Identifying When and Why Students Choose to Quit Jobs in a Science Exploration Game

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Abstract. Students in open-ended educational games have a number of different pathways that they can select to work productively through a learning activity. Educators and system designers may want to know which of these pathways are most effective for engagement, learning, or other desirable outcomes. In this paper, we investigate which prior jobs and factors are associated with higher rates of student quitting behavior in an educational science exploration game. We use a series of Chi squared analyses to identify the jobs with the highest rates of quitting overall, and we calculate logistic regressions within specific jobs to determine the potential factors that lead to students quitting those jobs. Our analysis revealed that for 23 of the 40 jobs examined, having experience in at least one previous job significantly decreased the chances of students quitting the subsequent job, and that completing specific prior jobs reduces quit rates on specific later jobs. In our discussion, we describe the challenges associated with modeling quitting behavior, and how these analyses could be used to better optimize students' pathways through the game environment. Specially, guiding students through specific sequences of preliminary jobs before tackling more challenging jobs can improve their engagement and reduce dropout rates, thus optimizing their learning pathways.

Keywords: Educational Games, Learning Analytics, Player Quitting

1 Introduction

Educational games represent useful and sophisticated tools for understanding how students learn in a wide range of educational contexts. Games have been used to improve or develop creativity [26], collaboration and problem-solving [29], communication [11], and interpersonal and decision-making skills [23]. They also have been used to assess spatial reasoning [15], computational thinking [27], and implicit science learning [28]. The complex nature of learners' potential interactions in educational games enables rich data collection and analysis of a complex range of behaviors and cognitive processes.

The design of these game environments requires careful attention to detail for educational designers, to maintain an appropriate level of challenge for students that optimizes both learning and engagement [18]. Difficulty can be adjusted in several ways – either by modifications to the game's structure [25], or by runtime adaptations based on current player behavior and affect [8]. Providing learners with appropriate degrees of challenge is particularly complex within open-ended games, where students can move freely between levels, seeking out or avoiding tasks based on their own goals and motivations within the game. When the design is truly open, what can be done to ensure learners have been cognitively prepared for a particular challenge and have a reasonable chance of success?

In this paper we build models that predict student quitting of individual game challenges, towards enabling future versions of the game to make real-time estimates of how prepared a student is for different challenges within their open exploration. Specifically, we explore cases where a student quits their current game activity and switches to a different activity within the game, such as a different level [13, 31].

We explore these questions in the context of the science exploration game *Wake: Tales from the Aqualab,* where students can self-select the order in which they move through the game's challenges, referred to within the game as "jobs", and quit the current task to move to a different task. Our analyses explore the differential rates of quitting that students exhibit depending on the trajectory that student has taken through the game's jobs prior to that point, with the intuition that some activities may be too difficult if the student has not mastered the relevant skills in previous jobs. We construct both Chi-Squared analyses to identify potential problem jobs with high rates of job quitting, as well as logistic regressions to better understand the factors that contribute to a student's decision to quit specific jobs. The overall goal for this work is to identify productive and unproductive pathways that students can take within the game to minimize the disengaging experience of quitting a job. By identifying productive pathways, we can revise game design to nudge students towards these specific pathways during play.

2 Related Work

Educational games are increasingly recognized for their ability to engage students and improve learning outcomes through interactive experiences [3, 6, 20]. Research has shown their effectiveness in supporting learning across various contexts. For instance, [12] highlight the educational potential of games with rich storylines, which not only engage but also enhance learning by fostering curiosity within compelling contexts. Likewise, [14] and [16] emphasize the importance of narratives and individualized feedback mechanisms in maintaining student interest and meeting individual learning needs. Further, studies by [1] demonstrate how strategic video gameplay can develop problem-solving skills, while [5] explores the motivational benefits of well-designed gamified elements, leaderboards, within business higher education.

Understanding why students quit games requires an in-depth analysis of the interplay between psychology, education, and game design. [24] examine the impact of social support in games and propose that enhanced in-game support can reduce player frustration and quit rates. [22] developed a model to differentiate productive and unproductive persistence in Mastering Math that enables real-time interventions to assist students at an early stage. [30] explore how factors such as affective state and in-game progression influence learning outcomes in the game Physics Playground and found that frustration and engaged concentration indirectly affect learning outcomes through first affecting in-game performance.

Considerable research has also attempted to predict player quitting and struggles within games. [7] modeled player retention in *Madden NFL 11* by using regression analysis on encoded gameplay patterns to predict the number of games played and identify key factors that influence player retention. Similarly, [32] used regression analysis to predict player churn in an MMO called *World of Warcraft* using features derived from demographic data, survey responses, and in-game activity data. [2] utilized a hidden Markov model to find a plausible mechanism of gameplay that could predict player performance and quitting in the game *Axon*. [13] used machine learning to develop models to identify student quitting in the game Physics Playground. [9] evaluated the accuracy of common machine learning algorithms in predicting quitting within two science learning games: *Crystal Cave* and *Wave Combinator*. Additionally, [31] used decision trees to analyze whether players' activity would decrease from one month to the next based on their behavior in the first month in two popular commercial online games: *I Am Playr* and *Lyroke*.

In our previous efforts to understand players in *Wake* [17], we constructed a model of points in the game where expert coders identified that students were struggling, developing machine learning models using features derived from the game's interaction log data to predict hand-coded observations of struggle behaviors. However, the performance of these models was modest, achieving an area under the curve (AUC) of only 0.64. This level of performance is sufficient for describing trends of struggle in aggregate, across many students, but not sufficient for predictions of an individual student's experiences in the game. Instead, in this study, we investigate the factors that lead students to quit game jobs in *Wake* in order to understand if completing specific preliminary jobs can improve students' overall experience and reduce quit rates within later target jobs. The broader goal of this analysis is to distill actionable insights that can improve learner experiences in *Wake* and inform the process of designing more engaging and effective educational gaming experiences in general.

3 Method

Wake: Tales from the Aqualab is a science exploration game, developed for grade 6-9 science classrooms and for use on Chromebook and web browser-based devices. In *Wake*, students take on the role of a young marine biologist, using observations, experimentation, modeling, and scientific argumentation to learn more about four biomes and their respective ecological systems in the game (See Fig. 1). The game is implicitly structured into 54 jobs, each comprised of a set of specific tasks. We refer to these segments as jobs rather than levels, because each job represents a distinct assignment or mission, similar to project-based activities, rather than consecutive challenges or stages. In the game, students have freedom to select any available job, though some jobs are gated behind the completion of previous jobs, or that require ship and tool upgrades purchased in the shop. The primary reason for this design is to facilitate analysis of the effectiveness of different pathways on learning outcomes. This design decision is also supported by previous research findings [4]; allowing learners to take on a virtual role within a story, deciding what paths to follow within a narrative, supports engagement and immersion in meaningful learning experiences.

Once a job has been started, if a player decides to leave that job for another before successful completion, this is considered a "switch" event for the original job. If the player accepts a job but never completes it, this is treated as quitting the job in our analysis. In other words, a student may switch from the job several times while still completing it (i.e., not quitting).

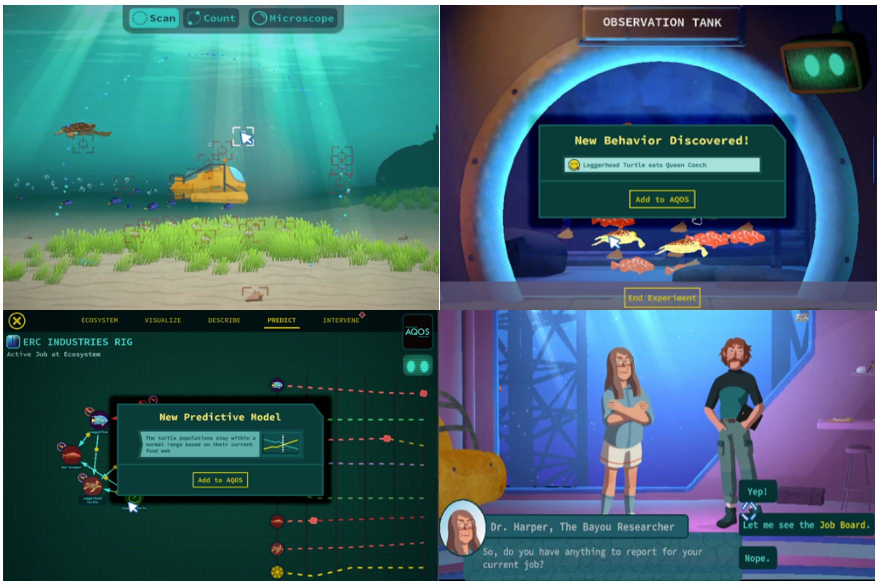

Fig. 1. Gameplay Screenshot for Wake: Collecting facts or evidence in one site (top left), conducting experiments in the observation tank (top right), modeling in the lab (bottom left), and completing an argument with the researcher to finish tasks (bottom right).

3.1 Data Collection

Wake uses the Open Game Data infrastructure for recording player interactions [10]. The opengamedata-unity package is integrated into the game, which allows it to connect with a cloud-based server that tracks and logs significant player activities during sessions. Each player is assigned a unique login, which tracks their patterns of play across multiple sessions, spanning multiple days. These recorded activities are collectively referred to as telemetry data. From a structural perspective, *Wake* transmits telemetry data using an event-based schema, influenced by the model suggested by [21]. It categorizes recorded events into three broad types: Player Actions, System Events, and Progression Events. Player Actions range from general navigation, such as moving to a designated research area, to more specific interactions like inputting species data in a modeling tool or choosing specific evidence during discussions. System Events capture moments like feedback on player choices or the appearance of characters guiding the player in new scenarios. Progression Events track milestones like the discovery of new facts or species, or the completion of tasks and jobs. *Wake* documents 33 different player actions, 12 system events, and 6 progression events, all of which are immediately uploaded to the Open Game Data server as they happen. Each event is detailed with metadata that includes the timing, sequence, player identification, and specifics about the event and the game's current state. These elements together provide a chronological account of all crucial interactions within a session, articulated in the game's specific language.

Wake: Tales from the Aqualab was made publicly available online in January 2023 via BrainPOP, a private educational media company, and PBS Learning Media, a public media distributor. As of April 30, 2024, the game has been played 128,488 times by 56,516 unique players. In the data we analyzed, there were 4,124 players. Among them, 79% completed the first three tutorial jobs, and 6.75% completed the final job. Game analytics suggest that the game is played primarily in formal learning contexts, with the majority of sessions taking place between 8am and 3pm local time on weekdays and excluding holidays. Jobs within the game are designed to take 5-15 minutes to complete individually.

3.2 Data Preparation

We segmented the chronologically organized log data into distinct job IDs, each representing a player's interaction history with a unique job until they decide to switch. Subsequently, the data is aggregated into a single row per job ID, which provides a summary of their engagement patterns and behaviors within that job. From this aggregation, several relevant features are derived to potentially capture nuances in student experience and performance for future analysis.

We begin by determining whether a student completed a job successfully or not, based on the presence or absence of a "complete_job" event in the log data (the alternative to successfully completing a job is quitting that job, unless the player quits the game entirely during that job and never resumes play).

Aggregated data also includes the number of jobs completed. In *Wake*, jobs typically center around a key question, like "What is causing the sea urchins to multiply so rapidly?" In each job, players must discover new insights about the ecosystem, formulate a hypothesis, and supply evidence to back it up. Players achieve these discoveries through direct observations at research locations, conducting experiments, and creating multiple scientific models. As players progress, the jobs introduce increasingly complex information and interdependencies within ecosystems. Consequently, the cumulative number of completed jobs can serve as a potential indicator of students' overall progress, engagement in the game, and possibly their mastery of fundamental concepts in the game.

The number of tasks completed is also calculated. In *Wake*, each job is further subdivided into smaller "tasks" to scaffold players. While certain tasks within jobs follow a specific sequence (e.g., scanning an organism before conducting an experiment with it), others can be completed in any order (e.g., scanning historical population data for a site and counting all current populations). Keeping track of the number of tasks completed provides a more fine-grained understanding of player progression. This information is particularly useful for tracking the progress of players who frequently switch jobs. Focusing solely on the total number of jobs completed might obscure noteworthy progress made by the student, as some players may have completed many tasks even if they haven't finished many jobs.

Acknowledging that students may not complete jobs in a single session, we also keep track of the number of usage sessions each student has engaged in so far. This feature allows us to distinguish between students who finish jobs in one session and those who require multiple sessions. These distinctions offer insights into students' task management strategies and their overall persistence in tackling complex challenges within the game environment.

We have also developed 4 supplementary features that cover the difficulty aspects of jobs that the students have previously completed and the extent of their visits to research stations within the game. The first three features quantify the average complexity of completed jobs. Based on a review of science learning trajectories for this grade band, we assigned each job a difficulty rating, ranging from 1 to 4, across three dimensions: argumentation, experimentation, and modeling [19]. Higher ratings denote greater difficulty. Given that students completing a series of easy tasks differ from those tackling more challenging ones, these features serve as indicators of students' proficiency within the game. The average argumentation difficulty, for instance, serves as a window into students' completion of complex reasoning tasks, while the average experimentation difficulty illuminates their proficiency in exploration and scientific inquiry skills. Similarly, the average modeling difficulty provides an indication of the student's ability to construct and comprehend complex systems across varied contexts. We choose to use average difficulty levels rather than maximum difficulty levels to reflect a student's performance across jobs; a student could complete a challenging job involving one skill while generally struggling with other skills. The fourth feature, the number of biomes visited, indicates a player's experience of different settings within the game, which may potentially influence their decision to quit jobs as well.

Following our feature development, we used two separate analytical approaches to determine how student quitting was associated with students' decisions to quit a job: a Chi-Square analysis to understand the impact of previous job completion, and a logistic regression analysis to investigate the role played by the other factors discussed in this section. In the next sections, we present our methods and results for each of these analyses.

3.3 Understanding the Impact of Previous Job Completion: Chi-Square Test

In order to investigate whether the previous jobs that a student completed are associated with their decision of whether or not to quit their target job without completing it, we conducted a Chi-square test of independence. This analysis allows for the assessment of the statistical significance of associations between categorical variables, which, in our analysis, consist of what jobs players completed before the target job they are on. In our analysis, we excluded (1) the first three tutorial jobs, which cannot be quit and are always played in the same order and (2) jobs with less than 30 successful job completion events (insufficient sample size), as well as jobs with fewer than 30 instances of quitting (insufficient evidence for quitting being a problem), which resulted in 40 total jobs in our dataset.

For each of the 40 jobs, we arranged the data into multiple contingency tables, with each table corresponding to a different previous job that students might have accepted (whether completed or not) before taking on the target job. Each table documents the frequency with which students either completed or did not complete (i.e., quit) the target job, in relation to their prior experiences—specifically, whether they have completed this previous job before attempting the target job.

A Chi-square is valid for these tests because these datasets satisfy all prerequisite conditions; there are no independence issues since each data point represents a distinct student, and there is a minimum expected count of 5 in at least 80% of the cells.

In our analysis, we also employed the Benjamini-Hochberg procedure (B&H), a statistical technique aimed at controlling the false discovery rate (FDR) when performing multiple comparisons. Because we conducted around 20-50 Chi-square tests for each target job analyzed, depending on the number of previous jobs students have played before their target job, our chances of any one of these tests being a false positive is relatively high. The B&H method allows us to manage this rate of false positives, by determining an adjusted significance threshold for our p-values. This technique orders the p-values in ascending sequence and compares them against adjusted critical values based on the total number of comparisons and the number of significant results thus far (i.e., adjusted alpha value). These adjusted values ensure that the expected ratio of erroneous rejections among all rejected null hypotheses does not exceed the FDR threshold of 0.05. Specifically, each p-value is evaluated against a progressively adjusted threshold: the lowest p value compared to 0.05 divided by the number of tests, the second lowest p value compared to 0.05 divided by the number of tests multiplied by 2, the third lowest p value compared to 0.05 divided by the number of tests multiplied by 3 and so on, down to 0.05 for the last p-value. A p-value that is below or equal to its respective critical value signifies statistical significance at the set FDR level, while a p-value above this threshold but less than twice the threshold suggests marginal significance at that level. The adjusted significance levels are calculated based on the number of previous jobs associated with each target job. For instance, if there are 20 previous jobs that students have played before a target job, then the adjustment calculated is based on 20 tests.

For each target job analyzed, we focus only on the top three previous jobs, selected based on their respective Chi-square statistics. These jobs are then included within subsequent logistic regression analysis. We only include the top three jobs in order to focus on the most impactful features in later efforts to nudge players to select better job sequences.

3.4 Chi-Square Results

Our Chi-square analysis revealed that for 23 out of 40 target jobs, at least one other job was associated with a significant difference in quit rate on the target, even after controlling for multiple comparisons. If we expand our significance threshold to marginal significance, this number increases to 29 jobs. This indicates that for the 40 target jobs analyzed, only 11 did not show any evidence of a relationship where completing prior jobs would decrease the quit rates of the target jobs.

For the regression analysis, we selected the top three jobs based on their Chi-square statistics from the Chi-square test. These jobs were included in the regression to assess whether completing these previous jobs significantly affects the likelihood of quitting the target job, while controlling for other variables. Our results showed that for 23 target jobs, experience in at least one previous job significantly reduced the likelihood of quitting that target job. For two additional 25 target jobs, at least one prior job was found to have a marginally significant effect on reducing the chances of quitting that target job.

Although there is a noticeable reduction in the number of target jobs significantly associated with prior jobs, this is expected as the regression analysis incorporates additional sources of variance that can explain quitting behavior. The findings suggest that while not all prior jobs strongly influence the outcomes of target jobs, a substantial number still demonstrate a potential impact.

Due to the extensive number of analysis results from our study, it is not feasible to list each individual result in this section; instead, we present findings from a Chi-square test and regression analysis on one specific target job with a notably high quit rate in the game: Hunting Lions in the station Coral Reef. Appendices of our full analysis are available on our project GitHub at `https://github.com/pcla-code/Wake-Job-Progression`. Hunting Lions requires players to conduct experiments on food web relationships for lionfish at a Coral Reef site, and then construct a predictive model of the future of that ecosystem if human hunters are allowed to hunt lionfish in that location. The job has the highest difficulty rating (5) across all three dimensions (argumentation, modeling, and experimentation) and involves 11 detailed tasks requiring players to collect 32 necessary facts.

Analysis of log data showed that out of the 631 students who accepted this job, 379 did not complete it, resulting in a quit rate of 60%. Through Chi-square tests and regression analysis, we explored the influence of completing prior jobs on the likelihood of quitting from the target job. Findings for the Chi-square test are detailed in Table 1.

The results highlighted that players who had completed the Reef Decision job, in the Bayou biome, were less likely to quit the target job, with a quit rate of 16.13%, compared to 42.27% among those who did not complete this job. This difference was statistically significant ($\chi^2(1, N = 631) = 26.392$, $p<0.001$, adjusted $\alpha = 0.017$), which indicates a significant effect of prior job completion on player decisions to quit the target job after the correction.

Further examinations showed similar patterns for jobs Hide n Seek and Methanogen. Players who completed these jobs also demonstrated lower quit rates from the target job. The Chi-square statistics were significant for both jobs and remained significant after the correction (Hide n Seek: $\chi^2(1, N) = 14.414$, $p < 0.01$, adjusted $\alpha = 0.017$; Methanogen: $\chi^2(1, N) = 11.486$, $p < 0.01$, adjusted $\alpha = 0.017$). The result shows how previous job completions may significantly influence player retention at the target job.

Table 1. Statistical Results from the Chi-Square Test on the Effect of Previous Job Experience on Target Job

Target Job	Prior Job	Played Before Target Job	# Quit Target Job	# Not Quit Target Job	% Quit Target Job	Chi-Square Statistic	p-value
(Coral) Hunting Lions	(Bayou) Reef Decision	Yes	20	104	16.13%	26.392	< 0.001*
		No	153	209	42.27%		
	(Bayou) Hide n Seek	Yes	35	113	23.65%	14.414	< 0.001*
		No	148	204	42.05%		
	(Bayou) Methanogen	Yes	41	121	25.31%	11.486	< 0.001*
		No	142	202	41.28%		

***Significant after B&H correction**

3.5 Assessing the Impact of Previous Job Completion and Other Factors: Regression Analysis

Following the initial analysis with the Chi-square test, we further explored other factors influencing players' decisions to quit the target jobs using logistics regressions. This statistical approach allowed us to incorporate a broader range of variables into our model. Through this analysis, we hope to understand how each factor, individually and collectively, affect the probability of a player quitting jobs.

The logistic regression model was constructed to predict the likelihood of a player deciding to quit jobs, based on the abovementioned 9 variables (from section 3.2). The analysis provided coefficients (scaled as odds) for each predictor, which reflect their respective impacts on the probability of quitting jobs. A positive coefficient indicated an increase in the likelihood of quitting jobs as the value of the predictor increased, while a negative coefficient suggested the opposite. The significance of each coefficient was assessed to determine which factors had a statistically meaningful influence on job-quitting decisions of the target job.

We applied the B&H correction method to the p-values obtained from our regression analysis, following the same procedure previously used for the Chi-square tests. The adjusted significance level for each target job analyzed was calculated based on 27 (3*9) tests, where 9 represents the number of features included in each regression (excluding the constant term, as it does not constitute an independent test of interest like the other features), and 3 represents the three previous jobs selected from the Chi-square tests.

3.6 Regression Analysis Results

The logistic regression analysis examined the effect of various factors, beyond merely completing the selected prior jobs, on the probability of players quitting Hunting Lions.

Table 2 presents a consistent negative correlation between completing those earlier jobs and the likelihood of quitting from Hunting Lions. For example, players who completed Reef Decision had a coefficient of -1.555 ($p < 0.001$, adjusted $\alpha = 0.002$), which implies a 79% lower probability of quitting during the target job compared to those who did not complete it. Similarly, completion of Hide n Seek resulted in a -1.382 coefficient ($p < 0.001$, adjusted $\alpha = 0.002$), which suggests a 75% reduced probability of quitting the target job, and completion of Methanogen showed a -1.274 coefficient ($p < 0.001$, adjusted $\alpha = 0.002$), which translates to a 72% reduced likelihood in quitting. These results support the hypothesis that completing these jobs decreases the probability of quitting from Hunting Lions, which corroborates the Chi-square test results.

The p-value for the number of jobs completed with higher difficulty in argumentation and experimentation was not statistically significant. However, the completion of jobs with greater difficulty in modeling and experimentation showed a significant negative relationship with target job completion. Specifically, coefficients for modeling ranged from -0.340 to -0.397, which remained significant after adjustment ($p < 0.001$, adjusted $\alpha = .002$). This indicates that for each additional job a student completes with a modeling difficulty greater than 2, the likelihood of them quitting the target task decreases by approximately 29% to 33%.

Interestingly, the overall number of jobs completed showed a slight positive relationship (coefficients 0.120 to 0.131, with p-values around 0.02), which suggests that completing one additional job is associated with a modest increase in the probability of quitting the target job, by 13%-14%. However, these findings did not retain significance following the correction for multiple comparisons (adjusted α ranging from 0.002 to 0.003). The time spent, the number of tasks completed, the number of biomes visited, and the number of times paused showed no significant association with the likelihood of job-quitting at the target job.

Table 2. Statistical Results from Logistic Regression Analysis on the Impact of Previous Job Experience on Target Job (p-values are shown in parentheses)

Part 1:

Target job	**Prior job**	**Prior job completed**	**# of jobs completed with Arg. diff.> 2**	**# of jobs completed with Mod. diff.> 2**	**# of jobs completed with Exp. diff.> 2**
(Coral) Hunting Lions	(Bayou) Reef Decision	-1.555 (<0.001)*	0.075 (0.440)	-0.340 (<0.001)*	-0.239 (0.045)
	(Bayou) Hide n Seek	-1.382 (<0.001)*	0.077 (0.426)	-0.345 (<0.001)*	-0.233 (0.048)

(Bayou) Methanogen	-1.274 (<0.001)*	0.093 (0.333)	-0.397 (<0.001)*	-0.181 (0.123)

Part 2:

Target job	**Prior job**	**Time (Min)**	**# of jobs completed**	**# of tasks completed**	**# of biome visited**	**# of time paused**
(Coral) Hunting Lions	(Bayou) Reef Decision	0.180 (0.237)	0.131 (0.016)	-0.012 (0.528)	-0.164 (0.477)	0.012 (0.648)
	(Bayou) Hide n Seek	0.189 (0.218)	0.129 (0.016)	-0.011 (0.549)	-0.156 (0.496)	0.001 (0.749)
	(Bayou) Methanogen	0.176 (0.224)	0.120 (0.024)	-0.012 (0.517)	-0.107 (0.642)	0.001 (0.667)

***Significant after B&H correction**

4 Discussion and Conclusions

This study explores the influence of prior job completions on the likelihood of quitting future target jobs in the educational game *Wake*. Additionally, we studied the influence of factors such as time spent on jobs and the difficulty level of completed jobs on the quitting of the target jobs. Target jobs were identified as any job within the game, excluding the first three introductory jobs and any job for which there was insufficient data (i.e., fewer than 30 players who completed it and 30 players who did not complete it), for a total of 40 target jobs.

The results show that students' decisions to quit from jobs in *Wake*, for more than 50% of the jobs analyzed, were influenced by whether they had played some specific previous jobs or not. Towards our goal of identifying productive and unproductive pathways for student learning in *Wake*, we have some evidence that specific sequences of jobs may be better for promoting student engagement than others.

In specific, the results from the Chi-square test demonstrated that completing the three prior jobs, Reef Decision, Hide-n-Seek, and Methanogen significantly reduced the likelihood of quitting the target job Hunting Lions. Logistic regression analysis showed that the impact of completing the three preceding jobs on quitting the target job was significant even after accounting for other factors. This finding could be attributed to several factors. Firstly, all three preceding levels have a difficulty rating of 4 for either experimentation or modeling, which indicates that these levels are still challenging but slightly less difficult than Hunting Lions. This allows players to develop and refine their skills at a manageable pace. Additionally, each of these levels helps players develop specific skills required for the more challenging target job. For example, Hide 'n Seek involves substantial tasks completed in the observation tank, Methanogen focuses on measuring rates and environmental effects, and Reef Decision emphasizes modeling and making predictions based on collected data. These skills are necessary for successfully completing the complex tasks in Hunting Lions. Lastly, players may become familiar with using various tools (e.g., Measurement Tank, Stress Tank, Flashlight) across these levels. This familiarity can reduce the cognitive load when encountering similar tools in Hunting Lions, which may make it easier for the players to focus on the tasks rather than figuring out how to use the tools.

Meanwhile, this finding also suggests that directing players through specific jobs before attempting the target job could potentially help reduce the rate of quitting. Specifically, for players finding the target job challenging, recommending a switch to any of these three previous jobs before retrying the target job might improve their gameplay experience and reduce quit rates and the experience of struggle with the target job.

The insights from logistic regression analysis highlight additional factors that play a role in the quitting of target jobs. One key observation is that completion of earlier jobs with a modeling difficulty rating greater than 2 is associated with lower probability of quitting of the target job. This suggests that facing and overcoming challenges in more complex modeling jobs can potentially improve player persistence at subsequent, potentially more difficult jobs. Moreover, it also suggests that designers should offer students extra scaffolding and support the first time they encounter a job with a modeling difficulty greater than 2. Providing support at this point can help students overcome the challenges and improve their ability to handle jobs of similar or greater difficulty in the future. This pattern is evident not only in the specific example presented but throughout the entire analysis.

Our findings indicate that not every target job has a prior job that, when completed, can reduce the target job's quit rate. However, many previous jobs do contribute positively to decreasing quit rates for the subsequent target jobs. This insight might be helpful for the game designers, as reducing the quit rate and easing struggles could potentially make the game more engaging and enjoyable for players. By strategically designing job sequences, and nudging players to more effective sequences, designers may improve the player experience and ultimately increase player retention and satisfaction.

However, there are limitations to our study. We used data collected from May to October 2023, a brief six-month period that may not fully capture the variability in player behavior influenced by factors like academic calendars, holiday seasons, or game updates. To develop a more nuanced understanding of what influences job completion and the propensity to quit later jobs in *Wake*, future research should aim to broaden the scope of data collection to include more varied player interactions over a longer period.

Additionally, our analysis might not fully capture the complex interactions between different factors. Important external factors, such as the age of the player, their previous gaming experience, or educational background, were not considered in our study. These elements could also play a role in a player's decision to quit jobs and their overall performance within the game.

Despite these limitations, our findings provide actionable recommendations for game designers. The effect of completing some prior jobs on maintaining persistence in subsequent target jobs highlights the benefit of strategically structuring game progression. In carefully designing the sequence of jobs to gradually improve player skills and confidence before introducing more significant challenges, game designers can potentially reduce player frustration and the likelihood of quitting and produce a more rewarding and educational gaming experience for players.

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