Chapter 5
Balancing Granularity and Context in Designing Evidence Models for Stealth Assessment:
A Case of Pause Distribution in a Digital Game-Based Learning Environment

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ABSTRACT

In the context of game-based learning environments, stealth assessment unobtrusively measures learning outcomes. However, designing a robust evidence model requires careful consideration of learning behaviors in context. This chapter presents a case on designing evidence models for stealth assessment in a game-based learning environment. In this study, the authors employ a finite mixture model to analyze players' pause behaviors in the game, interpreting the meanings of these behaviors under different contexts. The findings contribute to the understanding of how to balance granularity and context in designing evidence models, proving valuable for enhancing the efficacy of stealth assessments for game-based learning.

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The idea of a stealth form of assessment has attracted the attention of educators and educational researchers in recent years (Shute et al., 2020; Georgiadis, Van Lankveld, Bahreini, & Westera, 2020). The term *stealth assessment* first appeared in Shute (2011), but the principles and motivations behind the term have been driven by long-standing issues in teaching and learning. How can learning be seamlessly assessed and supported in an unobtrusive, and most importantly an enjoyable way?

Offline, in the physical world, assessment and support of learning rely on experienced instructors making observations and real-time instructional decisions. However, this in-person approach is only feasible on a small scale and the instructor requires time and effort to learn about their students, which is also an unscalable solution. Modern learning occurs either via digital tools (e.g., instructional video, educational robots) or in digital environments (e.g., educational games and simulations, learning management systems). These tools and environments can generate a large amount of digital data and the data can be used to help make inferences about learning. Hence, stealth assessment becomes possible (McCreery, Krach, Bacos, Laferriere, & Head, 2019; Min et al., 2019; Smith, Shute, & Muenzenberger, 2017).

STEALTH ASSESSMENT

The goal of stealth assessment is to make "quiet" inferences of learners' competencies, based on their observed behaviors, and provide "powerful'' instructional supports based on these inferences (Shute, Ventura, Bauer, & Zapata-Rivera, 2009; Shute., 2011). Instructional supports (e.g., feedback) should be delivered formatively based on the results of the assessment. In an assessment-only context, no intervention is given. In contrast, under the vision of stealth assessment, formative instructional supports are important as they are the source of learning through digital tools or environments without interruptions.

The stealthy approach can be very effective in terms of both assessment and learning. First, in terms of assessments, measurement occurs behind-the-scenes or *stealthily*. Learners do not need to know that they are assessed. They can continue with the learning activity uninterrupted while the assessment occurs unobtrusively and continuously in the background. Reducing the feeling of "being assessed or monitored," which may help to reduce test anxiety and affects both test performance and measurement validity (Gaye-Valentine, 2013; McDonald, 2001). Second, in terms of learning, stealth assessment provides a seamless learning experience through the uninterrupted learner-centered experience with assessment occurring under the hood. Stealth assessments are integrated into, although not required, digital learning games. Digital environments allow for automated data collection. The data that is collected during gameplay can then be used to infer learning based on behaviors—identified via log data—and inform real-time in-game adjustments (e.g., adaptive sequencing of events, providing support) and student progress (e.g., teacher-facing dashboard of performance, identification of missing prerequisite knowledge, etc.). Without the need to interrupt the learning process for the sake of assessment, students can remain engaged and more likely to achieve a state of flow while learning (Csikszentmihalyi, 2009).

Evidence-Centered Design (ECD) aims to establish an empirical model and build connections between what we can observe and what we want to measure (Almond, Kim, Velasquez, & Shute, 2014). Combining the ECD assessment and formative instructional support, a learning system with stealth assessment interweaves both assessments and learning while also creating a seamless and enjoyable learning experience.

Evidence-Centered Design

The engine of stealth assessment is founded on the principles of evidence-centered design (ECD, see Mislevy, Almond, & Luas, 2003). The process is both iterative and continuous. The more learners interact with the learning game, the more evidence (i.e., data) is generated. The data fed into the inference model, improving overtime, and recommendations are issues via dashboard to the instructor or in-game adjustments. For example, the difficulty of a task is tailored to learners' recent performance, so that (a) the completion result will provide the most information (Van der Linden & Boekkooi-Timminga, 1989) and (b) the task will be within the player's zone of proximal development (ZPD, see Vygotsky, 1978).

The ECD framework consists of a *competency model*, an *evidence model*, and a *task model* (Mislevy et al., 2003). The *competency model* (CM) describes the set of target knowledge or skills to be assessed. It acts as a profile of learners but at a fine-grain level. The CM (sometimes also called a student or proficiency model, see Mislevy, Steinberg, & Almond, 1999; Almond, Mislevy, Steinberg, Yan, & Williamson, 2015) needs to be well-operationalized and have high construct validity. The *evidence model* (EM) is the operationalization of the CM, defining the connection between what and how performances observed within the activity indicate the level of competence defined in the CM. The *task model* (TM) is used to select the appropriate task contexts where identified performances and actions in the EM are elicited. Tasks are mapped to the CM via the definitions outlined in the EM.

The EM bridges the CM and the TM by (a) using evidence in the TM to infer competency defined in the CM and (b) using the competency map in CM to inform the task selection in TM. As a result, we can systematically infer learners' target competency through observable behaviors that occur within a predefined task context. In addition, because the task selection is driven by inferences, the task difficulty is tailored to the learners' recent performance, so that (a) the completion result will provide the most information (Van der Linden & Boekkooi-Timminga, 1989) and (b) the task will be within ZPD. Through the coordination of the three models (e.g., EM, CM, and TM) the ECD-framework connects shreds of evidence purposefully collected to target competencies propose to be measured.

Challenges in Designing Observables

As ECD is the engine of SA, the EM is the engine of ECD. A challenge implementing ECD is connecting observed behaviors (i.e., *observables*) with complex competencies such as problem solving or collaboration (Arieli-Attali, Ward, Thomas, Deonovic, & Von Davier, 2019). ECD-assessment is largely task-driven, so when the contexts and interactions become complex, the ability to infer from data at a finer granularity becomes limited (Behrens, Mislevy, DiCerbo, & Levy, 2010). In one of our *Physics Playground* projects (viz., Shute et al., 2020), we built a stealth assessment model based primarily on summary statistics, such as time spent on task and overall in-game performance (e.g., level of reward earned at the end of each level) to represent learners' competencies. The results were promising in terms of construct validity and convergent validity on conceptual physics, but the model had limitations in differentiating more specific concepts nested within the broader construct because the nodes in the CM are interconnected and/or overlap at the lower level. In other words, as we look at more granular data, the overlap in concepts begins to grow, thus reducing our capacity to interpret variations in the learning progression.

Behrens et al. (2010) have suggested using "trace data'' instead of summary statistics within the digital learning systems to unpack this complexity because highly detailed behavioral data—such as performance traces—contains vast amounts of information. In a different example, Shute, Wang, Greiff, Zhao, & Moore (2016) designed specific rules in the EM to link behaviors to target competencies (i.e., problem-solving skills) using a modified version of *Plant vs. Zombie*. One target behavior was the use of "plant food when there are <3 zombies on the screen." This theory-informed observable targeting "effective tool usage" leverages trace data. However, this type of observable is specific to the game itself, which means it lacks transferability to other games or other instructional contexts without some process of conversion into the new game's context. In addition, learners may demonstrate effective tool usage that is not fully captured by one or two predetermined observables—especially in highly interactive and adaptive problem-solving environments. Both ends of the spectrum propose a challenge to designing EMs for stealth assessment.

Pause: A Simple Behavior in Complex Contexts

One possible way of addressing this type of challenge and balancing the granularity is to design observation-based behavioral interactions that are common to most learning challenges (i.e., improved transferability) and unpack the complex meanings of the interactions under different interactive contexts (i.e., fine granularity). In this study, we investigate the *pause* behavior (i.e., the duration of time between purposeful and relevant in-game actions)—a very common action to almost all multi-step cognitive tasks—in a game-based learning environment, and demonstrate its complex meaning under different contexts. By doing so, we intend to better understand the potential implications on learning that may be understood by analyzing pausing behavior.

Complex Meanings of Pauses in Games

While many assessments tend to focus on the final product (e.g., completion, accuracy, speed), learning in a self-governed interactive system such as in learning games, emphasize the problem-solving *processes* (Eseryel, Law, Ifenthaler, Ge, & Miller., 2014). Problem-solving processes and associated behaviors have been used to both measure the proficiency level of learners (Jitendra, Sczesniak, Deatline-Buchman, 2005; Stoeffler, Rosen, Bolsinova, & von Davier, 2020) and predict learning outcomes (Taub et al., 2017). One important indication of problem solving is how someone monitors and regulates the problem-solving processes (Bransford & Stein, 1984; Gick, 1986).

Regulation does not have to happen visibly as a behavior because reflection can be an internal and mental process (McAlpine, Weston, Beauchamp, Wiseman, & Beauchamp, 1999). Active reflection (in the form of a pause from the gameplay) can indicate a metacognitive strategy on managing limited cognitive resources, which is crucial in complex problem-solving environments (Rhodes, 2019; von Wright, 1992). In addition, pauses can also indicate cognitive reappraisal strategies such as affective regulation (Spann, Shute, Rahimi, & D'Mello, 2019; Gross, 1998). Studies have also shown that even a short passive pause from cognitive tasks can increase subsequent cognitive performance (Ariga & Lleras, 2011; Jansseen et al., 2014). Alternatively, pauses can also simply indicate disengagement. Learners might be distracted by other irrelevant tasks, completely overwhelmed, or bored with what they are asked to do. However, no matter if the pause is cognitive reflection, emotional regulation, or disengagement from the task, pauses are a rich source of data about the learning process. Therefore, in this study, we propose to unpack the complexity of pause behavior in an educational game with the purpose of designing a balanced observable using trace data collected from Physics Playground for stealth assessment.

A Conceptual Framework of Pauses in Games

Although problem-solving processes are diverse across individuals, researchers have managed to break the processes down into stages. Many theoretical frameworks have been proposed to interpret the process. For example, Polya (1957) proposed a four-step model (i.e., understanding problem, strategy design, strategy execution, evaluation of the strategies) to describe the general processes in problem solving. Based on Polya (1957), Schweizer and colleagues (2013) proposed a simplified two-step model of problem-solving: rule-acquisition and rule-application. Both the understanding and evaluation phases of the problem-solving process are for acquiring rules; while both design and implementation are for applying the rules to solve the problem. Learners may not necessarily be doing anything while in the rule acquisition state (e.g., analyzing a problem, evaluation on a solution), where more cognitive and metacognitive resources are engaged, hence fewer observable actions and longer pauses. Hence they may seem more inactive (i.e., longer pauses between two consecutive behaviors) from the behavioral level. On the other hand, the rule application state requires more active interactions and implementation, hence shorter pauses. Therefore, within the game problem-solving context, there should exist both active and inactive stages in terms of pauses. In addition, considering some students may occasionally disengage from the problem-solving activity, a disengaged stage is also plausible.

This study investigated the pause behaviors across different contexts in an education game. More specifically:

1. What does the pause behavior look like in an educational game? Do there exist various types of pauses in gameplay?
2. What is the relationship among various types of pauses, learning, and game enjoyment?

METHOD

Data

Participants. Participants for this study were a convenience sample of 199 students between 9th and 11th grade, from a large K-12 school in the southeastern United States. It is worth noting that this data was drawn from an experimental study where students were randomly assigned to one of the three game conditions. Each condition had a different sequence of gameplay (i.e., the order in which new levels were presented to the player). However, in our current study, we are not addressing performance differences between groups because all students received the same experience within each level. Further information regarding performance differences between groups are described in Shute et al., (2020).

Procedures. Students participated in six 50-minute sessions playing *Physics Playground*, a 2D digital game designed to develop middle and high school students' conceptual physics learning. The goal of the game is to use different physics agents (e.g., lever, pendulum, gravity) to direct a green ball to hit a red balloon. In Physics Playground, students can interact with the game in various ways: from drawing simple machines (e.g., levers, ramps, pendulums, etc.) to changing environmental parameters (e.g., gravity, air resistance). The game engine records every game interaction that happens over the course of someone's gameplay. Based on timestamp information, we operationalize the pause behavior as the interval between any two consecutive user-initiated game events:

$$Pause_i = Time_{i+1} - Time_i$$

Before generating the pause values, we removed all events that were not initiated by the user from the log files (e.g., earning a trophy, snapshots of objects positions) because they were created either in conjunction with a user-initiated event or auto-generated throughout gameplay. We then kept only the pause behaviors *within* a game task (e.g., removing pauses in switching game levels). And finally, we removed unfeasibly small pauses (e.g., outliers) that were identified as either system or user errors. For example, after removing the irrelevant data, we were left with a log file containing only the pauses each participant made throughout gameplay. Pause data was extremely skewed (i.e., skewness = 50.42) given the nature of pause time within gameplay where short pause between typical gameplay behaviors occur much more frequently and long pauses (e.g., > 1 minute) are rare. Therefore, we applied a natural log transformation to all pause data.

Analysis

Because of their complexity, pause distributions are believed to be a combination of potential behaviors from normal delays between game actions to disengagement. In other words, a pause of around a single second may be the movement from one side of the screen to another. More than five minutes of no activity may indicate disengagement. Therefore, we chose to use a finite mixture model to fit the pause distribution data.

Multi-modal distributions are an indication that multiple latent classes may be present within a single continuous distribution. Therefore, we begin our analysis using descriptive data (e.g., median values, density plots) to understand the potential mixture distribution of all pauses. We then used K-Means to identify potential cut-off points between modes within each distribution. The groups formed around the cut-off values are labeled (i.e., active, inactive, and disengaged) and used as priors in fitting the finite latent-class mixture model with the flexmix R package (Gruen, Leisch, Sarkar, Mortier, & Picard, 2015; Leisch, 2004). The initial labels were then verified and refined based on the results of the flexmix model. By labeling and refining the mixture distribution, we then obtained each student's potential frequency and proportion of different pause types.

Finally, we examined correlations between pause behaviors and the following variables collected before, during, and after gameplay: pretest scores, gain scores, the total number of levels completed, and a self-reported measure of enjoyment. The pretest was administered prior to playing and focused on the targeted physics concepts. The gain scores were the difference between the posttest (a parallel form of the pretest) and the pretest (for more information see Shute et al., 2020). The total number of game levels solved (i.e., puzzles completed) is self-explanatory. Players played at their own pace to complete as many levels as possible in the time allowed. Enjoyment was measured as a component of a concluding survey. Participants reported their level of enjoyment of the game on a 5-item questionnaire (Cronbach's $\alpha = .86$).

Estimation Methods

The goal of the estimation is to identify the finite latent classes of a continuous pause distribution. The estimation was done using the expectation-maximization algorithm with maximum likelihood and MCMC sampling under the Bayesian framework implemented by flexmix. A single type of pause distribution in cognitive tasks (e.g., writing tasks) can be simulated by a log-normal distribution which typically has long tails (e.g., Almond, Deane, Quinlan, Wagner, & Sydorenko, 2012; Guo, Deane, van Rijn, Zhang, & Bennett, 2018). Therefore, after log transforming the pause intervals, we can assume each potential component follows a univariate normal distribution, which makes the estimation into a latent class regression (DeSarbo & Cron, 1988). Flexmix can help to identify the component parameters including means and variances.

RESULTS

Descriptives of Pause Distribution

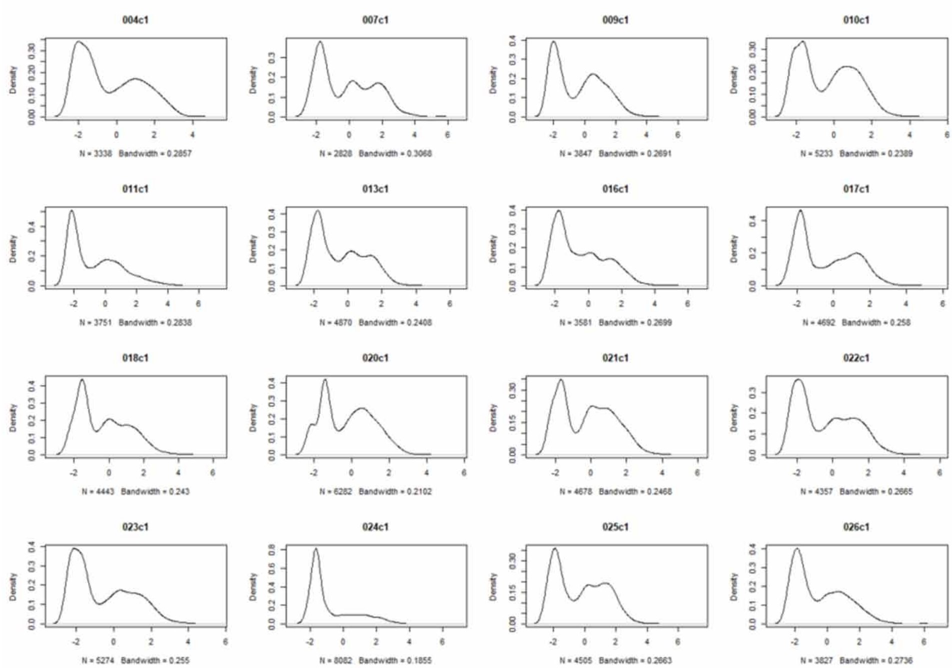
We first obtained the descriptive data of all 199 students' pause distributions (Table 1). Students in all three conditions behaved similarly. Overall pauses ranged from 0.08 seconds to 336.14 seconds with a median pause of 0.5 seconds across all participants. Although students in condition one (i.e., game levels were presented in a set sequential order) demonstrated slightly longer pauses in relation to the overall median, in general, students did not differ substantially across conditions.

Table 1. Descriptive data of pause distribution by condition

Condition	n	Min	1st Q	Median	Mean	3rd Q	Max
1	64	.080	.18	.58	2.68	2.49	358.48
2	68	.081	.18	.46	2.39	2.31	315.68
3	67	.080	.17	.48	2.34	2.20	335.67
Total	199	.08	.18	.50	2.47	2.33	336.14

We then produced density plots of the log-transformed distributions for each student (Figure 1). The density plots show that the distribution of pauses was multimodal—most students demonstrated a bi-model distribution of pauses but some were tri-modal or multimodal. This indicates that the continuous distribution of pause times may be a result of mixture distributions—different states possibly contributing to the different durations of pause.

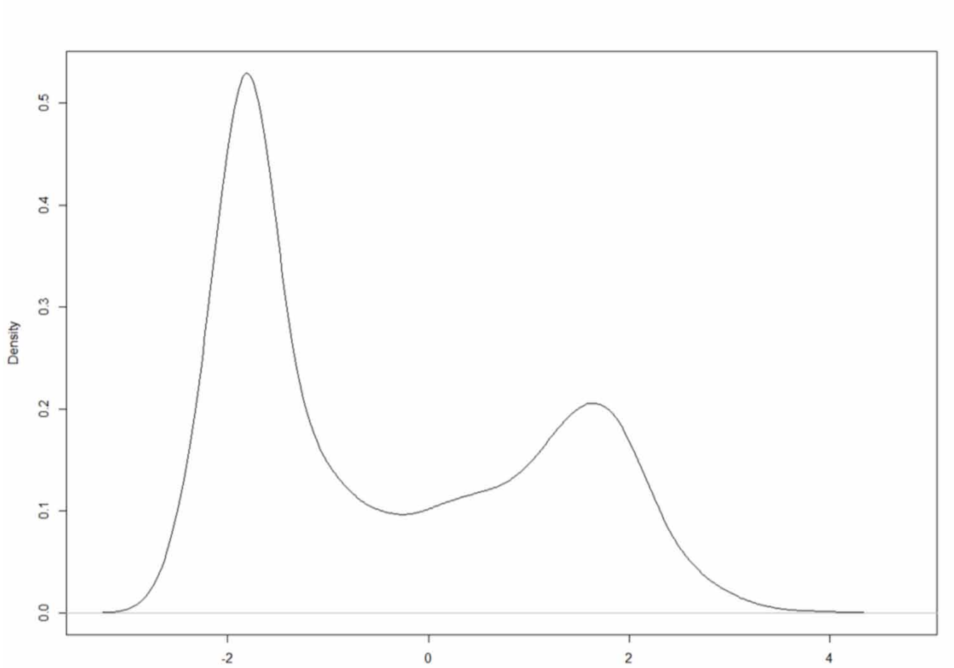
Figure 1. Sample density plots of pause times



Determining the Number of States in Pause Distribution

The literature provides theoretical support for constructing a mixture of an "active-inactive" pause distribution (i.e., a mixture of behaviors with shorter pauses in between and behaviors with longer pauses in between). In addition to the "active" and "inactive" states, learners could have been completely disengaged, which is out of the scope of regular problem solving in cognitive tasks—they could have taken much longer pauses because they are distracted (e.g., chat with friends, on their phone, bathroom break). As a result, we propose that a potential mixture distribution of pause times consists of three possible states: (a) active, (b) inactive, and (b) away-from-keyboard (i.e., disengaged, AFK). Depending on the amount of learner engagement, AFK may not exist throughout the gameplay. Figure 2 shows all pause behaviors demonstrated by all students. As the conceptual framework suggests, we identified three possible states. The shortest pause state (i.e., active states) possibly centered around 0.1 second (around e^2 seconds); The intermediate pause state (i.e., inactive) possibly centered around 1 to 3 seconds (around e^0 and e^2 seconds), while the longest pause state (i.e., AFK) possibly centered more than 50 seconds (around e^4 seconds).

Figure 2. Pause times of all students on a natural log scale



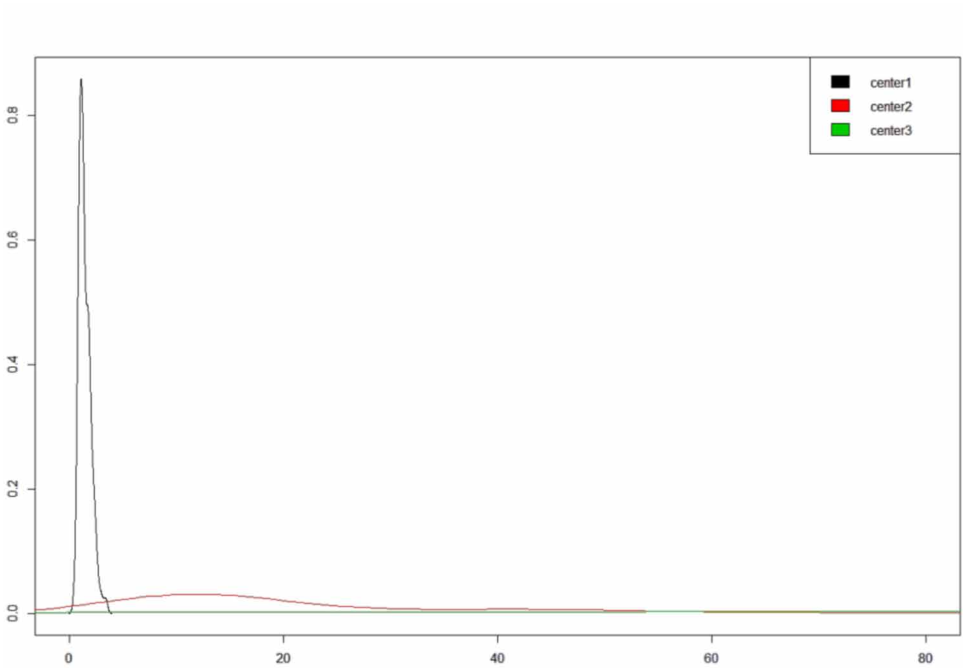
K-Means

Fitting a mixture model with latent class regression using the flexmix package takes a Bayesian approach, which requires a prior distribution. The priors were created from the results of the K-means analysis. Based on the conceptual framework we have discussed; we intended to identify three groups within the students' overall pause distribution. We used the K-Means algorithm to find three possible centers based on all pause times within each student's pause distribution (Table 2) and the distribution of possible centers is shown in Figure 3.

Table 2. Descriptive data for centers identified by k-means of each student's pause distribution

Center	Min	1st Q	Median	3rd Q	Max
1	0.08	0.18	0.40	2.15	39.57
2	39.63	47.69	60.87	88.21	200.44
3	14.17	71.75	149.56	321.27	1968.54

Figure 3. The distribution of centers identified by k-means of each student's pause times



Using the median of possible centers may not capture the majority of diverse students due to the large range of the center distribution, therefore, we decided to use the third quartile of the first (i.e., 2.15 seconds) and second centers (i.e., 88.21 seconds) as the preliminary cutoff for active, inactive, and AFK states. It is worth noting that AFK states vary and are quite infrequent during gameplay. Therefore, this type of behavior is not likely to be picked up by the flexmix model. On the other hand, AFK states are very different from active and inactive pauses, but disengagement is important to identify. Therefore, we hand-labeled the AFK states using the cutoff point of 88.21 seconds based on the results of the K-means analysis. In other words, inactive and active states were identified using flexmix (discussed in the next section), but AFK states were identified based on the results of K-means.

Flexmix

Because we manually labeled the AFK states, the task of the flexmix mixture model became differentiating active and inactive states. We used the aggregated results from K-Means classification as priors to train a mixed model with the expectation-maximization algorithm to label active and inactive states for each individual player. With flexmix, we were able to refine the initial labels of active and inactive pause times. With the refined labeling, we were able to calculate the individual students' proportional feature of pause behaviors (i.e., proportion of active states, inactive states, and AFK states among all pauses).

Relationship between Learning, Enjoyment, and Pause States

To validate the relationship between types of pauses and performance measures, we considered the following: (a) incoming knowledge, (b) level completion, (c) learning gain, and (d) the game enjoyment. The results suggest that prior knowledge was negatively related to the proportion of active states (r = -16, p < .05), positively related to the proportion of inactive states (r = .17, p < .05), and negatively related to the proportion of AFK states (r = -.30, p < .001). Level completion, on the other hand, was positively related to the proportion of active states (r = .19, p < .001), negatively related to the proportion of inactive states (r = -.17, p < .05), but again, negatively related to the proportion of AFK states (r = -.53, p <.001). Learning gain was not correlated to neither active nor inactive states, but it was negatively related to AFK states (r = -.17, p < .05). Finally, enjoyment was not related to active (r = .-11, p = .12), inactive (r = .11, p = .11), or AFK states (r = -.10, p = .18). The correlational matrix is displayed in Table 3.

Table 3. Means, standard deviations, and correlations with confidence intervals

Variable	*M*	*SD*	1	2	3	4	5	6
1. active	0.70	0.09						
2. inactive	0.29	0.09	-1.00**					
			[-1.00, -1.00]					
3. AFK	0.00	0.00	-.14*	.10				
			[-.28, -.00]	[-.04, .24]				
4. Pretest	11.82	3.53	-.16*	.17*	-.30**			
			[-.29, -.02]	[.03, .30]	[-.43, -.17]			
5. Gain	0.63	2.89	.08	-.08	-.17*	-.28**		
			[-.06, .22]	[-.21, .07]	[-.30, -.03]	[-.41, -.15]		
6. Level Completion	45.86	16.05	.19**	-.17*	-.53**	.44**	.21**	
			[.05, .32]	[-.30, -.03]	[-.62, -.42]	[.33, .55]	[.07, .34]	
7. Game Enjoyment	18.32	4.64	-.11	.11	-.10	.15*	.21**	.09
			[-.25, .03]	[-.03, .25]	[-.23, .05]	[.01, .28]	[.07, .34]	[-.05, .23]

Note. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

DISCUSSION

RQ1: What Does the Pause Behavior Look Like in an Educational Game?

We have shown, as a result of our analysis, that pause behaviors in Physics Playground are diverse. Pauses range from as short as .08 seconds to as long as 5 minutes. The multi-modal distribution indicates that there may exist multiple latent states behind the observed pause times. However, students may have utilized multiple approaches to solve in-game problems. Based on the previously defined framework and the present results, gameplay may be divided into a *problem-solving state* where students are engaged with the game—actively trying to complete the task— and an *AFK state* where students are disengaged from the problem-solving activity. The former state produces relatively shorter pauses while the latter produces much longer pauses. The problem-solving state can be further broken down into two types of shorter pauses: *active pauses* which are natural transitions between normal gameplay behaviors (e.g., moving objects on the screen, exploring learning supports, building structures, etc.) and inactive pauses which may manifest when students are engaged in thinking processes such as planning, prediction, and evaluation that do not result in observable behaviors.

Fitting the distribution to a mixture model, we were able to distinguish three possible states across the continuous pause distribution and identify the pause states for each student. This process is critical for modeling students' game behavior because it represents each students' distinctive gameplay pattern. Some students may be active in the game in terms of creating different physics agents or maneuvering the ball (e.g., consecutive nudging), while some students may have relatively parsimonious game actions because more time is devoted to planning or evaluation. Because these unique gameplay patterns can be considered behaviors elicited from unique problem-solving states, we can use observed pause behavior patterns to infer each student's in-game problem-solving states as the basis for stealth assessment design.

RQ2: The Relationship Between Pause, Learning, and Game Enjoyment

We observed a consistent negative correlation of AFK behavior and all performance indicators, meaning that extended pause durations are likely indications of disengagement from the game. However, this disengagement may not necessarily harm the enjoyment because disengagement can sometimes be a strategy for emotional regulation associated with difficult tasks. On the other hand, active states and inactive states have an interesting relationship between learning: Constant active gameplay may help the student finish more levels ($r = .19$, $p < .001$), but it did not necessarily transfer to learning or enjoyment ($r = .-11$, $p = .12$), nor was it related to higher incoming knowledge. The result further implies that active behaviors may not be necessary for an effective game-based learning experience.

Active engagement from the behavioral level does not suggest active cognitive engagement (Kim et al., 2017). On the other hand, inactive gameplay may not help learners solve more game levels within a given time, ($r = -.17$, $p < .05$) these learners could be learners with higher incoming knowledge and are more engaged with predicting/evaluation, which could take more time. Research in GBL and self-regulated learning has highlighted the importance of engaging in self-explanation, self-assessment, and reflection (Goldberg & Spain, 2014; Huang, Ge, & Eseryel, 2017; Moreno & Mayer, 2005). Overall, we demonstrated the potential underlying meaning of different types of pause behaviors, which supported the classification. Although they are all pauses, each pause behavior may carry a different meaning depending on its context.

Implications To Stealth Assessment: Finding Balance in Granularity

Leveraging Data Mining Methods to Unpack the Complexity

In this study, we have shown that the pause between gameplay actions, albeit less than a second at times, can be an ample source of meaning depending on the context. A brief pause within a cognitive task may be the natural transition from one behavior to another. However, the pause may also be an indication of a person's problem-solving approach. Are they taking a moment to predict the next outcome? Perhaps they are considering a new solution design. Or, perhaps they have become distracted by another irrelevant matter—total disengagement. This is the information we can distill from mundane game actions to gain a better understanding of the entire gameplay at a finer granularity. Therefore, different educational data mining methods may be beneficial for designing observables in stealth assessment.

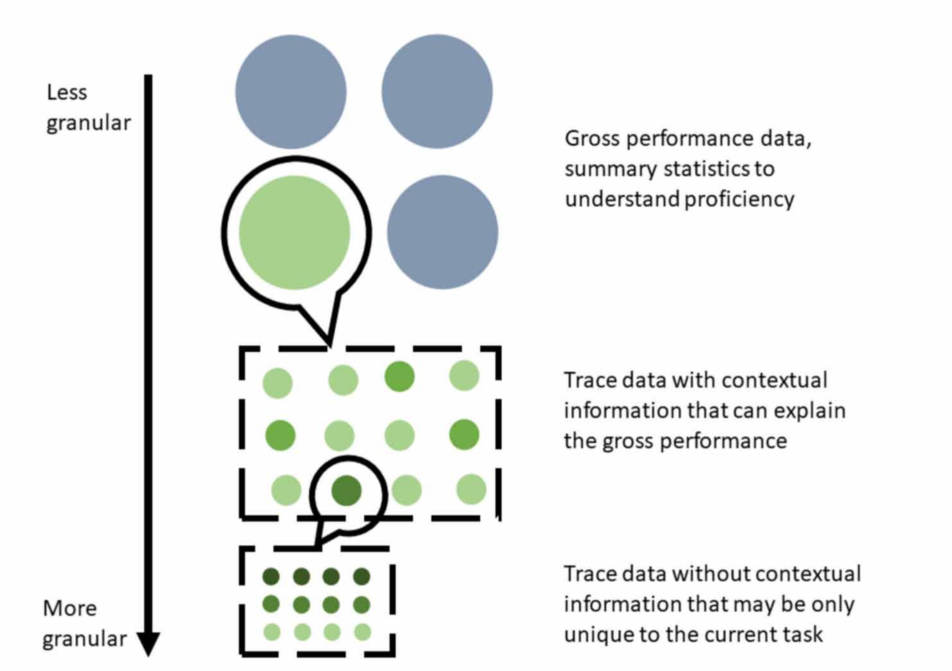
As discussed earlier, one challenge in stealth assessment is to shift the focus from gross performance (e.g., overall task performance) to trace data, a ripe source of underutilized data. However, trace data itself may not convey much information because of the fine granularity of the data. At first glance, trace data may appear too chaotic to yield any meaningful insight. However, in this study we have demonstrated a potential means to differentiate the types of pause behavior related to problem solving by fitting a mixture distribution model. This approach is similar to Grover et al. (2017)'s proposal in extending the classic ECD framework. In their work, data-driven techniques such as clustering, and pattern recognition are used to help the development of scoring rules. This approach is in addition to the traditional theory-based hypothesis-oriented way of defining scoring rules, which can be limited when the learning system becomes dynamic and complex.

Balancing the Granularity

It is important to balance the granularity issue in designing stealth assessment (Figure 4). At the least granular level, we need gross performance and summary statistics to capture students' general proficiencies. This approach has been well-established and strongly supported by past research (e.g., Shute et al., 2020). However, this approach overlooks valuable interaction data (i.e., trace data generated in a digital game system). At a moderate grain size, we need to apply contextual meaning to trace data. This could be an exploratory approach with unsupervised machine learning approaches (e.g., clustering or dimension reduction) or it could also be done in a theory-driven supervised approach (e.g. the classification approach demonstrated in this current study). Ultimately, the goal is to find emerging patterns within trace data to make better sense of higher level (i.e., larger grain-size) performance data. Trace data can also be a magnifier for looking into a specific context and understanding the variability in learning performances.

At the finest grain size, we can focus on the individual behaviors to design observables for use in stealth assessment (as illustrated in Shute et al., 2016), but we may lose the flexibility and transferability. Therefore, we must find a balance of granularity for designing observables. On the one hand, we can leverage various data mining methods to design observables that are detailed enough to capture the learning trajectory but also generic enough to be generalized to other tasks. On the other hand, we can gain understanding of how learning happens in a complex and interactive environment. The result of this type of knowledge could directly benefit both the instructional design and learning science communities.

Figure 4. The granularity in designing observables for stealth assessment



Validity Issues

Validity is a potential caveat in leveraging data mining methods for designing stealth assessment. First, at a less-granular level, defining and operationalizing the construct can be relatively straightforward (e.g., through creating a Q-matrix to link the performance in task model and competency model). As the granularity becomes finer, we as designers are trying to link more detailed interactions with cognitive tasks to the competency model. This linkage may be dynamic and complex, which presents a potential threat to construct validity of the observables—are we really sure what we see means what we think? Second, although the data mining approach can be theory-driven (as illustrated in this current study), the exploratory nature of data mining may mislead researchers and designers by showing a temporal correlation, which leads to a potential threat to internal validity. Third, a natural threat to external validity can arise: How much would the conclusion hold within cognitive tasks across different contexts? Therefore, it is crucial to (a) test the construct validity including convergent and divergent validity with other possible measures, (b) triangulate the claim through multiple methods (e.g., observations, interviews, or other analysis approaches) to enhance the internal validity, and (c) use conjecture mapping (Reimann, 2016) and iterations (Anderson & Shattuck, 2012) to test the extent to which the claim will hold in other settings.

Limitations and Future Directions

This study has a few potential limitations. First, as discussed in the previous section, this study did not have the chance to comprehensively examine potential validity issues. Although we attempted to provide explanations to the pause behavior with various learning and enjoyment measures, it is recommended that future research focus on either replicating the process in a different context and triangulate the conclusion with other quantitative or qualitative analytical methods. Second, we only have selected one behavior—pausing—to illustrate how to leverage data mining methods and find a balance granularity in designing stealth assessments. Many more cognitive-task-related behaviors such as resetting, revisiting, or help-seeking are worth investigating. And to this end, future research should focus on building a more generalized framework of stealth assessment for a variety of cognitive tasks. Third, we have not fully unpacked the AFK behavior because of its sparsity.

Anecdotally, during the experiment sessions, we noticed that some students break from the game as an emotional regulation strategy, which allows them to come back to the game with a fresher mind. This type of AFK is different from complete disengagement. However, compared to both active and inactive pauses, neither type of AFK behaviors have enough data for thorough analysis. As a result, we have chosen a hard cut-off to label this type of behavior. Yet, we recognize that there is still much information buried within the game traces we have collected.

CONCLUSION

In this study, we have discussed some challenges in the design of stealth assessment. We used a case study to demonstrate how to unpack the hidden information in game trace data with a simple yet complex behavior—pausing. We identified multiple possible meanings of pausing in the game and also demonstrated its relationship with performance and enjoyment data collected from the students. The findings of this study will help researchers and practitioners to design evidence models that can understand the complex learning behaviors under various contexts and shed light on implementing stealth assessment in educational settings.

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