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The productive role of cognitive reappraisal in regulating affect during game-based learning☆

Catherine A. Spann[a], Valerie J. Shute[b], Seyedahmad Rahimi[b], Sidney K. D'Mello[a,*]

[a] University of Colorado Boulder, United States
[b] Florida State University, United States

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ABSTRACT

We conducted an exploratory study on affect regulation during game-based learning where 110 college-aged participants (M_{age} = 22.14, SD_{age} = 1.24; 50.0% female; 70.0% White) played an easy, medium, and difficult level of an educational game (Physics Playground) while self-reporting their strongest affective state and regulation strategies associated with each level. Participants also self-reported their effort and completed a physics posttest after gameplay. We found that frustration, confusion, determination, and curiosity were the dominant affective states (81.4% of total reports) while cognitive reappraisal and acceptance were the major affective regulation strategies (others individually occurred less than 10.1% of the time). Engaging in cognitive reappraisal – an affective regulation strategy that involves changing the way one thinks about a situation – was beneficial for successfully solving a level when participants were frustrated or confused, but had no effect when participants were determined or curious. Engaging in cognitive reappraisal when experiencing high frustration/confusion positively predicted posttest scores, but only for those who put a high amount of effort into the game. For students who were low in effort or low in frustration/confusion, simply accepting one's emotions when experiencing high frustration/confusion was beneficial. We discuss theoretical implications and applications towards game-based learning supports to promote persistence and learning outcomes.

Introduction

Imagine you are learning physics while situated in front of your computer. Instead of reading terse texts on Newton's First Law, you are immersed in a game where you must *use* the relevant principles of the law to solve a level and advance in the game. Does this sound more appealing than reading? Now imagine playing a level where you feel stuck, unable to find a solution. You grow increasingly confused, frustrated, and possibly angry. You may pause, telling yourself that it is just a game and you can figure it out, take a deep breath to calm down, attempt a new strategy, and ultimately solve the level. This process of affect generation and affect regulation is part and parcel of game-based learning (GBL) (Gutica & Conati, 2013; Sabourin & Lester, 2014; Shute, D'Mello, et al., 2015 and Shute, Ventura, et al., 2015), and learning more generally (Calvo & D'Mello, 2011; Kim & Pekrun, 2014; Pekrun & Linnenbrink-Garcia, 2014). Whereas several studies have investigated the incidence of affective states in GBL (Gutica & Conati, 2013; Sabourin & Lester, 2014; Shute, D'Mello, et al., 2015 and Shute, Ventura, et al., 2015), few have investigated affective *regulation* in GBL, which pertains to the set of processes individuals use to increase, decrease, or maintain particular affective states in order to achieve desired outcomes (Gross, 1998), a gap we address in this paper.

In doing so we contribute to models of self-regulated learning by Zimmerman (1989), Boekaerts (1991), Winne and Hadwin (1998), Pintrich and De Groot (1990), and more recently, by Efklides (2011) and Järvelä and Hadwin (2013), especially those that espouse important roles for affect and its regulation, such as models by Boekaerts (1991) and Järvelä and Hadwin (2013). Some of these models (e.g.,Boekaerts, 1991; Järvelä & Hadwin, 2013) consider affect regulation as an important component of self-regulated learning, but empirical research on specific affect regulation *strategies* has been slow to emerge (Panadero, 2017). We advance the empirical knowledge base of these models by explicitly investigating affect regulation strategies and their relationship with the learning process and learning outcomes.

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* Corresponding author. 594 UCB, Boulder, CO 80309, USA.
E-mail address: sidney.dmello@colorado.edu (S.K. D'Mello).

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1.1. Background

We situated our work in the context of GBL because, compared to less engaging and interactive learning environments where affect regulation has been studied (Price, Mudrick, Taub, & Azevedo, 2018; Strain & D'Mello, 2014), well-designed games are known to produce emotionally-rich learning experiences (see Clark, Tanner-Smith, & Killingsworth, 2016 for a meta-analysis of digital games and learning). Accordingly, our work connects three research areas – game-based learning, affect during learning, and affect regulation; which we briefly review below.

Game-based learning. Game-based learning refers to using well-designed games as vehicles to support learning of various competencies, attributes, and outcomes such as visual-spatial abilities and attention (e.g., Green & Bavelier, 2007, 2012; Shute, Ventura, & Ke, 2015), openness to experience (Chory & Goodboy, 2011; Ventura, Shute, & Kim, 2012), persistence (Ventura, Shute, & Zhao, 2012), creativity (Jackson et al., 2012), civic engagement (Ferguson & Garza, 2011), as well as valuable academic content and skills (for reviews, see Tobias & Fletcher, 2011; Wilson et al., 2009; Young et al., 2012). Games that incorporate problem solving, adaptive challenges, and ongoing feedback can trigger and sustain interest and motivation, in turn supporting engagement and learning (e.g., Shute, Rieber, & Van Eck, 2011). In addition, adaptive challenges and dynamic performance feedback in a game helps create an environment that can foster the sense of flow (Csikszentmihalyi, 1990) and potentially cultivate the mindset that generates persistence and effort-driven competency development (Dweck, 2006; Yeager & Dweck, 2012). Moreover, educational games do, in fact, foster learning (Shute, Leighton, Jang, & Chu, 2016), by incorporating effective learning principles, such as the provision of ongoing feedback, interactivity, and active participation – factors known to lead to improvements in knowledge and skill acquisition (Gee, 2003; Ifenthaler, Eseryel, & Ge, 2012; Shute, Ke, & Wang, 2017).

Despite considerable progress in GBL over the last two decades, there is still much room for improvement. One of the key goals in the design of educational games is to create an engaging and flexible environment that supports learning for a broad range of learners. Achieving this goal depends on measuring pertinent learner characteristics—e.g., prior knowledge, affective states, motivation—and determining how to use that information to improve the gaming experience and learning outcomes (Conati, 2002; Shute, Lajoie, & Gluck, 2000; Shute & Zapata-Rivera, 2012). Here, we focus on how games can support learners by helping them regulate the affective states that they will inevitably experience during gameplay.

Affective States during Learning. From frustration to joy, anxiety to curiosity, learners experience a rollercoaster of affective states[1] during learning, with GBL being no exception (Shute, D'Mello, et al., 2015 and Shute, Ventura, et al., 2015). Although one strength of well-designed educational games is their ability to stimulate positive affective states (e.g., delight, eureka), which have the power to prime the cognitive system toward heuristic-driven processing and creative exploration (Clore & Huntsinger, 2007; Isen, Daubman, & Nowicki, 1987), the challenge-inspired nature of well-designed games can also trigger negative affective states (e.g., confusion, frustration). Students get *confused* when outcomes do not match expectations, when they encounter challenging impasses, and when they are unsure of how to proceed (D'Mello & Graesser, 2014a; VanLehn, Siler, Murray, Yamauchi, & Baggett, 2003). *Frustration* occurs when students make mistakes, get stuck, and run out of options on how to resolve obstacles that block goals (Kapoor, Burleson, & Picard, 2007; Stein & Levine, 1991). Negative affective states, however, play an important role in learning (D'Mello & Graesser, 2014b; Kim & Pekrun, 2014) because affect is more than just incidental; it is functional.

Affective states perform signaling functions (Schwarz, 2000), for example, by highlighting problems with knowledge (confusion), as well as evaluative functions by appraising events in terms of their value, goal relevance, and goal congruence (Izard, 2010; Stein & Levine, 1991). Affective states also perform modulation functions (reviewed in Fiedler & Beier, 2014) by constraining or expanding cognitive focus—as is the case when positive affective states facilitate creative problem solving by engendering broader, top-down, generative processing (expanded focus) (Isen et al., 1987), and when negative affective states trigger narrow, bottom-up, and focused modes of processing (constrained focus) (Barth & Funke, 2010; Schwarz, 2000).

But it is misleading to adopt a simplistic view that positive affect is beneficial and negative affect is harmful. The mechanisms by which affect influences learning depends on multiple factors, such as the level of arousal aligned with task demands (Mandler, 1984; Yerkes & Dodson, 1908) and the extent to which affective thoughts consume working memory resources, thereby increasing cognitive load (Eysenck, 1985; Fraser et al., 2012; Paas & Ayres, 2014; Ramirez & Beilock, 2011). Thus, both positive and negative affective states can be beneficial for learning in certain contexts, such as when happiness leads to more creativity (Isen et al., 1987), sadness leads to deeper analytical processing (Mills, Wu, & D'Mello, in press), or when feeling somewhat anxious can galvanize attentional resources (Pacheco-Unguetti, Acosta, Callejas, & Lupiáñez, 2010).

There are also situations where affective states can be harmful for learning (Gross & Jazaieri, 2014). Whereas some confusion and frustration are an important part of complex learning (D'Mello & Graesser, 2014a; Lehman, D'Mello, & Graesser, 2012), intense or prolonged confusion and frustration can lead to lower learning outcomes (Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010). Prolonged frustration, for example, can lead to anxiety and despair (Zeidner, 2007) and eventual disengagement (Pekrun et al., 2010). Instead of engaging deeply in creative exploration and knowledge construction, struggling and disengaged students exhibit problematic behaviors such as systematic guessing (Baker, Corbett, Koedinger, & Wagner, 2004) or trying to obtain solutions from other students rather than discovering them on their own (Nelson-Legall, 1987). Such instances of intense negative affective states necessitate the need for strategies to help learners regulate these states.

Affective Regulation. Affective regulation refers to efforts to influence which affective states one has, when one has them, and how one experiences or expresses them (Gross, 1998). Ranging from attempts to think about a situation differently, focusing on one's breathing, punching a wall, biting one's nails, or getting on social media for a distraction, affective regulation can take a variety of forms. Unsurprisingly, different regulation strategies produce different outcomes due to their differential effects on physiological and cognitive processes, such as physiological arousal, attentional focus, and cognitive load.

One popular framework for organizing these strategies is the *process model of emotion regulation* (see Gross, 2015 for a review), which frames the regulatory process in four distinct strategies (although regulation strategies are often used in combination; Werner, Goldin, Ball, Heimberg, & Gross, 2011). The first strategy, *situation modification*,[2] refers to taking steps toward altering a situation to change its emotional impact (e.g., getting on social media rather than doing a tedious homework assignment to prevent boredom). Although modifying one's situation can lead to short-term relief, this strategy is detrimental if it

[1] We use the broad term "affective states" rather than the more restrictive term "emotions", which does not cover the range of states learners experience, such as confusion and determination (see D'Mello & Graesser, 2014a).

[2] Because situation modification could involve creating a new situation, there is not a clear line between situation modification and situation selection (i.e., choosing which situation to engage in), though earlier models of affective regulation separated the two (Gross, 1998).

prevents exposure to a situation which has longer-term benefits (e.g., engaging in a tedious skill-building task is beneficial years later, Galla et al., 2014). The second affective regulation strategy, *attentional deployment*, refers to shifting one's attention either within a given situation (e.g., shifting attention from one game feature to another) or shifting attention away from the situation altogether (e.g., intentionally thinking about what you will eat for dinner while playing the game). It might also involve *ruminating* on the emotional experience, which can occupy working memory resources (Curci, Lanciano, Soleti, & Rimé, 2013).

The third strategy, *cognitive change*, refers to modifying one's appraisal of a situation (e.g., telling oneself that a game is really fun despite being frustrated). Cognitive reappraisal is the most well-studied form of cognitive change, which involves systematically changing one's appraisals about a situation in order to alter its affective impact. For example, participants instructed to think objectively in order to decrease emotional reactivity to affectively charged films, for example by taking the role of a medical professional or by focusing on technical aspects of disgust-inducing videos of surgical procedures, vomiting, and animal slaughter, experienced less negative affect than participants who used no reappraisal strategy (Goldin, McRae, Ramel, & Gross, 2008). Relatedly, emerging research has shown that cognitive reappraisal can be beneficial in learning contexts, including standardized test tasking and reading comprehension (Jamieson, Mendes, Blackstock, & Schmader, 2010; Strain & D'Mello, 2014).

The final strategy, *response modulation*, refers to directly influencing experiential, behavioral, or physiological components of the affective response. It can take many forms, one of which is relaxation or deep breathing to alter one's physiological responses (Thayer & Lane, 2009). One of the most studied forms of response modulation, however, is expressive suppression, or inhibiting one's emotion-expressive behavior. Suppression is generally a maladaptive regulation strategy and can lead to impaired memory (Johns, Inzlicht, & Schmader, 2008; Richards, Butler, & Gross, 2003) and greater activation in emotion-generative brain regions, which can negatively influence cognitive control (Goldin et al., 2008).

Affective regulation influences the quality of an affective state as well as its intensity or the time at which it is experienced (Gross, 1998). The use of adaptive affective regulation strategies has positive effects not only on obvious dimensions, such as subjective well-being, but also on academic performance (Gross, 2015; Voltmer & von Salisch, 2017) because affective regulation plays a central role in learning and memory (e.g., Gross, 2015; Järvenoja & Järvelä, 2009; McRae, 2016). In emotion regulation research, it is common to distinguish adaptive from maladaptive emotion regulation strategies depending on their associations with psychological well-being. However, this distinction might be too simplistic in learning contexts, in which positive and negative affective states can differentially impact learning outcomes (see above).

1.2. Current study

Most educational games promote a high degree of interactivity compared with existing alternatives (e.g., reading textbooks, listening to lectures). Play involves active cognitive and/or physical engagement that allows for the freedom to fail (and recover) and to experiment freely (Rieber, 1996). These features also contribute to a rich affective experience during gameplay, yet we know relatively little about how learners regulate those states and which regulation strategies are beneficial, harmful, or benign.

We address this gap by conducting an online study where participants played three levels of an educational game called Physics Playground (Shute & Ventura, 2013), and, after each level, reported their strongest affective state and what they did to regulate that state. After completing all levels, we assessed both effort put into gameplay (using a self-report survey) and physics knowledge (using a physics posttest).

Our study was designed to address the following research questions: (1) Which affective regulation strategies do learners engage in to manage their affective states during short but challenging gameplay with Physics Playground? and (2) What is the relationship among affective states, affect regulation strategies, and outcomes (gameplay success and posttest scores) and what factors moderate these relationships? In addition to advancing theories of self-regulated learning by contributing to the knowledge base on affect regulation, addressing these questions is also a first step towards a broader goal of developing in-game supports to help learners productively regulate their affect to promote engagement and learning.

It is important to consider a number of design decisions that guided the study design. Recall that our primary focus is on investigating affect regulation and its influence on gameplay outcomes. To keep scope manageable, we focused on the "strongest" affective state and the regulation strategy used to address it rather than consider multiple states or co-occurring affective states as this could quickly lead to a combinatorial explosion in possibilities.

Next, to keep total study time manageable, while maximizing gameplay time, we did not include a pretest. Thus, rather than examining learning gains (i.e., pretest to posttest improvement) as a function of gameplay, we focused on the relationships among in-game affective states, effort expended in the game, and affect regulation strategies relative to posttest scores.

To increase the likelihood of eliciting strong emotions and associated regulatory strategies, we manipulated level difficulty in that each participant completed one easy, one medium, and one difficult level. Because the manipulation was intended to induce strong emotional responses, it was necessary to limit gameplay to three levels for ethical purposes.

Finally, we wanted to ensure that participants meaningfully engaged in each level in order to experience a strong emotion and have an opportunity to regulate it rather than immediately quit. Therefore, we required participants to play each level for a minimum of 4-min before they were allowed to quit the level, unless they solved it within 4-min. They could resume playing after the initial 4-min had elapsed and many opted to do so; there was no further restrictions for the level in that participants could either solve the level or quit at any time. We do not think that the 4-min minimum of gameplay per level (unless they solved it within 4-min) impedes an analysis of affect regulation. Prior research has also successfully investigated affect regulation in much shorter time intervals (e.g., in as little as 5 min in a recent study on frustration tolerance (Meindl, Yu, Galla, Quirk, Haeck, & Goyer, in press)).

In summary, these choices were design decisions made to satisfy the goals of the present study, but should be considered when applying the findings more broadly because, like any study, our findings are constrained within the research context – in this case, an online study involving three, relatively short, levels of varying difficulty in Physics Playground.

2. Method

2.1. Participants

We recruited 125 individuals through TurkPrime (Litman, Robinson, & Abberbock, 2016), an Internet-based research platform that integrates with Amazon Mechanical Turk (MTurk) where individuals complete Human Intelligence Tasks (HITs) for monetary compensation. Participation in the study was voluntary and was approved by the Institutional Review Board at the first author's university. Participants received \$4.50 for completing the 30–40-min study. Participation was restricted to college students in the United States based on self-reported information on TurkPrime. The sample reduced to 110 (M_{age} = 22.14, SD_{age} = 1.24; 50.0% female; 70.0% White) after removing three participants who completed the study twice and 12 who did not have gameplay data.

2.2. Pilot studies

All materials and procedures were piloted prior to conducting the main study using small groups of participants recruited through MTurk. The goal of the pilots was to ensure that the technology functioned appropriately, the instructions and questions could be easily understood, relevant affective states were included, and the difficulty manipulation was effective. Participants had the option of providing open-ended feedback, which we used to make iterative modifications to the study.

2.3. Physics Playground

Physics Playground[3] (Shute & Ventura, 2013) is a 2D educational video game designed to enhance learning of qualitative physics principles (Ploetzner & VanLehn, 1997) related to the main concepts of Newton's laws of force and motion, linear momentum, energy, and torque. The game obeys the basic rules of physics and dynamically responds to players' interactions with the game. This responsiveness is accomplished via detailed formal simulation of a virtual physics "world" using actual, accurate physics formulas and calculations to account for mass, gravity, friction, momentum, and many other physics concepts.

The primary goal is for players to guide a green ball to a red balloon, resulting in "solving" the level (see Fig. 1). To do so, players must create *agents*—ramps, pendulums, levers, and springboards—that "come to life" on the screen. A ramp is any line drawn that helps to guide the ball in motion (e.g., to get the ball over a hole). A swinging pendulum exerts horizontal force, directing an impulse tangent to its direction of motion. Levers rotate around a fixed point while a springboard stores elastic potential energy provided by a falling weight, both of which are useful for moving the ball vertically. Game elements in Physics Playground include ongoing feedback, interactive problem solving, and adaptive challenges. The game also gives players the freedom to try/fail, where failure in this context is not a bad thing, but instead, provides valuable information on how to proceed next. Moreover, because there is not just one correct "answer" to a problem in Physics Playground, and the game allows players to create their solutions by drawing objects that come alive, these features foster curiosity, which is not typically present in more traditional learning environments.

Fig. 1 shows a sample level (medium difficulty – see below) where a player draws a pendulum on a pin (little black circle) to make it swing down to hit the ball (surrounded by a heavy container hanging from a rope). To succeed, the player should manipulate the mass distribution of the club (green mass on the right) and the angle from which it was dropped to accomplish just the right amount of force to get the ball to the balloon.

Shute, Ventura, & Kim (2013) reported that performance in the game significantly correlated with posttest scores. Further, after 4 h of gameplay with no instruction or any other learning supports, students improved in qualitative physics understanding from pretest to posttest (Cohen's $d = 0.23$). These findings have been replicated by Shute, D'Mello, et al. (2015) and Shute, Ventura, et al. (2015).

2.4. Difficulty manipulation

Physics Playground levels range in difficulty, which is based on a number of factors including the relative location of ball to balloon, number of obstacles present, number of agents required to solve the level, and novelty of the level. Level difficulty was quantified by experts

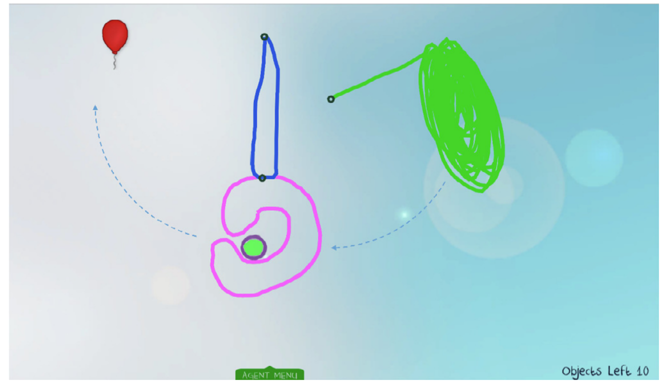

Fig. 1. Example of a pendulum solution in Physics Playground. The dashed lines (for illustrative purposes only; not shown in the game) demonstrate the trajectory of the pendulum to the ball (green circle) and then up to the balloon (target).

based on the game mechanics (1–5 scale) and complexity of physics principles (1–5 scale), with total difficulty scores ranging from 2 to 10. We selected 12 (out of 75) levels focused on two physics concepts ("Energy can Transfer" and "Properties of Torque") for the current study, and categorized them as easy (3 levels, $M_{\text{difficulty}} = 5.33$, $SD = 0.58$), medium (6 levels, $M_{\text{difficulty}} = 7.00$, $SD = 0.00$), and difficult (3 levels, $M_{\text{difficulty}} = 8.33$, $SD = 0.58$). Participants were randomly assigned one level from each of the three difficulty categories (i.e., each participant played one easy, one medium, and one difficult level). Everyone started with an easy level, but the order of the medium and difficult levels was counterbalanced across participants (easy-medium-difficult vs. easy-difficult-medium).

2.5. Measures

Perceived Difficulty. After playing each level, participants were asked to rate their perceived difficulty of the level ("I believe the level I just played was very difficult") using a scale of 1 = Strongly Disagree to 7 = Strongly Agree.

Strongest Affective State. Our goal was to study affect regulation strategies corresponding to specific affective states. Accordingly, after each level of gameplay, we asked participants to select the strongest affective state they experienced while playing that level ("During the level you just played, what was the *strongest* emotion you felt?"). Specifically, participants selected one (and only one) out of a list of nine options: anxious (stressed, nervous), bored (disinterested), confused, curious, happy (accomplished, relieved), determined (engaged, focused), frustrated (annoyed, angry), sad (unaccomplished, disappointed), and other (not listed). We selected these affective terms from previous work on affective states during learning with technology (D'Mello, 2013), a previous study which tracked affective states during Physics Playground (Bosch, D'Mello, Ocumpaugh, Baker, & Shute, 2016), and small pilots conducted before the main study.

We focused on a single choice protocol where participants select their strongest affective states rather than reporting all affective states using a Likert-type scale, or checkboxes where participants would select multiple affective states. This is because we were interested in understanding emotion regulation strategies targeted at upregulating or downregulating specific affective states (see below). It would be untenable to ask participants to select strategies aimed at all nine affective states, so we elected for the *strongest* state. However, to obtain additional information of affective intensity, after selecting their strongest affective state, participants self-reported the strength of that affective state ("How strongly did you feel this emotion?", 1 = Not at all, 5 = A great deal).

We further note that the retrospective self-report method utilized

[3] Please see https://www.youtube.com/watch?v=RRR2vBzCIQQ for a demo video.

Table 1
Affective regulation strategies situated within the process model of emotion regulation.

Steps in Process Model of Emotion Regulation	Affective Regulation Strategy	Item
No Regulation	Acceptance	"Accepted emotion and did not try to change it"
Situation Modification	Situation Modification	"Changed my situation, e.g., turned body, moved locations, changed lighting"
Attentional Deployment	Attentional Redirection	"Distracted myself. E.g., looked around the room, thought about something unrelated to the game"
Cognitive Change	Cognitive Reappraisal	"Focused on the game but thought about the situation differently, e.g., told myself things to change how I felt"
Response Modulation	Relaxation	"Relaxed my body, e.g., took deep breaths, unclenched my jaw, relaxed shoulders"
	Suppression	"Hid my emotion, e.g., looked calm so no one could tell I was experiencing an emotion"

Note. We presented the items in a checkbox format (in a random order after each level) where participants could choose as many emotion strategies as they used.

here relies on participants' ability to recall their strongest emotion during the past few minutes of gameplay. Whereas previous research indicates a strong correlation between retrospective and concurrent self-reporting, even after a much longer delay (D'Mello & Graesser, 2014b), there are tradeoffs to both approaches as discussed in a previous review (Porayska-Pomsta, Mavrikis, D'Mello, Conati, & Baker, 2013). We elected for the retrospective approach so as to not interrupt participants during gameplay, to not interfere with their affective regulation strategies because self-reporting an emotion is likely to be reactive, and due the relatively short time span between gameplay and affect reporting.

Affective Regulation Strategies. We assessed affect regulation strategies aimed at the strongest affective states with the following questions: "What did you do to manage your *strongest emotion*?" Participants selected among six affective regulation strategies (see Table 1) using a checkbox that allowed participants to choose multiple strategies. The items were modified from the Emotion Regulation Interview (Werner et al., 2011) to specifically refer to gameplay. We further modified the Emotion Regulation Interview so that participants simply reported whether they used the strategy rather than the percentage of time they used the strategy.

Effort. Participants reported the amount of effort they put into playing the game (e.g., "I tried very hard in this game", "It was important to me to do well in this game") using the five-item effort subscale ($\alpha = 0.85$) of the Intrinsic Motivation Inventory (Ryan & Deci, 2000). Participants provided responses on a scale of 1 = Strongly Disagree to 7 = Strongly Agree.

Gameplay Logs. The game was played online and the log files recorded what the participants did in the game (e.g., agents drawn, whether the level was solved). Here, we focus on whether participants successfully solved a level (i.e., in-game success). We did not analyze the choice to continue playing a level vs. quitting after the quit option was enabled (i.e., after the initial 4-min) because this option is only available to those who did not complete the level within 4-min, thereby further reducing the sample size and introducing a potential confound. Further, this variable is subsumed by the in-game success variable.

Physics Posttest. Participants completed four pictorial multiple-choice physics questions developed to assess their conceptual understanding of the selected physics concepts "Energy can Transfer" and "Properties of Torque." The items were patterned after the Force Concept Inventory (Hestenes, Wells, & Swackhamer, 1992), which comprises a far transfer assessment from qualitative understanding of physics in the game to more formal knowledge. For example, Fig. 2 depicts one item (targeting torque) that shows a picture of a tree with a branch on which hangs a weight. The question is: "An object is hanging on a tree branch. What would make the branch *more likely* to break?" The four response options include: a) by making the object lighter; b) by moving the object farther away from the tree trunk; c) by moving the object closer to the tree trunk; and d) moving the object won't make a difference. The correct answer is "b" because increasing the distance from the fulcrum (i.e., tree trunk) increases the torque. Two physics experts reviewed the tests and provided recommendations. The tests were then piloted with participants on MTurk prior to administration.

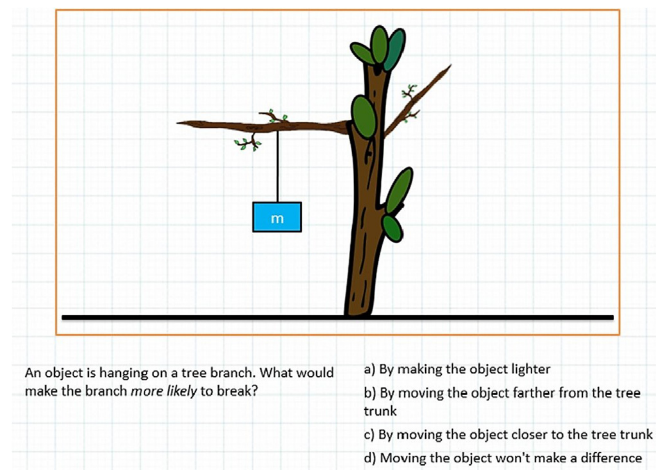

Fig. 2. Example test item. The correct answer is "b" because increasing the distance from the fulcrum (i.e., tree trunk) increases the torque.

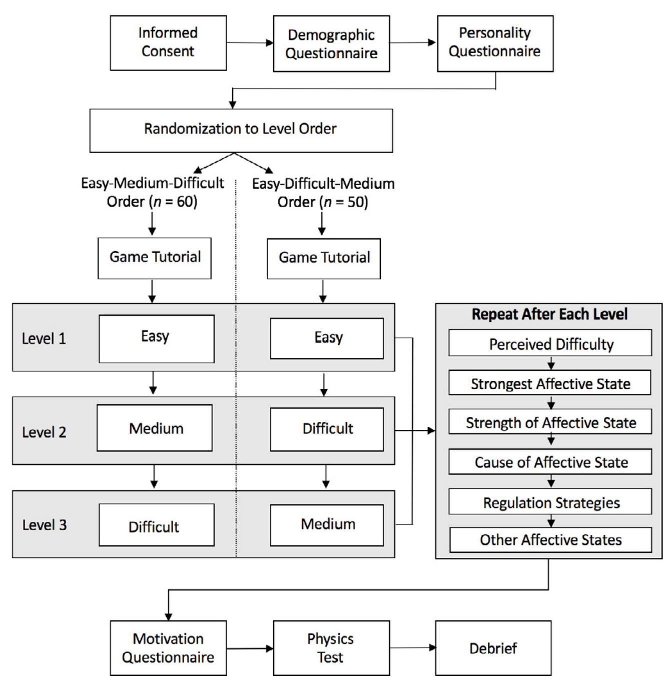

Fig. 3. Protocol flowchart.

2.6. Procedure

A flowchart of the protocol is shown in Fig. 3. After providing consent, participants completed demographic questions and a short personality assessment (not analyzed for the present study due to low reliabilities) and then learned how to play the game by completing a short 5-min tutorial. Next, participants were randomly assigned to one of the difficulty orders (see above). We did not inform participants about the difficulty of the levels. Of the 110 participants ($M_{age} = 22.18$, $SD_{age} = 1.21$; 38.3% female; 78.3% White) 60 of them completed the levels in easy-medium-difficult order and 50 ($M_{age} = 22.08$, $SD_{age} = 1.28$; 64.0% female; 60.0% White) were assigned to the easy-difficult-medium order.

Participants completed all measures using Qualtrics on a web browser on a PC as the game cannot be accessed via smartphone. Participants had 4-min to attempt each level before they were allowed to quit, beyond which they were provided with an opportunity to resume playing the level or to quit and move on. They could of course move on whenever they solved the level even within the initial 4-min. Next, participants rated the difficulty of the level. Then, participants selected the strongest affective state they felt while playing the level, rated the strength of that affective state, selected causes of the affective state (couldn't solve the level, solved the level, the level was difficult, other – not analyzed here),[4] and the affective regulation strategies they used to manage their strongest affective state. Then, participants had the option to select any other affective states they experienced while playing the level (choosing as many as applied) from the same nine options presented to them previously.[5] The procedure was repeated for the second and third levels, upon which participants completed the effort questionnaire and the posttest. Participants completed the study in an average of 35.2 min ($SD = 14.3$ min).

2.7. Data treatment

Statistical Models. Table 2 shows means and standard deviations for all variables analyzed. Due to the repeated, nested, and binary structure of the data, we used mixed-effects logistic regression models (Pinheiro & Bates, 2000) for all item-level analyses (a game level is an item) using the "lme4" library (Bates, Maechler, Bolker, & Walker, 2015) in R (R Core Team, 2017). Level difficulty and order were included as fixed effects covariates and participant was included as a random intercept. Omnibus effects were analyzed using a Type II Wald Chi-Square Test using the "car" package (Fox & Weisberg, 2011). We used the emmeans (estimated marginal means) package for posthoc comparisons with a False-Discovery Rate (FDR) adjustment (Yekutieli & Benjamini, 1999) for multiple comparisons. When physics posttest was the outcome, data were analyzed with ordinary least squares (OLS) regression models at the participant level. We used two-tailed tests with a significance criterion of 0.05 for all analyses.

Analytic Strategy. We measured a large set of affective states and regulation strategies because there was little prior research for guidance. However, the complexity of the data with nine affective states and six affect regulation strategies across three different levels of difficulty would yield a total of 162 unique relationships to explore for each dependent variable. To reduce complexity and to reduce the propensity of incurring Type 1 errors due to the large number of analyses as well as Type 2 errors by applying stringent creation for multiple comparisons, we opted to focus on the most frequent occurrences and strongest effects. We first examined the prevalence of the self-reported strongest affective states (anxious, bored, confused, curious, determined, frustrated, happy, or sad) after each level (Fig. 4). Across the three levels of play, participants primarily reported determination or frustration as their strongest affective state. Curiosity occurs when an individual detects an impasse but perceive that it can be resolved if they are sufficiently determined to do so (Berlyne, 1978; Loewenstein, 1994; Silvia, 2010). Curiosity is also an important component of intrinsic motivation that is central to self-determination theory (Deci & Ryan, 1985). Thus, we created one variable that reflected determination or curiosity (note the "or" instead of the "and" – i.e., we are not treating them as an affective blend). Similarly, confusion and frustration are closely linked to the process of impasse detection and resolution in that confusion signals an impasse and frustration occurs when repeated attempts to resolve the impasse fail, thereby reducing coping potential (D'Mello & Graesser, 2012; D'Mello, Lehman, Pekrun, & Graesser, 2014; D'Mello & Graesser, 2014b; Meindl et al., in press). Some initial research also suggests that frustration and confusion co-occur during learning across multiple contexts including expert tutoring, learning from MOOCs, and learning computer programming (Bosch & D'Mello, 2014; Dillon et al., 2016; Lehman, D'Mello, & Person, 2010) and often precede each other across short time internals of 15–20s (Bosch & D'Mello, 2017; D'Mello & Graesser, 2012). Hence, we created another variable called frustration/confusion to reflect the occurrence of either frustration or confusion.

Next, because the other affective states (anxious, bored, happy, and sad) individually occurred less than 10% of the time across levels, we only focused on these two sets of states. This required us to remove the two participants ($< 2\%$) who never reported determination/curiosity or frustration/confusion states during gameplay. Subsequent analyses include 82.4% of the levels (267 observations out of 324, $n = 108$) when either of these states were reported. Because we focused on the strongest affective state per level, for analyses conducted at the item-level (i.e., a game level), this could either be determination/curiosity or frustration/confusion, but never both. And because there was no difference in self-reported strength of determination/curiosity ($M = 3.76$, $SD = 0.83$) compared to frustration/confusion ($M = 3.90$, $SD = 0.93$), $p = .89$, for parsimony,[6] we created one binary variable reflecting the strongest affective state – determination/curiosity (reference group) vs. frustration/confusion. We note that this was only done for the item-level analyses; the two variables are treated separately for participant-level analyses.

Turning to affect regulation strategies, participants primarily reported using cognitive reappraisal or acceptance (i.e., no regulation) (Fig. 5). Because participants rarely ($< 5\%$) reported other regulation strategies (situation modification, attentional redirection, relaxation, and suppression), we focused only on cognitive reappraisal and acceptance. These two strategies are treated independently because participants could engage in either of them or in both. Thus, the subsequent analyses focus on associations between frustration/confusion (vs. determination/curiosity) and the affective regulation strategies of cognitive reappraisal and acceptance.

Level Difficulty Manipulation Check. We regressed perceived difficulty on actual level difficulty (easy, medium, difficult), order (easy-medium-difficult or easy-difficult-medium), and the level difficulty × order interaction. As expected, there was a significant effect of actual difficulty on perceived difficulty, $\chi^2(2, N = 267) = 34.1$, $p < .001$. Pairwise comparisons using an FDR correction revealed that participants' difficulty ratings were higher for the more challenging levels: difficult > medium > easy. There was no effect of order, $\chi^2(1, N = 267) = 1.29$, $p = .26$, and no difficulty × order interaction, $\chi^2(2, N = 267) = 0.16$, $p = .92$. Thus, the difficulty manipulation was successful.

[4] We do not include the cause of emotion in the analysis because the responses were synonymous with solving a level (e.g., I solved the level, I couldn't solve the level). Additionally, almost all respondents chose "The level was difficult."

[5] These data were collected as a further exploratory aim on co-occurring affective states and associated affect regulation strategies. We do not include them in our primary analyses because we do not have affect regulation strategies associated for these additional states and because our focus is on the strongest affective states.

[6] When analyzed separately, effects for one state would simply be (sign) reversed versions of the other, so it would be redundant to report both.

Table 2
Means (with standard deviations in parentheses) for all variables.

Measures	Item-level analyses			Participant-level analyses
	Easy Level	**Medium Level**	**Difficult Level**	**N = 108**
Manipulation Check	Range [1–7]	Range [1–7]	Range [1–7]	
Perceived Difficulty	5.08 (1.88)	5.47 (1.77)	6.43 (0.82)	–
Gameplay	Range [0–1]	Range [0–1]	Range [0–1]	
Resumed Level	0.39 (0.49)	0.38 (0.49)	0.28 (0.45)	–
Solved Level	0.46 (0.50)	0.24 (0.43)	0.04 (0.20)	–
Strongest Affective State	Range [0–1]	Range [0–1]	Range [0–1]	Range [0–3]
Determination/Curiosity	0.66 (0.48)	0.38 (0.49)	0.25 (0.43)	1.05 (0.91)
Frustration/Confusion	0.34 (0.48)	0.62 (0.59)	0.75 (0.43)	1.38 (0.96)
Regulation Strategy	Range [0–1]	Range [0–1]	Range [0–1]	Range [0–3]
Cognitive Reappraisal	0.73 (0.45)	0.45 (0.50)	0.45 (0.50)	1.49 (0.96)
Acceptance	0.38 (0.49)	0.49 (0.50)	0.54 (0.50)	1.44 (1.05)
Effort [1–7]	–	–	–	5.96 (0.93)
Physics Posttest [0–1]	–	–	–	0.48 (0.27)

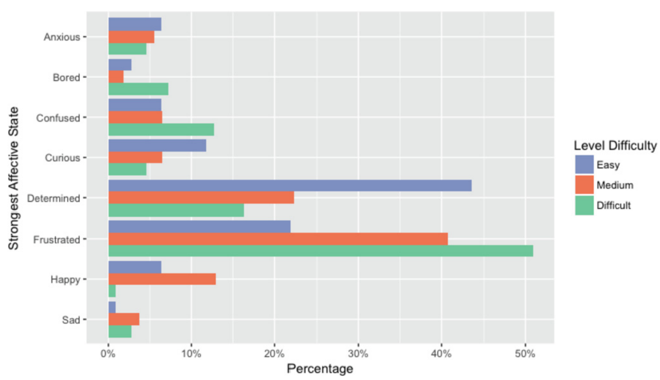

Fig. 4. Percentage of self-reported strongest affective states for each level of gameplay. Participants could choose only one affective state and primarily reported being determined or frustrated.

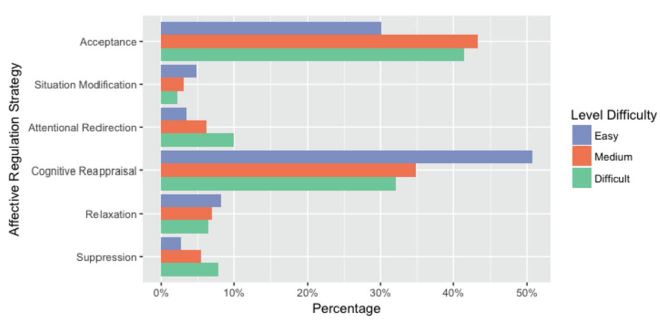

Fig. 5. Percentage of self-reported affective regulation strategies for each level of gameplay. Participants could select as many strategies as they used to manage their strongest affective state. Participants primarily reported cognitive reappraisal and acceptance (no regulation).

3. Results

3.1. Research question 1: which affective regulation strategies do learners engage in?

Focusing on the strongest affective state (frustration/confusion vs. determination/curiosity), we first examined how it was influenced by level of difficulty and order (a potential confound). As shown in Model 1 in Table 3, there was a significant effect of level difficulty (χ^2(2, N = 267) = 28.1, p < .001), with pairwise comparisons indicating that participants were significantly (ps < .04) more likely to report frustration/confusion as their strongest emotion as levels increased in difficulty (difficult > medium > easy). There was no effect of order on affective state, (χ^2(1, N = 267) = 0.61, p = .44).

To investigate specificity of regulatory strategy to affective state, we regressed cognitive reappraisal (1 [used] or 0) on strongest affective state controlling for level difficulty and order (Model 2 in Table 3). Strongest affective state was unrelated to cognitive reappraisal (χ^2(1, N = 267) = 0.09, p = .77), but level difficulty significantly predicted use of cognitive reappraisal (χ^2(2, N = 267) = 16.9, p < .001) with pairwise comparisons revealing the following pattern in the data: easy > [medium = difficult]. There was no effect of order on cognitive reappraisal (χ^2(1, N = 267) = 0.76, p = .38). Similarly, neither strongest affective state (χ^2(1, N = 267) = 0.12, p = .73) nor order (χ^2(1, N = 267) = 0.002, p = .96) predicted use of acceptance (the model did not converge with level difficulty included). Thus, participants were equally likely to reappraise or accept their strongest affective state but were more likely to engage in reappraisal for the easier levels.

3.2.

Research Question 2. What is the Relationship among Affect Regulation, Gameplay Success, and Posttest Scores, and what are the Moderation Factors?

In-game Success. We investigated whether strongest affective state, cognitive reappraisal, and their interactions predicted in-game success (i.e., solved level or not; Model 5 in Table 3). There was no effect of order on solving a level (χ^2(1, N = 267) = 0.03, p = .87), but, as expected, participants were significantly (χ^2(2, N = 267) = 15.8, p < .001) more likely to solve the easier levels compared to the medium or difficult level, which were on par with each other (easy > [medium = difficult]). Importantly, there was a main effect of strongest affective state on solving a level (χ^2(1, N = 267) = 13.9, p < .001), meaning that participants were less likely to solve a level when their strongest affective state was frustration/confusion compared to determination/curiosity. There was no main effect of cognitive reappraisal (χ^2(1, N = 267) = 1.1, p = .29), but there was a marginal interaction effect between strongest affective state and cognitive reappraisal (χ^2(1, N = 267) = 3.1, p = .077) (Fig. 6). Specifically, there was no effect of cognitive reappraisal on solving a level when the strongest affective state was determination/curiosity (p = .92), but those who engaged in cognitive reappraisal when frustrated/confused were more likely to solve the level (p = .04).

A similar analysis (see Model 5 in Table 3) with acceptance as the emotion regulation strategy did not yield a main effect of acceptance (χ^2(1, N = 267) = 0.18, p = .67) nor an interaction between strongest affective state and acceptance (χ^2(1, N = 267) = 2.53, p = .11). There was, however, a main effect of strongest affective state in that participants were more likely to solve a level if they were determined/curious rather than frustrated/confused (χ^2(1, N = 267) = 14.3, p < .001).

Table 3
Model coefficients (with standard errors in parentheses) and model fit for logistic mixed effects models.

Predictors	Strongest Affective State	Affective Regulation		In-Game Success	
	Model 1	Model 2	Model 3	Model 4	Model 5
	Frustrated/Confused vs. Determined/Curious	Used Cognitive Reappraisal [1 vs. 0]	Used Acceptance [1 vs. 0]	Solved Level [1 vs. 0]	Solved Level [1 vs. 0]
Observations (n)	267 (n = 108)	267 (n = 108)	267 (n = 108)	267 (n = 108)	267 (n = 108)
Intercept	−0.746 (.334)*	1.294 (.365)*	−0.116 (.306)	0.271 (.486)	0.254 (.407)
Covariates					
Level Difficulty					
Medium vs. Easy	1.519 (.401)*	−1.460 (.394)*	–	−0.496 (.415)	−0.641 (.408)
Difficult vs. Easy	2.314 (.443)*	−1.463 (.395)*	–	−2.507 (.631)*	−2.621 (.634)*
Order					
Easy-Difficult-Medium vs. Easy-Medium-Difficult	−0.294 (.377)	0.297 (.342)	−0.018 (.357)	−0.066 (.412)	−0.116 (.406)
Strongest Affective State Frustrated/Confused vs. Determined/Curious		0.099 (.334)	−0.108 (.312)	−3.107 (.899)*	−1.362 (.523)*
Affective Regulation					
Cognitive Reappraisal				0.047 (.494)	
Acceptance					0.252 (.487)
Interactions					
Strongest Affective State × Cognitive Reappraisal				1.713 (.969)†	
Strongest Affective State × Acceptance					−1.412 (.887)
Model fit					
Marginal/Conditional R^2	0.175/0.410	0.104/0.299	0.001/0.275	0.482/0.589	0.443/0.557

Note. *$p < .05$. †$p < .10$. For mixed effects regression models, marginal and conditional R^2 pertain to variance explained by fixed vs. fixed plus random effects, respectively.

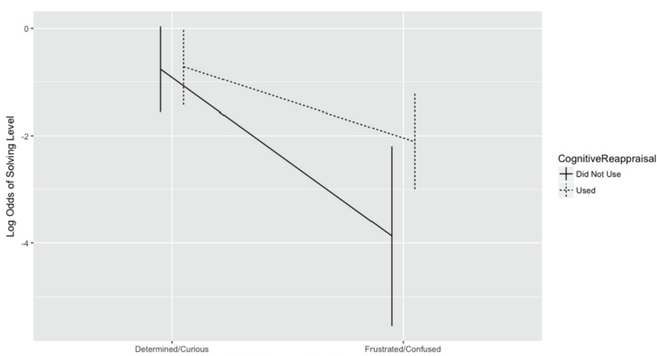

Fig. 6. The interaction effect between strongest affective state and cognitive. reappraisal on whether or not participants solved a level. Cognitive reappraisal had a significant effect on solving only when participants were frustrated/ confused.

Again, participants were more likely to solve an easy level ($p < .001$, easy > [medium = difficult]) and there was no effect of order ($\chi^2(1, N = 267) = 0.08, p = .78$).

Posttest Scores. We analyzed physics posttest scores at the participant level by first creating total scores for strongest affective state (determination/curiosity and frustration/confusion) and affective regulation strategy (cognitive reappraisal and acceptance) by adding the number of times participants reported the respective items across the three levels (possible score 0 to 3 for each variable). The regression models included the same participants ($N = 108$) as the mixed effects models (i.e., participants needed to report determination/curiosity or frustration/confusion at least once). Determination/curiosity and frustration/confusion were highly negatively correlated, $r(106) = -0.76$, $p < .01$, so we only report models for frustration/confusion. We also included perceived effort as a potential moderating factor on the relationship between affective state, regulation strategy, and posttest scores. Level of difficulty is no longer relevant at the participant level because of the within-subjects design and order was excluded since it was not significant in any of the above analyses.

Table 4
Model coefficients (with standard errors in parentheses) and model fit for ordinary least squares regression models (n = 108).

Predictors	Physics Posttest Scores	
	Model 1 (w. Reappraisal)	Model 2 (w. Acceptance)
Intercept	−1.306 (.483)*	0.226 (.483)
Effort	0.310 (.086)*	0.028 (.080)
Affective State		
Frustration/Confusion	1.176 (.338)*	−0.312 (.289)
Regulation Strategy		
Cognitive Reappraisal	0.655 (.318)*	–
Acceptance	-	−0.464 (.288)
Interactions		
Effort × Frustration/Confusion	−0.207 (.060)*	0.057 (.047)
Effort × Regulation	−0.113 (.053)*	0.087 (.048) †
Frustration/Confusion × Regulation	−0.560 (.211)*	0.455 (.155)*
Effort × Frustration/Confusion × Regulation	0.097 (.035)*	−0.080 (.026)*
Model Fit (Adj. R^2)	.098	.131

Note. *$p < .05$. †$p < .10$.

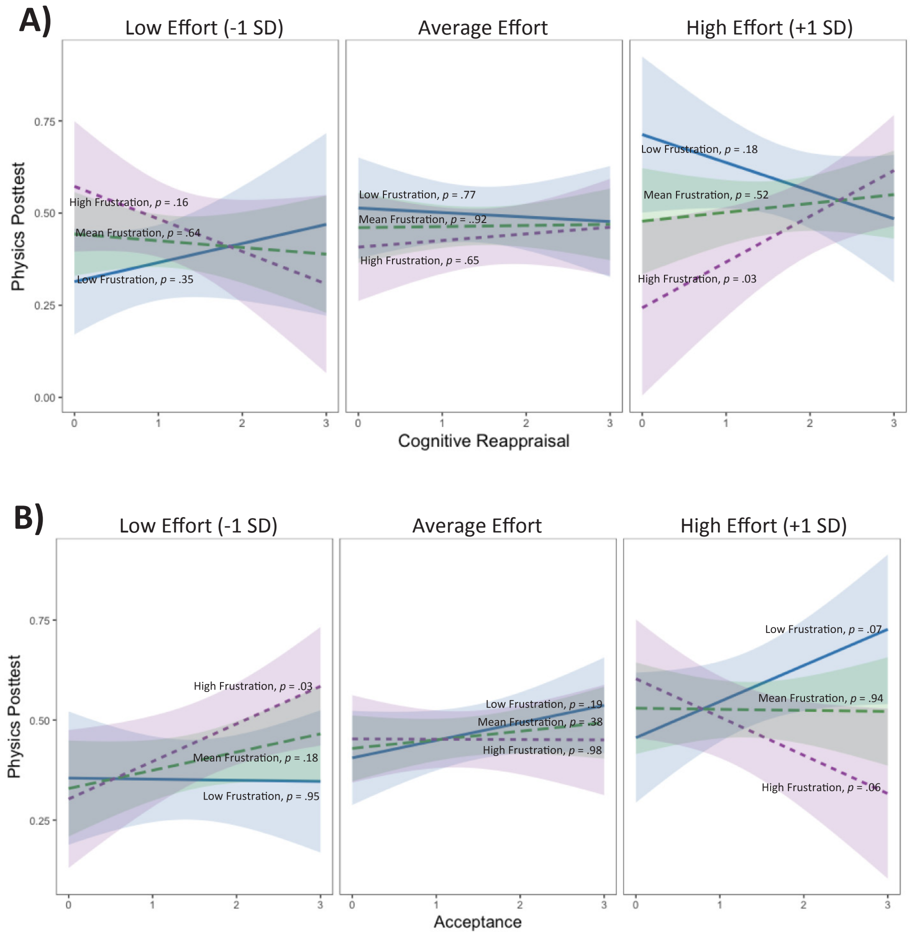

Fig. 7. The interaction effects of effort, total frustration, and affective regulation strategy. on physics posttest scores. A) Cognitive reappraisal was beneficial for posttest scores when participants were both high in effort and high in frustration. B) Acceptance was detrimental to posttest scores when participants were both high in effort and high in frustration, but was beneficial when participants were low in effort, yet highly frustrated or high in effort but low in frustration.

First, we regressed physics posttest scores on effort, total frustration/confusion (score 0 to 3), and total cognitive reappraisal (score 0 to 3), including all two-way and three-way interactions (Table 4, Model 1). We focus on the interaction in lieu of the main effects because significant interactions suggesting main effects may be misleading (Maxwell & Delaney, 2000). Effort, frustration/confusion, and cognitive reappraisal interacted to predict posttest scores ($p = .006$) (Fig. 7a). A simple slopes analysis revealed that the positive effect of cognitive reappraisal on posttest scores was only significant ($B = 0.12$, $SE = 0.05$, $p = .03$) for participants who put a high amount of effort into the game (+1 SD above mean) while also being highly frustrated/confused (+1 SD above mean). There were no other significant slopes for cognitive reappraisal on posttest scores ($ps > .16$).

Second, we regressed physics posttest scores on effort, total frustration/confusion, and total acceptance, including their interactions (Table 4, Model 2). Again, effort, frustration/confusion, and acceptance interacted to predict posttest scores ($p = .008$) (Fig. 7b). In contrast to engaging in cognitive reappraisal (see above), we found that acceptance had a marginal *negative* effect ($B = -0.10$, $SE = 0.05$, $p = .06$) on posttest scores during high effort and high frustration/confusion. However, acceptance had a *positive* effect on posttest scores when participants were either highly frustrated/confused but low in effort ($B = 0.09$, $SE = 0.04$, $p = .03$) or high in effort but low in frustration/confusion ($B = 0.09$, $SE = 0.05$, $p = .07$ - marginal).

4. Discussion

We investigated affect and affect regulation during gameplay with dual goals of expanding the self-regulation learning literature to include more research on affect regulation and on leveraging basic insights towards the design of game-based affective learning supports. Our first research question pertained to identifying the affect regulation strategies that learners engage in while playing Physics Playground in the context of the present study. We found that participants primarily experienced determination/curiosity or frustration/confusion in our game (the other affective states occurred less than 5% of the time) and that these affective states increased and decreased, respectively, in conjunction with game difficulty. We also found that cognitive reappraisal and acceptance were strategies participants reported using to regulate their affect whereas the others (e.g., attentional redirection, suppression) were exceedingly rare. Importantly, participants were more likely to use cognitive reappraisal for the easy compared medium and difficult levels, but its use was not systematically related to determination/curiosity vs. frustration/confusion.

Our second research question focused on the relationship between affect regulation and both in-game success and posttest scores and on factors that moderate these relationships. We found that cognitive reappraisal predicted successful gameplay when participants were frustrated/confused, but not when they were determined/curious. We also found that cognitive reappraisal positively predicted posttest scores when participants were frustrated/confused throughout gameplay, but only for those who reported putting a high amount of effort into the game. Conversely, participants benefitted (in terms of posttest scores) from using an acceptance strategy when either low in effort but high in frustration/confusion or low in frustration/confusion but high in effort; however, acceptance hurt posttest scores when both effort and frustration/confusion were high.

Our findings are consistent with contemporary theories on affect and affect regulation during cognitive processing. Intense negative affective states like frustration can undermine higher order cognitive processing skills like attention and planning (see Diamond, 2013 for a review). Moreover, inhibiting negative affect (e.g., not engaging in affective regulation when highly frustrated), requires cognitive effort (Pennebaker, 1997) and can lead to sustained heighted activity in affect-generative brain regions compared to regulating those states, and this elevated emotional responding can disrupt cognitive processing (Lieberman et al., 2007). Results from our exploratory study are consistent with this notion in that failing to regulate high levels of frustration/confusion predicted lower gameplay success and posttest physics scores. Importantly, engaging in affective regulation, particularly using cognitive reappraisal, may have buffered against the negative effects of high frustration/confusion on posttest scores, but only when accompanied with effort.

In general, our findings on the facilitative effect of cognitive reappraisal are in line with the process model of emotion regulation, which states that cognitive reappraisal is useful for reducing the impact of negative affect on various outcomes (Gross, 2015). Importantly, however, when it comes to learning outcomes, we found that cognitive reappraisal (vs. acceptance) only benefitted those who experienced high frustration/confusion *and* who reported putting considerable effort into the task. We interpret these findings through the lens of cognitive load theory (van Merriënboer & Sweller, 2005) and the Yerkes-Dodson Law of optimal arousal (Yerkes & Dodson, 1908). Participants who put substantial effort into gameplay likely had high cognitive load. If one experiences intense frustration with no regulation strategy to lessen its impact, one presumably has fewer cognitive resources to devote to gameplay, because affect consumes working memory resources and because the intense arousal generated from high frustration/confusion can lead to lower posttest scores.

However, those who were not highly motivated to succeed during gameplay (i.e., low effort) or those who were motivated but were not highly frustrated/confused, would not have as high of cognitive load. For these individuals, simply accepting their frustration/confusion was more beneficial for posttest scores than attempting to regulate it. There are two possible explanations for this finding. One hypothesis is that individuals who expended lower effort also had lower arousal, hence, the experience of high frustration might have increased their arousal to a point that was beneficial for cognitive processes – i.e., towards moderate levels of arousal as per Yerkes-Dodson. Others have shown that negative affective states can indeed benefit learning (D'Mello & Graesser, 2014a; Fiedler & Beier, 2014; Kim & Pekrun, 2014; Mills et al., in press), which is (partly) likely due to moderate increases in arousal ultimately leading to better performance (Yerkes & Dodson, 1908). Alternatively, it might be the case that frustration/confusion are qualitatively different and also differentially experienced when participants are exerting low vs. high effort akin to research on differences in boredom and its effects in underwhelming vs. overwhelming situations (Acee et al., 2010; Pekrun et al., 2010). If so, then different cognitive reappraisal strategies might have been used, resulting in different outcomes. Future research is needed to adjudicate among these and other possibilities.

Our results have implications for the design of next-generation educational games. Whereas learners might be successful on their own at regulating affective states in some circumstances, they might need interventions or supports to help them in others. But game-based affective regulation supports are virtually non-existent in the GBL literature, although some work in this direction is emerging (Sabourin & Lester, 2014). Given that affective regulation was linked to both gameplay success and posttest scores in our study, there is a convincing need to design and test interventions aimed at influencing affective regulation processes in favorable directions. That said, our results show that one cannot simply implement cognitive reappraisal interventions to all learners without considering the underlying affective states being regulated and expended effort. The challenge for researchers and designers of GBL environments, then, is to determine the appropriate level of frustration/confusion for different types of learners, and investigate whether targeted cognitive reappraisal strategies may help them maintain engagement and learn.

Like all studies, ours has limitations. First, we could not elucidate causal links between affective states, affective regulation, and gameplay outcomes due to the correlational nature of the design, which always raises the possibility of third variable confounds. Although we did manipulate difficulty and explored its effect on resultant affective states and regulation strategies, future work should focus on directly manipulating other key variables such as inducing specific affective states and/or instructing participants to engage in particular regulatory strategies (e.g., Sheppes & Meiran, 2007; Strain & D'Mello, 2014). Relatedly, the current study was an exploratory study of affective states, affective regulation, and effort. We did not specifically predict any of the interactions, which should be replicated in future studies with more sensitive measures (e.g., see below).

Second, requiring participants to spend at least 4-min per level (unless they solved it within 4-min) and selection of specific levels may have influenced affect and regulation strategies. In a similar vein, a different prevalence of affective states and/or strategies to regulate them may appear in other games or even in other levels within the current game. Similarly, the overall short duration of gameplay limited to three levels does reduce the "gameness" of the experience. Hence, replication in more open-ended game environments for longer periods of game-play is warranted.

Third, we opted to focus our analyses on the strongest affective states and the most frequent regulation strategies in order to manage the complexity of the potential associations we could explore. We think that this decision was well motivated for this early stage of research (see Methods). Nevertheless, as a consequence, additional weaker, but potentially interesting effects, have yet to be explored. For example, an analysis of co-occurring affective states and/or multiple regulation strategies might yield additional insights. Because exploring these and more complex relationships would require much larger samples, future work should consider considerably ramping up the sample sizes of similar studies.

Fourth, the online nature of the study using a convenience sample via MTurk did pose some limitations with respect to the types of data we could collect. We could not collect extensive individual difference measures, such as pretest scores, interest in Physics, and prior experience with gaming, due to time limits, and had to rely on self-reports of inclusion criterion rather than considering verifiable information. We also did not record physiology, which would be needed to address some of the questions pertaining to optimal levels of arousal for gameplay success. Thus, future studies should also focus on more background measures as well as measures of physiological arousal.

Lastly, unlike studies using cognitive reappraisal interventions (e.g., Strain & D'Mello, 2014) where participants are given specific instructions on how to modify their appraisals of situations, we cannot be sure of the specific reappraisal strategies participants used during gameplay. Future studies of self-reported affective regulation strategies should include follow-up questions to probe the exact strategies players use to self-regulate. This data could be used to develop game-specific affective regulation strategies for future investigation.

In summary, well-designed educational games can be intrinsically motivating and engaging (Fullerton, Swain, & Hoffman, 2008; Malone & Lepper, 1987; Shute et al., 2011) and can lead to a range of positive and negative emotional experiences (e.g., Shute, D'Mello, et al., 2015 and Shute, Ventura, et al., 2015). Hence, interventions aimed at influencing the intensity and duration of affective states in game-based settings via targeted affective regulation interventions may be particularly useful. The current study took a step in this direction by identifying the affective regulation strategies that learners spontaneously utilize during game-based learning and investigating how these strategies interact with affective states and effort to influence posttest scores. This next step is to leverage these insights to develop and test game-based supports that help learners manage their affect and ultimately benefit from the "hard fun" of learning from well-designed educational games while simultaneously enhancing our understanding of affect regulation, an important component of self-regulation learning.

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