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Exploring Failure and Engagement in a Complex Digital Training Game: A Multi-method Examination

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Research Paper

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Abstract:

Digital games are ideal for training complex decision making skills because they allow players to experience decision making processes and consequences. However, training complex skills often results in failure, which may undermine learning engagement. Traditional training methods employing observational learning (e.g., training videos) do not cause learners to fail but forfeit experiential learning that makes training games so engaging. Our exploratory work addresses the trade-off between experiencing and observing failure and explores their effect on the level of training engagement. Building on past engagement research, we argue that learning engagement contains both cognitive and affective facets and that these facets may diverge, especially when individuals experience failure. To test these ideas, we conducted an experiment (N = 156) comparing engagement in game-based training, in which participants experienced failure, and video-based training, in which participants observed failure. We collected cognitive and affective indicators of engagement using physiological and self-report measures. We found game-based experiential learning increased such indicators of engagement as attention and temporal disassociation even though players widely failed to meet game objectives. Players also experienced elevated arousal and decreased positive affect. In addition, we compared physiological measures of engagement with self-reported measures and discuss their merits and limitations.

Keywords: Engagement, Training Games, Cognitive Bias, Eye-Tracking, Heart Rate, Skin Conductance.

1 Introduction

Researchers and practitioners increasingly use digital games as instructional media: the global market for training and education games will reach an estimated US$10 billion in 2015 (Rooney, 2012). Although digital games can be expensive to produce and may require more time than other instructional methods, a variety of contexts have adopted them. Training and educational games teach players about diverse topics such as appropriate cultural interaction (Chatham, 2007), difficult concepts in science and technology (Mayo, 2009), and cognitive skills (Green & Bavelier, 2003).

One of the main reasons for adopting digital games for training is to promote engaged learning (Annetta, Minogue, Holmes, & Cheng, 2009; Dickey, 2005; Gee, 2005). If learning is engaging, individuals will likely invest more resources (e.g., time, effort) in completing the task and, thus, improve learning outcomes. Scholars have defined engagement in many ways (O'Brien & Toms, 2008). However, scholars generally agree that engagement is a desirable user experience during which learners become deeply involved with the learning materials (Annetta et al., 2009). One can promote engaged learning via focused goals, compelling challenges, clear rules, protection from adverse consequences, performance feedback, and sense of authenticity (Schlechty, 2003). A well-designed training game can contain all of the characteristics that make learning engaging (McGonigal, 2011; Santhanam, Yi, Sasidharan, & Park, 2013). A training game can simulate an authentic problem for players to solve without fear of serious consequences, and, in these environments, players are encouraged to learn the rules of the game and seek out creative solutions to reach their goals (Bogost, 2007; Shaffer, 2006; Squire, 2003). Engaging games draw users into relevant tasks, heighten their attention, and cultivate their interest in the training (Chapman, Selvarajah, & Webster, 1999). Greater engagement during learning also leads to better retention of educational material over time (Hannafin & Hooper, 1993).

Although engagement is a desirable outcome of training games, it is not guaranteed. Some players may experience failure during their gameplay, which may undermine engagement. Failure is especially likely if the game’s goal is to modify deeply engrained cognitive processes such as heuristics and biases (e.g., Ehrlinger, Gilovich, & Ross, 2005; Kahneman, 2011). When players fail in training games, they may be likely to attribute the failure to their lack of skills. In contrast, other traditional training environments (e.g., recorded lectures, third party demonstrations) do not directly allow learners to experience failure. Watching a training video may allow learners to observe others fail while avoiding experiencing failure themselves. Such observational learning poses none of the ego threats commonly associated with failure (Hagtvet & Benson, 1997). However, observational learning excludes many of the experiential learning components that make training games so engaging. Thus, there is a potential trade-off between experiencing failure in training games, which may undermine engagement, and the interactive characteristics of training games that enhance engagement.

In this exploratory work, we describe an experiment that compares engagement in a complex training game in which participants experience a high rate of failure, to a training video in which participants view others fail. Both stimuli (training game and instructional video) focus on teaching participants difficult cognitive skills to correctly identify and mitigate deeply engrained cognitive biases. The game places players in situations that expose biases and allow players to experience the consequences of their biased decisions. The training video depicts others demonstrating the biases and shows the consequences of others’ biased decisions. We compare the level of engagement produced by the game with that produced by the training video. To measure engagement, we used a multi-method approach involving both self-report (cognitive absorption and affect) and physiological measures (skin conductance, heart rate, eye tracking, and pupil dilation). We discuss our findings along with implications for theory and practice.

1.1 Theoretical Development

Engagement is a multifaceted concept describing characteristics of an experience that draw people into a task. When people experience elevated engagement, they are intensely focused and curious about novel stimuli; they feel challenged and tend to lose awareness of themselves and time (Trevino & Webster, 1992). When engaged, people feel in complete control and are intrinsically motivated to perform the task. Scholars often regard engagement as the foundation for effective training (Corno & Mandinach, 1983). Engaged learners are more likely to take an active role in the learning, analyzing, synthesizing, and applying critical thinking skills to decide their course of actions (Dickey, 2005). Scholars have described deep levels of the engagement as “flow”, the state of being “so involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at great cost, for the sheer sake of doing it" (Csikszentmihalyi, 2013, p. 4).

1.1.1 Facets of Engagement

One can roughly separate engagement into two related facets: cognitive engagement and affective engagement (Appleton, Christenson, Kim, & Reschly, 2006). Cognitive engagement is the amount of attention and mental resources that one invests in an activity. Cognitive engagement is particularly crucial for learning complex skills that require individuals to construct knowledge by comparing and combining multiple pieces of information, reflecting on their experience, and elaborating on what they observe (Pintrich & De Groot, 1990). High degrees of cognitive engagement can foster self-regulated learning during which individuals actively plan and manage their own learning activities (Corno & Mandinach, 1983). High cognitive engagement and self-regulated learning instill a sense of autonomy and competence, which can further motivate learners (Przybylski, Rigby, & Ryan, 2010). A well-designed training game can facilitate cognitive engagement through presenting learners with interesting problems to solve, clear goals to achieve, and feedback to help learners evaluate and rapidly adjust their performance (Dickey, 2005).

Affective engagement refers to the emotional investment in an activity. A learner may be emotionally attached to the task itself and find pleasure and enjoyment in it. A learner may also be emotionally attached to the people and community surrounding a learning activity (Annetta et al., 2009). Developing affective engagement requires attentional resources. However, cognitive engagement differs in that it requires conscious deliberation in search of efficiency to reach a certain goal. Learners are often less aware of how their affective engagement develops and influences their perceptions of the task and learning in general. Literature on affective engagement in learning has assumed that positive affect such as liking, enjoyment, and sense of achievement increase engagement (Ainley & Ainley, 2011; Garris, Ahlers, & Driskell, 2002; Wigfield & Guthrie, 2000)

Cognitive and affective facets of engagement are closely related and often work in tandem and reinforce each other to create an involving experience. Previous attempts at measuring engagement (e.g., cognitive absorption; Agarwal & Karahanna, 2000) have spanned both cognitive and affective facets in a single scale. However, in this work, we distinguish between these two facets because, although they frequently coincide, there are situations wherein cognitive and affective facets of engagement function independently. For example, research has found that allowing learners to make choices increases affective engagement but not cognitive engagement (Flowerday & Schraw, 2003; Skinner & Belmont, 1993). Prior research has also revealed that negative affect (rather than positive affect) can be associated with high engagement (Higgins, 2006; Lang, Newhagen, & Reeves, 1996). For example, using physiological measures to examine engagement in reaction to unpleasant stimuli, Smith, Löw, Bradley, and Lang (2006) found that higher affective engagement resulted from their study participants' viewing unpleasant stimuli as compared to viewing positive stimuli of equal intensity.

1.1.2 Measuring Engagement

Studies have most often measured engagement through self-reports (Mazer, 2013) recorded either via survey or response systems (e.g., clickers; Denker, 2013). Some have also captured it through coding student behaviors (Cooper & Brna, 2002) or recording time spent with the materials (Ming, Ruan, & Gao, 2013). Fewer studies have examined learner engagement through physiological measures (e.g., Richards & Casey, 1991). We incorporate both physiological and self-report measures in our investigation of engagement, and we detail the reasons for incorporating both below. First, to gain a more holistic description of engagement, it must be measured both during the activity of interest (e.g., playing a training game or watching a training video) and retrospectively. Although retrospective measures of engagement can effectively summarize a learning experience, measures gathered *during* the learning experience capture engagement (or lack thereof) while it is actually occurring. Second, many of the behaviors associated with engagement (e.g., gaze, arousal) are often difficult for individuals to recall and may occur outside the individuals' awareness (see Derrick, Jenkins, & Nunamaker, 2011; Djamasbi, 2014). Third, self-report measures are subjective and may be susceptible to self-report biases such as acquiescence and desirability (Wilson & Nisbett, 1978). Self-reporting biases may increase when individuals discuss their failures (Ravaja, 2004). Physiological measures, on the other hand, are relatively more objective. Finally, some facets of engagement may return divergent results that indicate an increase of one type of engagement and a simultaneous decrease in another type (see Flowerday & Schraw, 2003; Lowry, Gaskin, Twyman, Hammer, & Roberts, 2012; Skinner & Belmont, 1993).

1.1.3 Failure in Learning

Most people dislike failure and try to avoid it whenever possible. The desire to avoid failure is a central assumption of motivation theories that explain human behaviors (Atkinson, 1957; Elliot, 1999; Elliot & Covington, 2001). People try to avoid failure because it can elicit painful negative affect such as anxiety, embarrassment, loss of status, and esteem (Hagtvet & Benson, 1997). Research on decision making has suggested that individuals are particularly sensitive to failure (e.g., financial loss; Tom, Fox, Trepel, & Poldrack, 2007). When faced with even the slightest chance of failure, people are likely to disproportionately weigh losses due to failure than equivalent gains that are due to success (Kahneman & Tversky, 1979). Failure can also lead to loss of confidence, which can make people less likely to attempt similar tasks in the future (Seifert, 2004).

Some learners go to great lengths to avoid failure. Studies have found that students may deliberately choose easy tasks and not challenge their own abilities to avoid failure (Dweck & Leggett, 1988). Some may even cheat to avoid failure (Blackwell, Trzesniewski, & Dweck, 2007). Ironically, to protect their egos, students can be so afraid of failure that they may handicap themselves by procrastinating so that they can blame any failure on their lack of effort rather than their ability (Covington, 1992).

1.1.4 Experienced and Observed Failure

Previous research suggests that both direct and vicarious methods of learning effectively help learners acquire knowledge (Wood & Bandura, 1989): Individuals may successfully learn through both their own experience and through watching others' modeling behavior. Wood and Bandura (1989) describe modeling, or vicarious learning through watching an effective display of the behavior or task to be learned, as a method that creates generative behavioral patterns. Compeau and Higgins (1995) found mixed support for the effectiveness of observing modeling relative to traditional instruction; however, both methods increased self-efficacy.

Early research concerning failure in learning suggests that failure may undermine self-efficacy and threaten individuals' motivation to complete a task (Bandura, 1982). Observing failure may offer protection from the consequences of falling short and may simultaneously offer the chance to learn from others' mistakes. However, directly challenging individuals' existing ability levels is essential to creating task engagement (Kubey & Csikszentmihalyi, 1990). Individuals continuously stretching their ability may regularly experience failure. If an individual's ability exceeds the difficulty posed by the task, the individual will feel boredom. If the task difficulty exceeds the individual's ability, the individual will feel anxious (Csikszentmihalyi, 2013). Anxiety, though unpleasant, can motivate individuals to improve their skills. A review of several studies suggests failure can lead to increased efficacy if individuals frame failure as a lack of effort rather than characterizing the task as too difficult (Gist & Mitchell, 1992). In other words, when individuals conceptualize their failure as manageable, they will typically increase efforts to obtain the goal (Bandura, 2001). However, if the difficulty of a task is consistently too high and individuals repeatedly fail, they will likely feel helplessness or lose self-efficacy and, eventually, stop engaging in the activity (Nakamura & Csikszentmihalyi, 2002).

2 Hypotheses

When individuals play digital games, they have some degree of control over the actions that occur during play. Players make decisions about what they do in the game, and their actions have consequences. As players experience the consequences in the game, they receive feedback about which actions will bring them closer to the game's end goal. Therefore, players can alter their actions over the course of play to achieve the game's goal. Control over game actions and feedback are two of the defining features that separate training games from other pedagogical methods in which one observes but does not experience failure (see McGonigal, 2011). As players attempt various strategies to win the game and achieve some success in reaching their goals, they will also expect some degree of failure as they navigate a path of trial and error. However, implicit in this approach is the expectation of some success to balance out the failure and preserve engagement. We suggest that a training game can be more engaging than a training video without the need for immediate success to balance out the failure.

Although players may expect failing somewhat in a game, they may also view failure as evidence of their inadequacy. As Juul (2013, p. 7) writes:

> *When you fail in a game, it really means that you were in some way inadequate. Such a feeling of inadequacy is unpleasant for us, and it is odd that we choose to subject ourselves to it. However, while games uniquely induce such feelings of being inadequate, they also motivate us to play more in order to escape the same inadequacy, and the feeling of escaping failure (often by improving our skills) is central to the enjoyment of games*.

In sum, as players attempt to escape the inadequacy that failure in the game represents, they will be motivated to improve their in-game performance. Since a game offers players more control over and feedback about their actions than a training video, any failure in the game is more likely to be the player's responsibility (McGonigal, 2011). Therefore, players will focus more on determining what actions return success in the game even if the training game teaches a complex skill and results in repeated failure. Players will devote cognitive resources such as attention and effort to achieve the game's goals. Thus, when players fail in training games, they will still manifest cognitive engagement with the game. The level of cognitive engagement with the game will be greater than the level of cognitive engagement with a training video, which does not create a sense of inadequacy by revealing personal failure and does not offer the possibility to escape the inadequacy. Based on the above reasoning, we offer the following predictions:

Hypothesis 1: Compared to observing others' failure in a training video, experiencing failure in a training game increases the amount of eye gaze focused on the training.

Hypothesis 2: Compared to observing others' failure in a training video, experiencing failure in a training game increases cognitive absorption as measured by a) temporal dissociation, b) focused immersion, c) enjoyment, d) control, and e) curiosity.

Because failure threatens a player's self-image, the player will likely experience arousal as a result of being challenged and falling short. Moderate increases in arousal are typically associated with increased attention and elevated engagement (Lang et al., 1996; Sanbonmatsu & Kardes, 1988). Attributions for success and failure are typically asymmetric, with people more willing to claim credit for successes rather than failures (Zuckerman, 1979). Failure, compounded by this asymmetry, induces physiological arousal (Brown & Rogers, 1991). In a training game where players have control over the actions they take, any failure is more directly attributable to the players relative to the situations where players only observe failure because they have no control over the actions depicted (e.g., which is the case in a training video). This reasoning results in the following prediction:

Hypothesis 3: Experiencing failure in a training game is more physiologically arousing than observing others' failure in a training video.

Finally, we predict that, if players perceive the inadequacy that accompanies failure, even if they feel they are able to achieve the game's goal, the result will be evident when measuring affective engagement. Consistent with past literature (e.g., Smith et al., 2006), we argue that people will experience adverse affective consequences when they fail in learning tasks. Separate from the level of enjoyment that individuals may experience as part of absorption with a particular task, the affective consequences resulting from failure will likely manifest in reports from individuals about their general positive and negative affective states. Previous research supports a positive relationship between competence and affect (Ryan, Rigby, & Przybylski, 2006). Thus, in a game that results in failure, positive affect may decrease because players are faced with evidence of a lack of competence. In a similar vein, players will likely experience negative affect because they feel they remain inadequate and have not yet overcome their challenge or stretched their skills far enough.

Hypothesis 4: Experiencing failure in a training game reduces positive affect more than observing others' failure in a training video.

Hypothesis 5: Experiencing failure in a training game increases negative affect more than observing others' failure in a training video.

3 Method

3.1 Participants

We recruited 156 student participants via mass emails and classroom announcements at a large South-Central university (site 1; n = 85) and a large Southwestern university (site 2; n = 71). The sample included 53 percent females (n = 83) and 47 percent males (n = 73) who ranged from 18 to 59 years of age (M = 24.50, SD = 7.84). English was the first language of 75 percent (n = 117) of the participants. Participants reported completing between 1 and 10 years of education since high school (M = 4.20, SD = 2.23). We did not financially incentivize performance to clearly observe the treatments' effects on engagement. However, we compensated all participants with US$20 for their time.

3.2 Training Materials

We developed a digital training game called Mitigating Analyst Cognitive Bias by Eliminating Task Heuristics (MACBETH) in the strategy/simulation genre (Dunbar et al., 2013, 2014). In the game, players are immersed in a fictional environment where they gather and assess intelligence data in an attempt to thwart simulated terrorist threats around the world. The game helps players understand how deep-seated cognitive biases (confirmation bias, fundamental attribution error, and bias blind spot) can influence their decision making. Since cognitive biases are so ingrained in individuals' minds, scholars have shown that they resist traditional forms of instruction (Ehrlinger et al., 2005; Kahneman, 2011). In a novel attempt to teach individuals about the consequences of cognitive biases on decision making, we purposely designed MACBETH's scenarios to penalize players if they demonstrate cognitive biases. The game provided players with corrective feedback on what they did wrong and taught them strategies to mitigate cognitive biases[1].

Before participants played MACBETH, we gave them a short verbal tutorial and several illustrations about the function of the game controls. Additionally, MACBETH provided guidance concerning gameplay via popup hints to orient and assist players. During the game, players formed a series of hypotheses about three components of the threat: location of the attack, the weapon that would be used, and the perpetrator's identity. Through successive turns, players gathered information from a variety of sources (e.g., signal intelligence, human intelligence, and open sources) and worked with other virtual agents to refine their hypotheses. To settle on a correct hypothesis, players had to synthesize information from all of these sources in 30 minutes to decipher the three components of the threat. Figure 1 shows a screenshot of the game. Out of the 75 participants who played MACBETH, only four correctly identified all three components of the threat in 30 minutes. However, the four successful players also experienced failure during portions of the game, and, thus, we retained them in the sample. The average number of correctly identified threat components was .95, SD = .84 (less than one out of three). In sum, after 30 minutes of playing the game, players predominantly experienced failure, not success.

The training video was also 30 minutes in length and depicted a narrator discussing each of the three biases (confirmation bias, fundamental attribution error, and bias blind spot). The narrator defined each bias and then introduced short vignettes that depicted each bias. The video also showed the negative consequences that resulted from using cognitive biases. The discussion of each bias concluded with the narrator's reviewing strategies that viewers may use to mitigate the bias. A total of 81 participants watched the training video[2].

[1] Since we focus on engagement here, we do not discuss the learning outcomes of MACBETH (e.g., bias knowledge, bias mitigation). However, detailed reports of the learning outcomes are available (Dunbar et al., 2013, 2014).

[2] The Intelligence Advanced Research Projects Activity (IARPA) funded this work via their SIRIUS program. They created the instructional video without input from the research team, who did not see the video until MACBETH development was nearly complete.

Figure 1. Screenshot of the Game

3.3 Procedure

After arriving and signing consent forms, participants entered another room to complete the experiment. Experimenters administered pre-test measures, the experimental treatment, and post-test measures. We alternated experimental conditions (game or training video) for participants to maintain roughly equal cell sizes.

In all conditions at site 1 (n = 85), an experimenter attached the physiological feedback sensors to the participant: two sensors for collecting electrodermal responses measuring the skin conductance level (SCL) and one sensor for heart rate (HR) using photoplethysmography (PPG). While attaching the sensors to each participant's non-dominant hand, the experimenter explained the nature of the data to be collected and the sensors' purpose. The experimenter instructed participants to keep their sensored hand as still as possible for treatment's duration. The experimenter then recorded baseline SCL and HR data for 30 seconds after which either the experimenter administered either the game or video treatment. During treatment, sensors continuously gathered SCL (10 Hz.) and HR (100 Hz.) data. We discarded SCL and HR data from 15 participants because of excessive participant movement, errors in applying the sensors, or technical difficulties in estimating the HR or SCL.

Each location had one computer with an eye tracker, a Tobii X120 Eye-Tracker at site 1 and an ASL Eye-Trac 6 at site 2. Whenever an eye-tracker station was available, the experimenter directed participants to complete the experiment using the eye tracker. A subset of 28 participants at site 1 and 36 at site 2 participated in the eye-tracking sample. Participants using the eye tracker sat in a rigid, non-swiveling chair. The experimenter then initiated the calibration process requiring participants to trace an on-screen object with their eyes. After successful calibration, the experimenter began either the game or training video. We eliminated two participants (at site 1) from eye-tracking analysis because we recorded their data less than 40 percent of the time due to excessive movements or equipment failures.

3.4 Measures

Table 1 summarizes the engagement measures. We describe each measure in greater detail below. While these measures do not represent an exhaustive list of possible methods to capture engagement, they reflect cognitive and affective facets of engagement as gathered via self-report and physiological data collection.

Table 1. Physiological and Self-report Measures of Engagement

Category	Engagement measure
Physiological	Eye-tracker (site 1) Skin conductance (site 1) Heart rate (site 1) Pupil dilation (site 2)
Self-report	Cognitive absorption Positive affect Negative affect

Note: where we indicate the location (e.g., site 1 or site 2), only that location provided that type of data due to the equipment available at each location.

3.4.1 Attention

To measure attention, we used the Tobii X120 Eye-Tracker at site 1. The Tobii X120 captures 120 samples of gaze data per second and can record when a participant's gaze enters an area of interest (AOI) on the screen (defined here as the window containing the game or video). We analyzed gaze by computing a percent of gaze fixation in the AOI (i.e., gaze focused on the game or video) during the treatment segment.

3.4.2 Absorption

Cognitive absorption (Agarwal & Karahanna, 2000) captures how deeply users engage with technology using a seven-point Likert scale ranging from "strongly disagree" to "strongly agree". The measure includes five subscales: temporal dissociation (five-item $\alpha = .76$; e.g., "Time flew when I was engaged in the training tool."), focused immersion (five-item $\alpha = .87$; e.g., "While I was engaged with the training tool, I was able to block out most other distractions."), enjoyment (four-item $\alpha = .90$; e.g., "I had fun when I was engaged with the training tool."), control (three-item $\alpha = .70$; e.g., "When I was engaged with the training tool, I felt in control."), and curiosity (three-item $\alpha = .86$; e.g., "The training tool excited my curiosity.").

3.4.3 Arousal

Both HR and SCL reflect increased sympathetic nervous system arousal (Nes, Segerstrom, & Sephton, 2005). Scholars have used co-registration of indicators of physiological arousal as an indicator of engagement (Keil et al., 2008). We measured HR and SCL using UFI's six-channel BioLog. The HR was based on PPG, which illuminates skin and measures changes in light absorption over time as blood flows into and out of the measurement area (i.e., finger). The HR was sampled at 100 Hz and was estimated using a proprietary algorithm from UFI that records output in heart-beats per second. The SCL was based on level of resistance between two sensors placed on adjacent fingers sampled at 10 Hz. As mentioned above, to avoid interference with gameplay, we placed HR and SCL sensors on the players' non-dominant hand.

To measure arousal from oculesic responses, we sampled participants' pupil diameters using the ASL Eye-Trac 6 at 60 Hz. Pupil dilation also corresponds to sympathetic activity (Bijleveld, Custers, & Aarts, 2009). Widening pupils indicate interest level (Hess & Polt, 1960) assuming lighting conditions remain constant and distractions are minimized. Scholars have also previously linked pupil diameter to engagement (Marshall, 2005).

3.4.4 Affect

The positive and negative affect schedule (PANAS; Watson, Clark, & Tellegen, 1988) is a scale of positive and negative affect indicating to what extent participants experience certain feelings, emotions, and affective states. Two 10-item subscales (one for positive and one for negative affect) measured affect on a five-point Likert scale ranging from “very little” to “extremely”. The 10-item positive affect subscale ($\alpha = .92$ at pretest, $\alpha = .94$ at posttest) included: attentive, strong, inspired, alert, active, excited, proud, enthusiastic, determined, and interested. The 10-item negative affect subscale ($\alpha = .93$ at pretest, $\alpha = .92$ at posttest) included: irritable, afraid, upset, guilty, nervous, hostile, jittery, ashamed, scared, and distressed. We administered the PANAS twice during the experiment, once before and once after treatment to capture participants’ changes in affect.

3.4.5 Personality and Attitude Scales

Because we collected data at two different research sites, we used several personality and attitude scales to rule out systematic differences between the two locations. We used the ten-item personality inventory (TIPI) to measure the big-five personality traits (Gosling, Rentfrow, & Swann, 2003). Each of the five traits included two subscales with two items per subscale, which significantly correlated at $p < .05$ (extraversion, $r = .74$; agreeableness, $r = .48$; emotional stability, $r = .60$; conscientiousness, $r = .50$; openness, $r = .33$) (Rosenthal, 1982). We also gauged computer comfort (5 items; $\alpha = .73$, e.g., “I am an expert computer user”) and assessed gaming experience (5 items; $\alpha = .90$, e.g., “I consider myself a gamer”) on seven-point Likert scales ranging from “strongly disagree” to “strongly agree”.

4 Results

4.1 Comparability of Samples and Conditions

To confirm the two location samples were comparable, we performed a MANOVA with the location (site 1 or site 2) as the independent variable and the personality and attitude scales and self-reported measures of engagement as the dependent variables. The omnibus test for location (Wilks’ $\Lambda = .87$, $F(14, 136) = 1.45$, $p = .14$) was non-significant. In addition, none of the univariate tests produced significant results (all were $p > .05$), which suggests approximate comparability between the two locations. Therefore, unless we used different instruments at the two locations, we combined the site 1 and site 2 samples for subsequent analyses.

Additionally, we examined participants’ personality traits, computer comfort, and gaming expertise to rule out potential differences between conditions as a result of perceived self-efficacy. We performed a MANOVA with the game or video condition as the independent variable and the personality and attitude scales as the dependent variables. The omnibus test for condition (Wilks’ $\Lambda = .98$, $F(7, 147) = .38$, $p = .92$) did not produce significant results. Similarly, all univariate tests were not significant ($p > .05$), which suggests comparability between conditions for personality traits, computer comfort, and gaming expertise.

4.2 Attention

For the site 1 eye-tracking sample, we first conducted a univariate ANOVA with game or video condition as the independent variable and percent of gaze directed at the game or video as the dependent variable. Consistent with H1, participants in the video condition ($M = 84.3\%$, $SD = 6.6\%$, $n = 13$) looked at the AOI significantly less ($F(1, 24) = 11.50$, $p = .002$, $\eta_p^2 = .32$) than those in the game condition ($M = 93.5\%$, $SD = 7.1\%$, $n = 13$), which demonstrates that participants paid significantly greater attention to the game compared to the video condition.

4.3 Absorption

To determine the effects of the game versus the video on cognitive absorption, we conducted a MANOVA with the five cognitive absorption subscales as the dependent variables. The omnibus test for the treatment effect was significant (Wilks’ $\Lambda = .86$, F (5, 148) = 4.67, $p = .001$, $\eta_p^2 = .14$). Univariate tests showed a significant difference in the expected direction between the game and video conditions on the amount of temporal dissociation experienced during the treatment ($F(1, 152) = 13.96$, $p = .001$, $\eta_p^2 =.07$). However, no other differences were significant on other cognitive absorption subscales; thus, these results provide limited support for H2. Table 2 presents the means, standard deviations, and pairwise comparisons of the means using a Bonferroni adjustment.

Table 2. Means, Standard Deviations, and Pairwise Tests Comparing Training Video to Game on Cognitive Absorption (n = 156)

Subscale of cognitive absorption	Training video M (SD)	Game M (SD)	Pairwise test p-values
Temporal disassociation	4.26 (1.13)	4.86 (1.12)	.001
Focused immersion	4.78 (1.16)	5.05 (1.10)	.163
Enjoyment	4.50 (1.17)	4.46 (1.24)	.868
Control	4.36 (1.32)	4.64 (1.00)	.137
Curiosity	4.69 (1.25)	4.57 (1.25)	.537

4.4 Arousal

4.4.1 Heart Rate and Skin Conductance

We collected the physiological response data from participants only in the site 1 sample (*n*Game = 34 and *n*Video = 36). For the analysis, we isolated and established mean HR and SCL for each 30-second baseline and 30-minute treatment segment using the Biolog software (see Table 3). To analyze the data, we entered the baseline and treatment means into two, one-way, mixed-model ANOVAs—one for HR and one for SCL—with experimental treatment as the between-subjects factor and baseline/treatment segment as the within-subjects factor.

Participants' HR increased from the baseline to treatment segments ($F(1, 68) = 17.41$, $p < .001$, $\eta_p^2 = .20$) in both video and game conditions. Although the pattern observed in HR was consistent with expectations, HR did not differ significantly between game and video conditions ($F(1, 68) = 0.34$, $p = .56$). In contrast, there was a marginally significant effect of condition by baseline/treatment interaction for SCL ($F(1, 68) = 3.13$, $p = .08$, $\eta_p^2 = .04$). Participants in the video condition demonstrated a decrease in SCL from the baseline to treatment segments, while participants' SCL in the game condition remained relatively constant. These tests suggest mixed support for H3.

Table 3. Means and Standard Deviation of Physiological Measures (n = 85)

Bio-physiological measure	Training video baseline	Treatment	Game baseline	Treatment
Heart rate	72.79 (11.97)	75.77 (9.77)	69.89 (11.40)	75.80 (11.38)
Skin conductance level	3.56 (2.29)	2.60 (1.79)	4.31 (3.20)	4.24 (4.39)

4.4.2 Pupillary Response

To analyze changes in pupil dilation over time, we used a growth curve analysis approach, which affords an ideal method for pupil diameter comparisons via a regression technique accounting for changes across time while simultaneously examining both within-subject and between condition effects (Mirman, Dixon, & Magnuson, 2008). For each participant, we calculated a pupil diameter trend line for the entire task by regressing pupil diameter on time to determine whether participants' arousal was increasing or decreasing with time. The 36 trend lines produced an unstandardized beta (slope) value for each participant. A positive slope represented increased pupil dilation over time, whereas a negative slope represented narrowing pupils over time. In an independent samples *ds* test, we compared the slopes for the game and video conditions: we found the average pupil dilation slope for participants in the video condition was slightly negative ($M = -0.06$, $SD = 3.23$), that the average pupil dilation slope for participants in the game condition was positive ($M = 11.06$, $SD = 4.77$), and that the difference between these slope means was significant ($t(34) = 2.32$, $p = .026$, Cohen's $d = 2.73$). These results support H3.

4.5 Affect

Since we administered the PANAS prior to and following the video or game treatment, we conducted two one-way mixed-model ANOVAs. The first ANOVA examined the treatment's influence on positive affect and the second on negative affect. For both ANOVAs, the experimental treatment served as the between-subjects measure and the time of measurement (pre vs. post) served as the within-subjects factor. Table 4 shows the means and standard deviations for both analyses. The participants' positive affect significantly decreased from the pre- to post-measures (F(1, 151) = 16.23, p < .001, v = .10). In addition, there was a condition by time of measurement interaction on positive affect (F(1, 151) = 6.44, p = .012, η_p^2 = .04). Consistent with H4, game players experienced a greater decline in positive affect than participants who watched the video. Contrary to H5, there was also a significant decrease in negative affect from the pre to post measures (F(1, 152) = 11.96, p = .001, η_p^2 = .07). However, the condition by time of measurement interaction failed to reach significance (F(1, 152) = 2.48, p = .117).

Table 4. Means and Standard Deviation of Positive (n = 153) and Negative Affect (n = 154)

	Pre-training video	Post-training video	Pre-game	Post-game
Positive affect	2.83 (0.97)	2.73 (1.00)	3.17 (0.69)	2.75 (0.83)
Negative affect	1.63 (0.78)	1.43 (0.64)	1.81 (0.78)	1.73 (0.72)

5 Discussion

Table 5 summarizes our findings.

Table 5. Summary of Research Findings

Summarized hypotheses	Measure type	Measure	N	Finding
H1: Compared to observing others' failure in a training video, experiencing failure in a training game increases the amount of eye gaze focused on the training.	Physiological	Gaze at area of interest	26	Supported
H2: Compared to observing others' failure in a training video, experiencing failure in a training game increases cognitive absorption as measured by a) temporal dissociation, b) focused immersion, c) enjoyment, d) control, and e) curiosity.	Self-report	Cognitive absorption	156	Limited support: significant only for temporal dissociation
H3: Experiencing failure in a training game is more physiologically arousing than observing others' failure in a training video.	Physiological	Heart rate	70	Not supported
		Skin conductance	70	Limited support
		Pupil dilation	36	Supported
H4: Experiencing failure in a training game reduces positive affect more than observing others' failure in a training video.	Self-report	Positive affect	153	Supported
H5: Experiencing failure in a training game increases negative affect more than observing others' failure in a training video.	Self-report	Negative affect	154	Not supported

Individuals go to great lengths to avoid failure. Scholars have shown that experiencing failure evokes negative affect and leads to loss of status and to lower esteem (Hagtvet & Benson, 1997). Intuitively, failure could undermine learning engagement, especially when the failure is directly the result of one's own actions. In our study comparing engagement between a game in which virtually all the participants experienced failure to achieve the game's objectives to an instructional video in which participants only observed failure experienced by others, we found some differences in engagement between game players and passive video observers. Our findings imply the effects of failure in a game-based learning environment may be more nuanced than intuition would suggest.

Despite their increased cost and higher requirement for instructional time, digital training games can generate more engagement than a standard lecture-based learning format (Garris et al., 2002). The present work contributes to existing research by demonstrating elevated levels of engagement even when failure in the training game was prevalent. Game players remained cognitively engaged even when they clearly failed to win the game. Players devoted more attention to their learning tasks and reported that they were more temporally disassociated than individuals who watched the training video. In addition, game players demonstrated elevated arousal (measured by pupil dilation and skin conductance) beyond that observed in individuals who watched the training video. However, the findings also showed a decrease in positive affect after individuals played the game, and no such drop emerged for those watching the training video. Taken together, these findings suggest a complex interplay between the facets of engagement when individuals watch versus experience failure. Failure does not completely undermine engagement nor completely promote engagement. Our results indicate that experiencing failure clearly has costs, but these costs appear to be initially limited to the affective facets of engagement. Cognitive facets of engagement actually increase as a result of experiencing failure. These findings are important for complex training tasks such as altering the use of heuristics and mitigating cognitive bias where learners are likely to experience a significant level of failure during learning.

The game players could have possibly ascribed their failure to some source other than themselves. For example, if players had difficulty playing the game (e.g., with game controls, goals of the game), they may not have felt responsible for their failure to win the game. To ensure that the participants did not perceive difficulty playing the game to be the source of failure, we took steps to orient the players and familiarize them with game controls. Additionally, the game offered guidance to players in the form of popup hints during game play. Finally, at the conclusion of the experiment, we asked players two free-response questions about any questions or concerns they had about the experiment and any suggestions for improving the training materials or the questionnaires. Four game players made comments about the game. Two players desired better instructions, one player wished for a friendlier user interface, and one player was initially confused that gameplay included multiple turns. Since only four out of 75 game players commented on the game’s difficulty, we concluded that some participants could have perceived game difficulty as a source of failure. However, such perceptions were likely not widespread.

These findings also have implications for the concept of flow, the deep level of involvement in a task or activity. Our results suggest that game players can become deeply engrossed in a task that is neither intrinsically rewarding nor pleasant for them to experience. Game players devoted 97 percent of their gaze to the game and reported that they lost track of time while they played—both hallmarks of deep involvement in the task. Prior research has suggested the necessity of aligning ability and the level of task difficulty (Nakamura & Csikszentmihalyi, 2002). Our results indicate that there may be greater flexibility in aligning ability with difficulty to achieve a level of deep task involvement than has been previously been believed. Other researchers have observed this phenomenon (e.g., Juul, 2013; McGonigal, 2011), and our research provides additional empirical support. Cognitive engagement, it appears, can be achieved even when difficulty overmatches ability.

For other researchers interested in measuring engagement with stimuli, we present a multi-method approach for capturing engagement containing both physiological and reflective self-report measures. Such a measurement approach balances out the benefits and limitations of each method and provides a holistic view of engagement. In this study, we found only some overlap between the self-report and the physiological measurements, which suggests that each measure captures different aspects of engagement. As expected, the multi-method approach was crucial to demonstrating facets of engagement that diverged as the result of experiencing failure. It is possible that facets of engagement may diverge in their indication as the result of characteristics in other learning environments, and we offer our measurement approach as a model for testing such nuanced predictions. Triangulating different measurements of engagement is an understudied area of research that should be explored in future research.

Note that the video and the game were both novel training stimuli and relatively short in duration (30 minutes). It is possible that the increase in cognitive engagement we observed may be due to the training’s short duration or novelty. Additionally, it is possible that, if players experience repeated failure over an extended period, the promise of escaping the implied inadequacy would fade. The results presented here do not explore how long elevated cognitive engagement will persist in the face of persistent failure. These results only suggest that, at least initially, cognitive engagement could increase as a result of failure in a game-based learning environment. We need additional experiments to determine the robustness of these findings over time.

Another important boundary to consider when discussing the possible generalizability of these findings to other tasks where failure may be experienced is that we focused on a learning task. Unlike many video game studies, the task was not a hedonic pursuit with pleasure as the primary goal. This critical boundary is especially relevant for training games because player motivation for other types of games is typically entertainment. With training games, players may be more tolerant of failure because the purpose of the game’s design, mechanics, and feedback is to help players to succeed. Thus, players may be more resistant to failure because the purpose of the game is to help them escape failure.

6 Limitations and Future Research Directions

Our study has several limitations. First, we drew the experiment sample from an undergraduate student population. While this population is susceptible to cognitive biases and while we specifically developed the training materials for them, we need additional research to determine the effects of failure with a more diverse sample of individuals. Second, we have explored only one type of complex task in this work that is focused on cognitive biases and used only two instructional methods (game and training video). We need further research to determine whether these findings apply to other complex tasks or instructional methods where learners are being instructed on deeply ingrained behaviors or practices. Finally, we examined how observed and experienced failure influenced engagement. Our findings suggest that differences in engagement exist between observed and experienced failure, but we acknowledge that we need additional research to examine different levels of failure *in* each training medium to more clearly determine the effect of failure on engagement. Further, our research opens new questions about how one should conceptualize engagement and how cognitive and affective facets of engagement are related. These issues merit future attention from researchers.

7 Conclusion

Training games are a valuable mechanism for teaching learners about a variety of topics. By using both self-report and physiological measures of engagement, we demonstrate that the benefits from interactive training environments such as digital games may outweigh the drawback of experiencing failure. Since failure does not undermine cognitive engagement and actually increases it in the short term, one should consider using training games to teach complex topics.

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