Boosting Engagement With Educational Software Using Near Wins

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Abstract. Boosting engagement with educational software has been promoted as a means of improving student performance. We examine two promising and relatively understudied manipulations from the realm of gambling: the *near-win effect* and *anticipation*. The near-win effect occurs when an individual comes close to achieving a goal, while anticipation refers to the build-up of suspense as an outcome is revealed (e.g., losing early vs. late). Gambling psychologists have long studied how near-wins affect engagement in pure-chance games but it is difficult to do the same in an educational context where outcomes are based on skill. We manipulate the display of outcomes such that artificial near-wins are introduced largely independent of a student's performance. In a study involving thousands of students using an online math tutor, we examine how this manipulation affects a behavioral measure of engagement. We find a near-win effect on engagement when the 'win' indicates to the student that they may continue to the next lesson. Nonetheless, when we experimentally induce near wins in a randomized controlled trial, we do not obtain a reliable effect of the near win. We conclude by describing manipulations that might increase the effect of near wins on engagement.

Keywords: near-win, educational applications, anticipation

1 Introduction

The *near-win effect* is a manipulation that has been studied extensively in the gambling addiction literature. This effect occurs when a player almost wins a game, e.g., getting two cherries and a lemon in slot machine. Reid [1] argues that near-win events are useful in skill-based games, such as darts, because they provide feedback that winning is close. Even though such feedback is useless in games of pure chance, Reid notes that gamblers still think they can influence the outcome with behaviors such as whispering to the dice, choosing lottery numbers carefully, or consulting books of lucky numbers. Differences in engagement are often found between losing early (also known as a *clear loss*) and nearly winning. For example, Reid cites a study in which subjects preferred a near-win over a clear-loss. Reid's own study also showed a trend in that direction. A complementary manipulation that often gets studied alongside the near-win effect is *anticipation*, which refers to the build-up of suspense as an outcome is revealed. For example, revealing cherry-cherry-lemon in that order drives expectations of winning more than revealing lemon-cherry-cherry.

We explore whether the benefits of near-wins and anticipation transfer to an educational context. We designed a novel manipulation of the near-win effect that independently induces near-wins in a skill-based context, and we continuously manipulate anticipation using Bezier-curve-based animations. Finally, we analyze the impact of those two manipulations on a behavioral measure of engagement in a large-scale math-tutoring software used by thousands of students.

1.1 Related Research

In an educational setting, one wishes to maximize learning or performance on a test. However, conducting experiments to evaluate learning is difficult; it requires pre- and post-testing of students in a controlled setting. We use *engagement* as a proxy for learning, with the assumption that greater engagement leads to greater learning gains. Engagement has no precise definition and researchers have operationalized it via surveys, such as the Game Engagement Questionnaire (GEQ) [2], physiological measures, such as galvanic skin response, and behavioral measures, such as voluntary duration of play, also known as *persistence* [3].

Researchers have explored the impact of various *overt* task-irrelevant game-like manipulations on engagement in educational contexts. Cordova and Lepper [4] looked at contextualization, personalization, and choice, Denny [5] studied virtual achievements, and Katz et al. [6] investigated the removal of gamification features. Less-salient or *covert* manipulations have been explored in video games. Denisova and Cairns [7] manipulated players' prior information about adaptive AI in the game, and Khajah et al. [3] covertly assisted players in simple two-dimensional casual games.

The near-win effect is also a subtle manipulation but it has not received much attention outside of the gambling psychology literature. In gambling, near-wins can be induced by rigging a slot machine to deliver a certain frequency of almost-winning sequences. Kassinove and Schare [8] found that subjects voluntarily play a slot machine for longer when the proportion of near-wins is medium, not too small nor too large. In education, Lomas [9] studied the effect of close/far losses/wins on engagement in an fraction learning game used by thousands of students. Lomas found that the number of additional exercises attempted increased as the absolute difference between the target criterion and the actual score decreased. However, Lomas' work is observational, and without randomized controlled trials we cannot determine whether near wins have a causal effect.

2 Experimental Manipulation

In this paper, we manipulate near-wins independently of actual performance in a skill-based context. This enables assessment of the effect of near-wins on engagement. We also vary anticipation by manipulating the temporal dynamics of the animation that reveals a student's performance score.

Woot Math® [10], an interactive web-based fraction learning software used by thousands of students, served as our platform to implement the near-win and anticipation manipulations. In Woot Math, students engage in a series of lessons where each lesson consists of a set of exercises that are chosen dynamically depending on the student's performance. After every lesson, a scorecard is shown with a *performance bar* indicating the score and three *goal posts* corresponding to thresholds for earning an additional *star* (Figure 1). Between zero and three stars can be awarded on any lesson, and the performance bar range is continuous in $[0, 3]$. Through animation, the performance bar (the yellow coloring in the figure) is filled from left to right, and then stars appear based on the goal posts and the student's score. Replay and continue buttons on the scorecard allow students to retry the current lesson or return to a main lesson-selection screen.

The awarding of one star is of critical importance to students because they cannot advance to the next lesson unless they score at least one star. The additional stars may be intrinsically rewarding to a student, but over the population of students, the common goal is passing the threshold to obtain one star.

Near-wins are artificially induced at random. Artificially induced near-win events boost the score to within 0.1 of the next goal post The score is not manipulated if the student's true score is already within 0.1 of the next goal post—a *natural* near win—or is just over the goal post. The time course of animating the performance bar is determined by a parameter $\eta \in [0, 1]$, which we refer to as the *ease-out magnitude*; η controls the deceleration of the animation as it approaches the target score. Figure 1 graphs the proportion of the performance bar that is colored as a function of time for various ease-out magnitudes and for various target scores. Animation duration depends on the score because otherwise the mean speed would change, enabling prediction of the target score early on. We hypothesized that $\eta = 1$ produces more anticipation than $\eta = 0$ because in the case of near-wins, the first creates more anticipation as the animation slows down while the latter distributes anticipation evenly over multiple goal posts.

Engagement is assessed by whether students replay the lesson. Students were randomly assigned to a an ease-out magnitude η. Although students typically practice over multiple sessions, we simply concatenate lessons from multiple sessions to form one sequence per student for analysis.

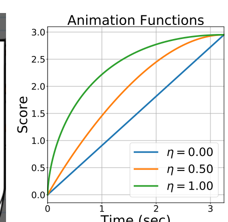

Fig. 1: (left) Post-lesson scorecard in Wootmath. (right) Examples of manipulating anticipation for a given score.

3 Results

After excluding perfect and zero scores and instances where the student moved on before the progress bar animation had completed, the dataset has 29,470 completed lessons from 5,953 students. The median number of lessons per student is 3 (std. 6.54, range 1-124), over 2 sessions (std. 3.20, range 1-39).

Figure 2 shows the mean replay probability as a function of score (the graph abscissa), type of near-win event—*natural* (first row) or *induced* (second row)—and anticipation level—low, medium, high (left, middle, and right columns, respectively). In each graph, as the score increases, there is a clear downward trend in mean replay probability for both near-win and non-near-win lessons (orange and blue bars, respectively). Students are most likely to replay following lessons in which their displayed score is lower than 1.0—which makes sense given that 1.0 is the criterion for advancing to the next lesson. These lessons also show a reliable near-win effect in case of natural near-wins but the effect is not reliable for induced near-wins. One explanation is that students who achieve natural near-wins may be more skilled than those who get induced near-wins because the manipulation only induces near-wins when the score is not within 0.1 of a goalpost. It may also be that effective near-wins require high anticipation to build suspense; the figure does show an unreliable trend that direction.

That students typically completed only 3 lessons (the median) was problematic for the study of engagement. Also, the anticipation manipulation may not have been effective in building suspense due to a duration limit of 3 seconds. For future studies, we suggest completely de-coupling near-wins from performance (e.g., by showing the student a fake class rank), and increasing the maximum animation duration. If a near-win effect can be made to reliably influence behavior, lesson replay can be encouraged or discouraged based on an adaptive controller's expectation of benefit to the student.

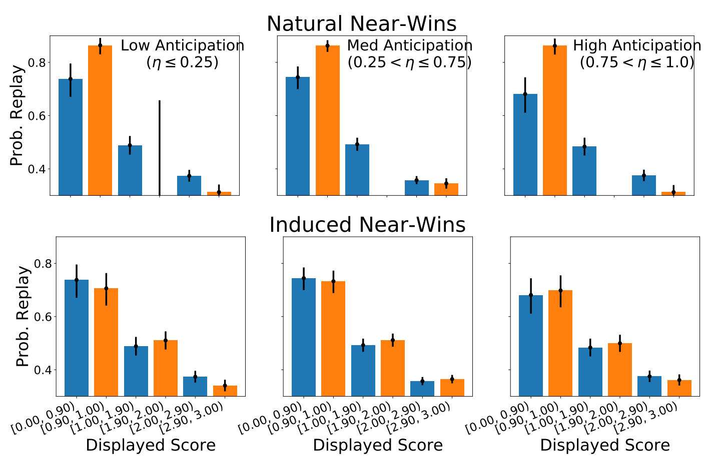

Fig. 2: Analysis of replay rates as a function of the displayed score. Each bar corresponds to a score range $[a, b)$, with a included and b excluded. Bar heights indicate the mean replay probability of observations in the corresponding score range. Blue and orange bars correspond to no-near-win and near-win events, respectively. Error bars correspond to the 95% confidence interval for a binomial proportion, using Wilson's score interval.

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