920)

Same As Last Target
The learner intended to move the same target as the last action (κ = .869)

Intended strategy: Move toward goal
The learner intended to move the player particle toward the goal (κ = .809)

Intended strategy: Stop/slow down
The learner intended to stop or slow the motion of the player particle (κ = .720)

Intended strategy: Keep player path clear
The learner intended to move non-player particles to keep the path of the player particle clear (κ = .819)

Intended strategy: Keep goal clear
The learner intended to move non-player particles to keep the goal clear (κ = .832)

Intended strategy: Buffer
The learner intended to create a buffer between the player and other particles to avoid collision (κ = .772)

Connecting Moves to Strategies

We have identified a series of moves that we believe may link to cognitive strategies related to physics learning.

Explicit Learning Outcome	Implicit Game-Based Knowledge	Cognitive Strategy	Game-Based Moves
Newton's First Law	Each particle will keep moving on its path without an impulse or force rom another particle	Slow particle down by using an opposing force	Consistently use opposing force on particle to stop it
Newton's Second Law	The different mass particles react differently to the same force	Impart more force to move heavier particles than lighter particles	Consistently click more frequently next to heavier particles than lighter particles

Linkages among desired learning outcomes and the implicit knowledge, cognitive strategies, and moves in Impulse that might be leveraged for those outcomes

Building Detectors

Classifiers for each code were created within RapidMiner 5.3 that map the student behaviors in the features distilled from the clickstream data to the training labels, using J48 decision trees with 4-fold cross-validation at the student level. Kappas for these classifiers ranged from 0.45 to 0.94 and A' values all exceeded 0.80. Strong paths from the Float (Kappa = 0.727, A' = 0.914) and Stop/Slow Down (Kappa = 0.522, A' = 0.804) are presented here.

Float

- 0 < Time since last impulse ≤ 1.092 → Impulse within close proximity of Player → NO FLOAT
  - 1674 correct predictions
  - 102 errors
  - 94% confidence
- Time since last impulse > 1.672 → Distance traveled since last event >15 pixels → FLOAT
  - 1078 correct predictions
  - 73 errors
  - 94% confidence

Stop/Slow Down

- Player Speed ≤ 100
  - Impulse > 54 pixels from Other particle → Direction of impulse relative to particle was NOT opposite of the player motion → NOT Stop/Slow down
    - 1245 correct predictions
    - 32 errors
    - 97% confidence
  - Impulse < 54 pixels from Other particle → NOT Stop/Slow down
    - 1472 correct predictions
    - 9 errors
    - 98% confidence
- Player Speed > 100 → Impulse > 61 pixels from Other particle → Direction of impulse relative to particle was opposite of the player motion → Stop/Slow down
  - 72 correct predictions
  - 10 errors
  - 88% confidence

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