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Tenacious Assessments

Using In-Game Behaviors to Measure Student Persistence and Challenge Navigation

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Abstract

Video game log data provides a unique opportunity to study how student gaming behavior relates to learning. Literature has investigated embedded assessments for learning in games, but less work measures students' motivational behaviors in games. This paper explores a variety of persistence and challenge navigation measures based on student behaviors taken from log data of students playing a coding video game. Some of these measures are highly correlated with learning, and a classic measure of persistence. Results suggest new ways of measuring motivational behaviors in games. These new measures provide more fine-grained data than traditional assessments of motivation, and they can be used to assess positive learning behaviors during gameplay.

Introduction

To engage in practices that foster deep learning, students must learn how to approach and respond to challenging situations effectively. Highly motivated individuals – those with growth mindsets, mastery learning goals, high self-efficacy, or high intrinsic motivation – more often choose to engage in challenging learning tasks and persist at them (Bandura, 1977; Deci, Koestner, & Ryan, 1999; Dweck & Molden, 2005). These motivated behaviors are productive for learning, particularly with content that is challenging or requires multiple attempts, such as inquiry and creative problem-solving tasks.

Games are an interesting space in which to study and measure how people navigate challenging situations, especially since challenge is one of the defining elements of games (Baranauskas, Neto, & Borges, 1999; Garris, Ahlers, & Driskell, 2002). Games often present challenging problem-solving situations, and many games are leveled such that the next problem is just beyond the player's current ability, naturally imposing some degree of challenge on the player. Paradoxically, working through a challenge, particularly when it leads to failure, can be both motivating (Malone, 1981) and emotionally taxing (Juul, 2013).

And yet, games are a space where people voluntarily engage in challenge and persist at it. Children and adolescents spend an average of 90 mins/day playing video games (Rideout et al., 2010), and over half of adolescents find online games "addictive" (Yee, 2006). Bracing statistics of video game sales ($15.4 billion in the U.S. in 2014, Adkins, 2015) echo these findings. One study even found that adult gamers spent more time attempting to solve a challenging task than non-gamers (Ventura, Shute, & Zhao, 2013). Thus, even though games present players with challenging situations, players seem to respond productively. This makes games an ideal place for measuring how students navigate a challenge, which includes challenge-approach and challenge-response behaviors.

Another reason why games are an ideal place to measure how students behave around challenging situations is that games provide an incredible amount of choice and control (Garris, Ahlers, & Driskell, 2002; Malone, 1981). For instance, players can often choose to revisit previous levels or approach a challenging problem in more or less complex ways. Contrast this with the intelligent tutoring system (Corbett, Koedinger, & Anderson, 1997), a popular computer-based learning environment, where learners cannot choose the problem they want to work on, and there is a limited number of solutions that the system deems correct. The large set of choices provided within games enables the exploration of what people naturally do when given alternatives.

Finally, computerized games can collect fine-grained, moment-to-moment log data, which affords detailed investigations of student behavior in learning situations. For instance, log data allows us to explore the frequency and time spent on specific in-game behaviors or how learners approach individual problem attempts vs. their final solution. Many of these measures of in-game behavior historically have been used in an effort to create embedded assessments that avoid the necessity of paper-and-pencil tests (Nelson, Ketelhut, & Schifter, 2009; Shute, 2011). However, our focus is somewhat unique in that we measure non-cognitive behaviors, such as persistence at challenging tasks or challenge-seeking behaviors. Ultimately, many of these measures relate to how much students learn from the game.

Measuring student persistence and motivation during learning is not novel, but fine-grained video game log data provides much more information than standard behavioral measures of motivation. Classic behavioral measures of motivation include persistence times and the choice to engage in different types of tasks (Schunk, Meece, & Pintrich, 2012; Toure-TiIlery & Fishbach, 2014). To measure persistence during challenge, researchers frequently give learners an “unsolvable task” and measure how long students work on it before quitting (Baumeister et al, 1998; Fishbach, Dhar, & Zhang, 2006; Ventura & Shute, 2013). However, clickstream level data provides a much more nuanced picture of motivated behavior such as the moment-to-moment decisions learners make around challenge and whether they choose to solve problems in effortful ways or not. These more fine-grained measures may predict learning better than more global, traditional measures of persistence and choice (Schwartz & Arena, 2013).

In this paper, we explore several measures of three constructs that relate to how people navigate challenge in the context of an educational game that teaches computer programming. The first is how players *approach* a challenging situation. In addition to the usual challenge-approach measures (such as whether people choose easy or hard problems), we can also explore the kind of learning behaviors students choose to engage in (e.g., what kind of code do they choose to attempt?). The second construct we set out to measure is how players *respond* to challenge. We first looked at traditional measures, like time spent on a challenging task before quitting. We then explored the specific behaviors learners chose to engage in after failure. Did they immediately retry the problem or did they spend time reflecting on a hint before trying again? Did they stop writing complex code when they couldn’t get it to work? The third construct we examined is what we call *general persistence*. While measures of players’ response to challenge focuses on what players do when given a particularly hard task or after failing a task, general persistence is simply the willingness to continue playing the game. While we have argued above that games are generally challenging, there are certainly easier and harder levels, and the category of general persistence does not distinguish amongst them (whereas the first two constructs explore approach and response to only the most challenging situations within the game).

Our broad goal is to identify promising measures of in-game behavior that are indicative of players' motivations for solving challenging problems in an educational game. We focus on measuring three constructs: *challenge approach, challenge response, and general persistence.* To do this, we embarked on several analyses. First, using a set of *a priori* constraints (defined in the Methods section), we identified several logged actions that relate to these constructs. To whittle this list of measures down to those that are the most valid, we examined their relationship with a standard behavioral measure of motivation that assesses persistence in the face of challenge – how much time players were willing to spend on an unsolvable coding task. Finally, we explored the association between each of these measures and learning outcomes on a paper posttest, to identify which types of challenge navigation behaviors are associated with learning. Our findings have implications for the creation of novel behavioral measures of motivation, particularly in the context of challenge, both within computerized games and potentially in other computer-based learning environments.

Methods

Participants

Thirty-seven fifth grade students (54.1% female) were recruited from an urban charter school after-school program. Prior to the study, 89% of participants had no programming experience; the rest had less than a month's worth of programming experience.

Procedure

Students were randomly assigned to the Full Game condition (n=18) or the Minimal Game condition (n=19). Both games used block-based code, similar to Scratch (Maloney et al., 2010). In each game level, students solved problems by writing code to navigate an agent over obstacles and reach a goal. If students solved a problem correctly, they would move on to the next level. If not, students would see an automatically generated hint about how to solve the problem and were given the chance to attempt the problem again. Both games contained identical problems and hints. However, the Full Game contained additional standard game features such as a narrative story, high quality graphics, sound, feedback and performance metrics and just-for-fun bonus levels (that contained no coding content). For both conditions, the relationships both amongst motivational measures and between learning outcomes and motivational measures were similar, so the analyses in this paper collapse across conditions. For information on how game conditions affected persistence, challenge navigation, and learning see Malkiewich et al, 2016.

During gameplay, students had access to "action" blocks, that make the character walk or jump, or "parameter" blocks such as repeating loops and if/then conditional commands that need to be filled with action blocks to work. Student produced codes that only used action blocks were labeled "basic". Codes that implemented rote usage of parameter blocks were labeled "intermediate", and codes that adapted parameter blocks to suit the given problem were labeled "complex". Each game level was assigned a difficulty level, depending on how parameter or action blocks could be used in that level. Easy levels only had action blocks, medium levels had action blocks and one parameter block, and hard levels had action and multiple parameter blocks. In addition to generic problem difficulty, levels were labeled as "relative-hard" if the level proved particularly hard for that one student (the student needed an above average number of attempts to solve the problem). Levels were gated, meaning that a student could not progress to the next level in the game until the current level had been completed. Levels were "completed" with successful problem solutions. Players were given an unlimited number of "attempts" to solve each level. After a student played through the whole game once, all levels were "unlocked" and the student could choose to play any level.

Each student participated in the study for five, 40-minute sessions: a pretest session, two game play sessions, a challenge session, and a posttest session. In the pretest session, students took a paper pretest to assess their prior knowledge of coding. In the two game play sessions, students played the game individually on iPads. In the fourth session, students attempted an unsolvable coding challenge (the challenge task). In the final session, all students completed a paper posttest.

Measures

Learning was measured by assessing student scores on the pretest and posttest. The paper pretest consisted of four test items on constructing code, interpreting code, and planning, a relevant skill to programming (Pea & Kurland, 1984). The posttest was a 16-question paper test that included isomorphic problems to all the pretest questions, plus an additional 12 questions about conceptualizing, writing, interpreting, and debugging types of code that the students had not seen until playing the game.

Our classic persistence measure recorded the amount of time students spent working on the challenge task. The challenge task was an unsolvable, novel level embedded in the game the students were playing. Students were told that to complete the challenge level, they had to solve the challenge task using no more than a certain number of blocks. Unbeknownst to the students, this number of blocks was less than the minimum required to successfully solve the problem. Therefore, students experienced failure at every attempt; even when students thought that they solved the problem, they were told by the researchers that they used too many blocks in their solution and they could try again. At any time, students were given the option to continue trying to solve the challenge level (for up to 40 minutes), or quit to explore computer-based science simulations.

Challenge approach, challenge response, and general persistence measures were created from behaviors observed in gameplay data. Gameplay data was collected using screen recordings and embedded log capture. Due to technical difficulties, some video and log data was lost, so all measures of student coding behaviors and time spent coding only involve a portion of the total study sample (N=18; n=9 for each group). Over 150 measures were created to capture various behaviors relating to how students navigate challenge. Of those, eleven measures were chosen – seven measures of how students approach challenge, three measures of how students respond to challenge, and one measure of general persistence (Table 1). Measures were chosen according to the following guidelines:

1. Measures of how frequently students engaged in behavior (count data) were not used because the two game conditions moved at different speeds (i.e., students could play more levels in the

same amount of time in one condition), and we didn't want behavioral measures to be confounded with condition. Instead, all measures were recorded as percent occurrence or time spent on a behavior.

2. Measures were chosen to assess behaviors where students were dealing with challenge. Challenge was defined as tasks in the game that were particularly difficult for students in general (e.g. completing hard levels, successfully writing complex code, failed level attempts) or relatively (these "relative-hard" levels are those for which a student took many attempts to solve the problem).

3. Measures were only picked if they were not confounded with student skill. For example, the number of attempts a student takes on a level measures both persistence (how long a student is willing to try a problem before quitting) and competence (how well a student can code). Since there is no way to parse out how much attempt count accounts for student persistence versus competence, measures like these were not used.

4. Behaviors that occurred rarely in our dataset (less than 5% occurrence) were not included.

Using these guidelines, the following measures were created to assess challenge-approach, challenge-response, and general persistence:

Construct	Measure	Description	Type of Behavior
Challenge Approach	Immediate Replays	% levels immediately replayed after successful completion	Negative, choose to play non-challenging levels
	Hards Replayed	% hard levels replayed after game completed	Positive, choose to play challenging levels
	Moves to Hard	% non-chronological transitions to harder levels	
	Hards Solved Complex	% hard levels solved with complex code	Positive, choose to try challenging code
	Hards Started Complex	% hard levels with complex code on 1st attempt	
	Levels Solved Complex	% all levels solved with complex code	
	Relative-Hards Solved Complex	% relative-hard levels solved with complex code	
Challenge Response	Careful Hard Retries	% hard level attempts where students spent above-average time after a failed attempt	Positive, reflect after challenge (failure)
	Careful Hint Reads	% hints where students spent above-average time looking at the hint after a failed attempt	
	Relative-Hard Code Downgrades	% transitions to simpler code on the next attempt of relative-hard levels (e.g. move from complex to basic code)	Negative, give up on trying challenging code
General Persistence	Coding Time Day 2	Total coding time on Day 2 of game play, excluding off-task time (e.g. bonus levels, etc.)*	Positive, persist at game

* On Day 1 of gameplay the game was novel, so students spent the majority of their time coding, but on Day 2 students spent more time off-task, and few students persisted at coding for the entire session.

Table 1. Measures of challenge navigation behaviors.

Results

Challenge navigation measures were first correlated with challenge time, our classic behavioral measure of motivation in the face of challenge, as a means of validation (Table 2). Four measures of in-game student behaviors were significantly correlated with challenge time. Hards Solved Complex (r = 0.54, *p* = .02), Relative-Hards Solved Complex (*r* = 0.67, *p* = .003), and Coding Time Day 2 (*r* = 0.57, *p* = .01), were all positively associated with challenge time, indicating that students who persist more on a challenging game level also write more complex code in challenging levels and generally persist longer in the game. Similarly, the response to challenge measure Relative-Hard Code Downgrades (*r* = -0.56, *p* = .02) was negatively associated with challenge time, which indicates that students who persist less on a challenging game level also choose to give up on writing challenging code more often. After applying the Benjamini-Hochberg correction (Benjamini & Hochberg, 1995) to control for false discoveries, only Relative-Hards Solved Complex and Coding Time Day 2 were significantly correlated with challenge time, suggesting that these in-game measures of approach to challenge and general persistence are potentially good measures of student motivation in challenging situations.

To determine which measures most effectively predicted student coding knowledge after gameplay, we then computed correlations between posttest scores and measures of challenge navigation and persistence. Only measures for challenge approach were highly correlated with posttest scores. These included Hards Solved Complex (*r* = 0.76, *p* < .01), Hards Started Complex (*r* = 0.71, *p* < .01), and Levels Solved Complex (*r* = 0.70, *p* < .01). All three of these correlations maintained significance after the Benjamini-Hochberg correction. Their relationships suggest that taking risks in challenging situations, operationalized as general student willingness to use more sophisticated code when attempting difficult problems, was positively associated with learning outcomes.

			1	2	3	4	5	6	7	8	9	10	11	12
Classic Persistence	1	Challenge Time	.	.	.	.	.	.	.	.	.	.	.	.
Learning	2	Posttest Score	.14	.	.	.	.	.	.	.	.	.	.	.
General Persistence	3	Coding Time Day 2	.57*	.17	.	.	.	.	.	.	.	.	.	.
	4	Immediate Replays	-.16	.15	-.16	.	.	.	.	.	.	.	.	.
	5	Hards Replayed	.00	.16	.09	-.32	.	.	.	.	.	.	.	.
	6	Moves to Hard	-.29	-.18	-.60*	-.13	.19	.	.	.	.	.	.	.
Challenge Approach	7	Hards Solved Complex	.54*	.76**	.38	-.09	.30	-.19	.	.	.	.	.	.
	8	Hards Started Complex	.43	.71**	.30	-.09	.44	-.07	.90**	.	.	.	.	.
	9	Levels Solved Complex	.46	.70**	.17	.14	.18	-.12	.84**	.83**	.	.	.	.
	10	Relative-Hards Solved Complex	.67**	.46	.26	.18	-.09	.08	.70**	.49*	.67**	.	.	.
	11	Careful Hard Retries	-.27	.19	-.25	.24	.14	.19	-.08	.01	.23	-.07	.	.
Challenge Response	12	Careful Hint Reads	.17	-.08	.45	.02	-.05	-.16	.00	-.08	.09	.22	.10	.
	13	Relative-Hard Code Downgrades	-.56*	.17	-.26	.14	.07	.05	-.12	.08	.02	-.57*	.61**	-.21

***** p < .01, * p < .05***

Table 2. Correlation matrix of challenge navigation behaviors.

These correlations suggest that certain in-game behaviors can be used to measure student persistence and learning. However, many other factors could still be confounded with these measures, including students' prior knowledge. Are students who exhibit these positive challenge-seeking behaviors only persisting and learning because they have more prior knowledge? One potential explanation for why students who exhibit more challenge seeking also persist longer on the challenge task, is that they simply know more coding techniques to try while attempting to complete the challenge task. To explore this question, correlation matrices were re-run as partial correlations, controlling for pretest scores (Table 3). After applying the Benjamini-Hochberg correction, both Relative-Hards Solved Complex (*r* = 0.64, *p* < .01) and Relative-Hard Code Downgrades (*r* = -0.62, *p* < .01) maintained significant correlations with Challenge Time, while Hards Solved Complex (*r* = 0.70, *p* < .01) and Hards Started Complex (*r* = 0.62, *p* = .01) maintained significant correlations with posttest score. This suggests that choosing to write challenging code and persisting at it is related to players' motivations in the face of challenge and learning respectively, even when controlling for student prior knowledge.

			1	2	3	4	5	6	7	8	9	10	11	12
Classic Persistence	1	Challenge Time	.	.	.	.	.	.	.	.	.	.	.	.
Learning	2	Posttest Score	.04	.	.	.	.	.	.	.	.	.	.	.
General Persistence	3	Coding Time Day 2	.60*	.25	.	.	.	.	.	.	.	.	.	.
	4	Immediate Replays	-.26	.22	-.20	.	.	.	.	.	.	.	.	.
	5	Hards Replayed	-.15	.15	.02	-.40	.	.	.	.	.	.	.	.
	6	Moves to Hard	-.09	-.17	-.61*	-.08	.53*	.	.	.	.	.	.	.
Challenge Approach	7	Hards Solved Complex	.47	.70**	.48	-.13	.26	-.03	.	.	.	.	.	.
	8	Hards Started Complex	.33	.62*	.40	-.13	.47	.10	.86**	.	.	.	.	.
	9	Levels Solved Complex	.37	.59*	.27	.18	.14	.06	.77**	.74**	.	.	.	.
	10	Relative-Hards Solved Complex	.64*	.52*	.29	.14	-.09	.08	.75**	.52*	.79**	.	.	.
	11	Careful Hard Retries	-.30	.19	-.24	.26	.17	.21	-.11	-.01	.29	-.07	.	.
Challenge Response	12	Careful Hint Reads	.24	-.03	.48	.02	-.01	-.28	.08	-.02	.23	.23	.11	.
	13	Relative-Hard Code Downgrades	-.62*	.05	-.24	.22	.12	-.02	-.26	-.02	-.14	-.60*	.63*	-.20

***** p < .01, * p < .05***

Table 3. Partial correlation matrix of challenge navigation behaviors, controlling for pretest.

These partial correlations suggest that certain in-game measures predict unique variance in challenge time and posttest scores. To identify which measures predicted significant unique variance, and how much, we ran a series of step-wise linear regressions by first adding pretest to the model, and then adding the most strongly correlated measures first. When pretest score was linearly regressed on Challenge Time, it did not explain significant variance in Challenge Time, $p = .87$. Relative-Hards Solved Complex, when added to the model, ultimately explained 44.7% more unique variance in Challenge time than pretest alone, $F(1,14) = 11.36$, $p < .01$. Finally, Relative-Hard Code Downgrades was added to the model, and failed to explain any more unique variance in Challenge Time, $p = .23$. To examine associations with learning, pretest score was linearly regressed on posttest score but failed to explain any unique variance, $p = .15$. Hards Solved Complex, when added to the model, explained 50.2% additional unique variance in posttest score, controlling for pretest, $F(1,15) = 20.09$, $p < .01$. When Hards Started Complex was added to the model, it did not explain any more unique variance in posttest score ($p = .83$) most likely because Hards Solved Complex and Hards Started Complex were very highly correlated, $r = 0.90$, $p < .01$. Results suggest that students who are committed to writing complex code in challenging situations are more motivated in the face of challenge and learn more.

Discussion

Based on this exploratory analysis, challenge approach in-game behaviors seem to best measure student motivation and learning, while challenge response and general persistence were less productive measures. Relative-Hards Solved Complex, a measure of how willing students were to use complex code to solve problems that they specifically struggled with, was the best predictor of how much time students spent trying to solve a novel, impossible problem that acted as a classical measure of persistence in the face of challenge. Meanwhile, students' willingness to solve hard problems with complex code more generally was a weaker predictor of challenge time but the best predictor of posttest scores.

Together, these measures suggest that the more willing students are to approach challenge the more they were willing to persist, and ultimately learn in this game environment. These measures demonstrate how fine-grained log data can be used as valid assessments of behaviors that have positive effects on student learning. It is important to note that in this study, more traditional measures of challenge navigation (e.g. choosing to play a hard vs. an easy level) and general persistence did not relate to learning outcomes. This suggests a strong benefit of exploring more fine-grained behavioral measures of challenge navigation.

Conclusion

This study was ultimately able to identify a few measures of student behaviors that predicted persistence and learning. Specifically, challenge-approach measures that assess a student's willingness to try out difficult strategies on hard problems were the most predictive. This research suggests that game log data has a largely unexplored potential for measuring situated instances of student persistence and challenge navigation. Additionally, it suggests that game researchers should be more varied in the ways they define, operationalize, and measure student motivation. Instead of just looking at total persistence times, measures relating to student's willingness to engage productively in challenging tasks seem to be important, and relate strongly to student learning.

Ultimately, we were limited in this study by our small sample size and the fact that students only played one game. Our measures of challenge approach, challenge response, and general persistence were confined by the structure and mechanics of this particular game. Future work should consider the effects of other measures of challenge navigation, and how these measures might be adapted for different game environments. For example, if a game did not have gating, then the next level a student chooses after failure would be more indicative of challenge-response behavior, and less of a challenge-approach behavior. Future work should also seek to replicate these findings with a larger sample of student players.

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