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Quantifying the Benefits of the Reread-Before-Answer Strategy in Japanese High-School EFL

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Abstract: Digital e-book platforms collect detailed logs of students' reading behaviors, yet it remains unclear whether brief revisits of previously viewed pages before answering open-book quiz questions significantly improve outcomes. This study investigates whether "Reread-Before-Answer" (RBA) loops, brief backward navigation immediately preceding quiz responses, impact quiz performance. Analyzing one month of BookRoll logs from 263 Japanese high-school English learners, we applied sequence mining to detect RBA loops and logistic regression to quantify their effects, controlling for session duration, navigation length, and prior English proficiency. Results show RBA loops occurred in approximately 40% of sessions and consistently predicted better performance, with learners who engaged in these loops showing significantly higher quiz accuracy compared to strictly linear readers. Pattern analysis further revealed that successful students preferred concise review behaviors over prolonged rereading. These findings highlight that encouraging short, intentional revisits to relevant content just prior to assessment can effectively enhance students' quiz performance. Consequently, integrating structured rereading prompts within digital textbooks could serve as a practical intervention for educators and instructional designers to optimize learning outcomes.

Keywords: Reread-before-answer (RBA), Navigation Motifs, Learning Analytics, Sequence Mining, Mixed-Effects Logistic Regression, Japanese High-school EFL

1. Introduction

Educational e-book platforms provide rich data on how students navigate digital texts. Analyzing these navigation patterns can reveal strategies that contribute to learning success. Prior research on systems like BookRoll, a digital textbook reader, has shown that logs of student reading behaviours (page flips, backtracking, annotations) can predict performance (Flanagan et al., 2022). The Learning and Evidence Analytics Framework (LEAF) integrates such e-book data for learning analytics research (Kannan et al., 2022). However, much of the early work focused on summative measures (e.g., total pages read or total time) rather than the sequence of actions (Valle Torre et al., 2024). Recent studies argue that learning is a temporal process and that simply aggregating click counts is limited in explanatory power (Valle Torre et al., 2024). Instead, examining how students move through content, i.e., their navigation sequences, can yield deeper insight into study strategies and their effectiveness (Woollaston et al., 2025).

One particular sequence pattern of interest is the reread-before-answer (RBA) loop, defined as a navigation loop where a learner, before answering a quiz question, goes back to review earlier pages and then returns to answer. Formally, an RBA loop can be represented as: *page i → page (i-k) → page i → answer*, where $k \geq 1$ denotes the number of pages the learner jumped back. This pattern reflects a deliberate backtracking to previously read material just before attempting an assessment item. Theoretically, such "constructive re-processing" aligns with findings from reading research: rereading text can foster deeper comprehension and better recall, especially for second language (L2) learners. For example, Thomas and Healy (2012) found that rereading improved understanding in both first and second language reading tasks, supporting the idea that reviewing content strengthens memory and clarification of concepts. In an open-book learning context, an RBA loop may indicate a metacognitive strategy where the student verifies facts or concepts right before answering, potentially leading to higher accuracy. We hypothesize that learners who engage in RBA loops will achieve higher mastery on within-unit multiple-choice questions (MCQs) than those who follow a strictly linear reading path. Specifically, preliminary observations from our e-book platform suggested a performance gap: sessions containing an RBA loop had on average about 10% higher quiz accuracy than linear sessions with no backtracking. *Figure 1* illustrates this difference in our dataset: learners who backtracked at least once before answering tended to score higher on the unit quiz, as evidenced by the higher median and narrower high-performance spread for the RBA group (orange) compared to the linear group (blue). This motivates a deeper, controlled analysis of the RBA effect. To systematically investigate this phenomenon, we pose the following research questions (RQs):

1. **RQ1:** Is there a relationship between learners' reread-before-answer (RBA) behaviour and their multiple-choice-question (MCQ) performance?
2. **RQ2:** To what degree do RBA behaviours correlate with MCQ performance after controlling for time-on-page, sequence length, and prior English ability?
3. **RQ3:** Which navigation behaviours uniquely and significantly distinguish sessions with top-quartile MCQ performance?

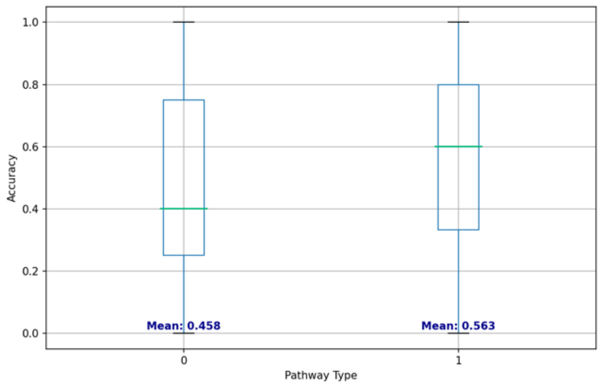


Figure 1. MCQ Accuracy by Pathway Type

In this study, we analyze anonymized e-book reading logs collected with informed consent from a Japanese high-school English course (Wijerathne et al., 2024) from a high school English course to answer these questions. We use sequence mining to detect RBA loops and other navigation motifs (Jacquemont et al., 2009) and apply mixed-effects logistic regression (with student and unit as random effects) (Ozechowski et al., 2007) to estimate the impact of RBA on quiz performance while controlling for potential confounds. Our findings confirm that RBA loops correspond to higher quiz success (about a 10.5 percentage-point gain raw, and ~6% gain after controls), and we identify specific navigation patterns prevalent among the top-performing students. We also discuss how these insights can inform the design of adaptive e-book features to support better study habits. The remainder of the paper is organized as follows: we first describe the dataset and methodology, then present results for each research question along with robustness checks, and finally discuss implications, limitations, and future work.

2. Methodology

2.1 Context and Data Collection

The data for this study come from a Japanese high school e-book learning environment in an EFL course. The platform consists of the BookRoll digital reading system integrated with the

LEAF learning analytics framework (Chen & Su, 2019; Flanagan & Ogata, 2018). BookRoll offers PDF educational resources and meticulously records user interactions. These records adhere to the xAPI standard, documenting events such as PDF access, page navigation, text highlighting, and quiz responses, along with their respective timestamps. Our analysis encompasses one month of interaction data from 263 high-school students engaging with 56 distinct PDF content units. Each content unit generally concludes with multiple-choice assessments designed to evaluate the students' comprehension of the material presented. Given the "open-book" format of these assessments, the logs reflect students' navigation patterns during quiz completion.

The raw log data comprised 57,532 events and 6,023 quiz answers, with a correct response rate of 55.4%. The logs were preprocessed for reliability before analysis. Timestamps were adjusted to Japan Standard Time, sorted, and any duplicates or errors were eliminated. Subsequently, the data was sessionized, grouping interactions into sessions defined by 30-minute inactivity periods. Consistent with widely adopted practice in learning-analytics sessionization (e.g., Kim et al., 2014; Kovanovic et al., 2015; Ming et al., 2019), we defined a new session after 30 minutes of inactivity in the BookRoll logs. Various session gap thresholds were evaluated for robustness (5, 15, 30, 45 mins), with 30 minutes selected for primary analysis due to its conventionality and logical representation of a session unit. After sessionizing, each event in the log was labeled with a session ID (*Table 1*).

Within each session, the navigation sequence of pages for each learner's attempt at the content was reconstructed. This sequence represents the ordered list of page IDs accessed by a student during that session before submitting their quiz answers. Additionally, quiz outcomes (correct/incorrect) were recorded alongside page transitions for the sequence. For instance, a simplified navigation sequence may appear as: [*Page 1 → Page 2 → Page 3 → Page 2 → Page 3 → Answer*]. In this case, the student accessed pages 1 through 3, returned to *page 2*, went back to *page 3*, and subsequently answered the questions. Such sequences are encoded as necessary to facilitate pattern detection.

2.2 Identifying RBA Loops

An RBA loop is defined as any purposeful backtracking that occurs immediately before a quiz attempt. For a session with ordered page numbers $(\boldsymbol{P_1}, \boldsymbol{P_2},, \ldots, \boldsymbol{P_n})$ and a quiz event Q, we inspect the k pages that precede ***Q (k = 10)***. If within this window there is at least one index ***j*** where $\boldsymbol{P_j} > \boldsymbol{P_{j+1}}$, the learner has "jumped back" $\boldsymbol{\Delta} = \boldsymbol{P_j} - \boldsymbol{P_{j+1}} + \mathbf{1}$ pages. When ***Δ ≤ k***, and the quiz page either matches $\boldsymbol{P_{j+1}}$ or re-appears later in the window, the session is flagged ***has_RBA = 1***; otherwise ***has_RBA = 0***. The actual implementation is a single *O(n)* scan: using a 30-min inactivity rule, we obtained 1,843 learner-content sessions; 39.6% contained at least one RBA loop, implying that roughly two of every five study bouts involved rereading before answering. *Figure 1* contrasts MCQ accuracy by navigation type. RBA sessions show a higher median and narrower inter-quartile range, with a gap of ≈ 10 percentage points over linear sessions, an initial affirmative answer to RQ1. To test robustness, we repeated the detection with progressively stricter back-jump caps ***(k = 1…5)***. Although the proportion of flagged sessions drops as ***k*** shrinks, the accuracy advantage remains virtually unchanged, indicating that even a single-page revisit is pedagogically beneficial (§3.3). For subsequent models (RQ1-RQ2) we analyze only the binary indicator, presence versus absence of an RBA loop, because the theoretical claim concerns whether strategic rereading occurs, not how many times or how far learners back-track.

2.3 Measures and Variables

The primary outcome variable is MCQ Accuracy, defined as the proportion of quiz questions a student answered correctly for each learner-content pair. In cases where a quiz contained only one question, this measure is binary (0 or 1), while quizzes with multiple questions yielded fractional scores between 0 and 1. Each learner's attempt on a given unit constitutes one data point. The main explanatory variable is the **presence of an RBA loop**, classifying sessions as either RBA or linear. To control for potential confounds, we included three covariates. **Total Time-on-Page** represents the total time spent reading, calculated by summing the time between page events, with a cap on excessively long gaps to minimize idle-time inflation. This value was standardized using z-scores. **Sequence Length**, also standardized, refers to the number of distinct page transitions during a session. While linear readings of an n-page unit produce (n-1) transitions, sessions with backtracking result in longer sequences, which may reflect more thorough engagement or confusion. Finally, we included **Prior English Ability**, drawn from students' pre-course placement test scores (out of 100), standardized (mean=0, SD=1) for analysis. Missing values were addressed via multiple imputation. These covariates allow us to isolate the specific effect of RBA on MCQ accuracy, answering RQ2 comprehensively.

2.4 Statistical Analysis

To quantify the impact of RBA loops on quiz performance (RQ1 and RQ2), we employed a mixed-effects logistic regression model. Logistic regression is appropriate since our outcome can be considered binary at the quiz attempt level. We chose a mixed-effects approach to account for the nested structure of the data: multiple observations per student (some students attempted several contents) and per content unit (multiple students per the same content). By including random intercepts for Learner and Content Unit, we control for unobserved heterogeneity in individual ability (beyond the prior score) and question difficulty. This approach is similar to modeling each student and each unit having a baseline performance level, and we focus on the fixed effects that explain deviations from those baselines.
Our main regression model (Model 1) can be described as:

$$\boldsymbol{logit(P(Correct)) = \beta_0 + \beta_1 \cdot RBA_{present} + \beta_2 \cdot TimeOnPage + \beta_3 \cdot SeqLength + \beta_4 \cdot PriorAbility + (1 \mid Learner) + (1 \mid Unit)}$$

Here β_1 is the coefficient testing our hypothesis, a positive β_1 would indicate higher odds of a correct answer when an RBA loop is present, even after controlling for the other factors. We report this effect as an Odds Ratio (OR) for interpretability. An OR > 1 for RBA means the odds of quiz success are higher with an RBA loop than without. We also examine β_2 (time-on-page) and β_3 (sequence length) to ensure RBA isn't simply a proxy for "spent more time" or "looked at more pages."

Due to the absence of prior ability scores for all students, a Multiple Imputation (MI) method was employed to address missing data. Ten imputed datasets were generated, predicting missing scores through a regression-based imputer, and a logistic model was applied to each, with results aggregated via Rubin's rules (Royston, 2004). This approach provides a more reliable estimate without omitting students lacking prior scores. Additionally, a simplified model (Model 0) was executed without prior ability to evaluate the extent to which the RBA effect could be attributed to higher-skilled students' propensity to utilize RBA. The outcomes of these models are illustrated in forest plots. (see Results, *Figure 3*).

2.5 Pathway Pattern Mining

To address RQ3, we went beyond the RBA/non-RBA dichotomy and explored frequent navigation motifs in the sequences. We leveraged sequence pattern mining to identify which specific page transition patterns were over-represented among top-performing sessions. We first divided sessions by performance level: for example, "top quartile" sessions are those in the highest 25% of unit quiz scores (which in many cases means they answered all questions correctly), whereas "bottom quartile" would be low-scoring sessions. We then applied two complementary analyses: **Frequent Subsequence Mining:** Using the PrefixSpan algorithm (Bermudez et al., 2020), we mined for common subsequences of length 3-5 pages that occurred in at least 2% of sequences. PrefixSpan finds patterns like *"Page 2 → Page 3 → Page 2*" (a back-and-forth) or "*Page 1 → Page 2 → Page 3*" (a linear read) that appear frequently. **Motif Occurrence by Performance:** For the top 10 most frequent motifs, we computed how often each motif appeared in sessions of different performance quartiles. This is visualized as a heatmap (*Figure 6*) where each row is a navigation motif and columns correspond to quartile groups, with cell color indicating the percentage of sessions in that group containing the motif. We also highlight which motifs have markedly higher presence in the top quartile compared to lower quartiles.

Additionally, we constructed a navigation transition network (pages as nodes, transitions as directed edges) and computed PageRank centrality for pages, as well as visualized overall flows with a Sankey diagram. While these network visualizations (e.g., *Figure 2*) are not the core of RQ3, they provided context, identifying which pages or transitions were "hubs" in the reading activity. For instance, if certain pages are frequently returned to by many students, that page might contain crucial content that warrants emphasis by instructors. By combining the statistical modeling and the motif analysis, we aim to paint a comprehensive picture: not only confirming if RBA loops help but also understanding what other navigation patterns characterize successful learning sessions. All analyses were conducted in Python, using libraries such as pandas for data handling, statsmodels for logistic regression, and custom scripts for sequence mining. The significance level was set at α = 0.05 for hypothesis testing, and we report 95% confidence intervals for model coefficients.

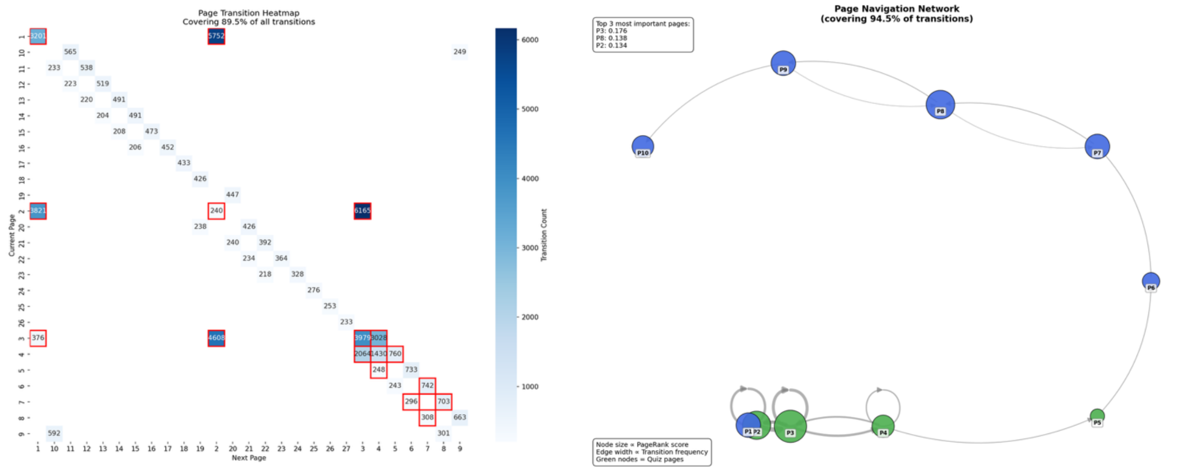


Figure 2. L: Page Transition Heatmap | R: Page Navigation Network

Table 1. *Raw MCQ Accuracy by Navigation Type and Session-Gap Threshold*

Gap (min)	RBA *n*	RBA *Acc*	Linear *n*	Linear *Acc*	Diff (pp)	Cohen's *d*
5	685	0.5651	188	0.4748	+9.0	0.299
15	720	0.5643	153	0.4576	+10.7	0.354
30	729	0.5629	144	0.4582	+10.5	0.347
45	730	0.5627	143	0.4584	+10.4	0.346

3. Results

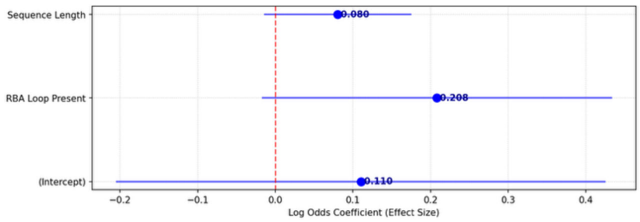
3.1 RQ1: Relationship between RBA behaviour and MCQ accuracy

Sessions that include an RBA loop yield significantly higher MCQ accuracy compared to linear navigation sessions. Specifically, sessions containing at least one reread-before-answer loop had an average quiz accuracy of 56.4%, compared to 46.3% for purely linear sessions (*Table 1*), an absolute difference of roughly 10 percentage points in favor of RBA. In practical terms, a student who reviewed pages before answering got roughly 1 extra question correct out of 10, compared to a student who never looked back. This gap is illustrated in *Figure 1* (described earlier), where the distribution for RBA sequences is shifted upward relative to linear sequences. A two-proportion z-test confirmed the gap was highly significant (Cohen's d ≈ 0.35, z = 4.9, p < .001), reinforcing the practical importance of the 10-percentage-point advantage. It is important to note that RBA sessions also tended to involve slightly more reading activity -

for example, they had a longer median sequence (the median number of page transitions was 12 for RBA vs. 9 for linear) and on average a bit more time spent. This raised the question addressed in RQ2: is the performance gain simply due to spending more time or other factors, or is there an independent contribution of the RBA strategy?

3.2 RQ2: Effect of RBA after controlling for time, sequence, and ability

To address RQ2, we utilized mixed-effects logistic regression models, with results displayed in Figure 3 (L and R) as forest plots of effect sizes (log-odds coefficients with 95 % confidence intervals) for RBA and other predictors. Figure 3 (L) excludes prior ability, while Figure 3 (R) includes it via multiple imputation. Both models assess whether students answered MCQs correctly, with fixed effects for RBA presence, total time, and sequence length. Significant random effects for student and unit highlight variability across individuals and content. In Figure 3 (L), without prior ability, the RBA Loop Present coefficient is approximately 0.208 log-odds (odds ratio ~1.23), indicating a 23 % higher likelihood of answering correctly in RBA sessions compared to linear sessions.



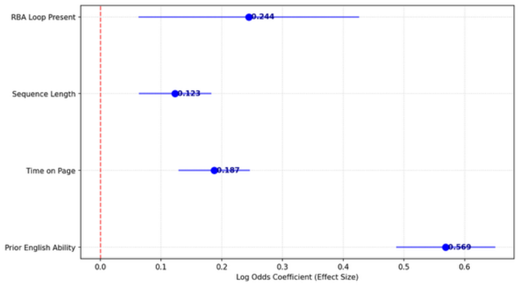


Figure 3. Effect size of predictors L: Without prior ability | R: With Multiple Imputation 95% CIs

Sequence length shows a modest but reliable benefit (*β = 0.123, OR = 1.13, 95 % CI [1.07, 1.20], p < 0.001*), indicating that visiting more pages is associated with slightly higher success. Time-on-page has a comparable, significant effect (*β = 0.188, OR = 1.21, 95 % CI [1.14, 1.28], p < 0.001*). When prior ability is included (*Figure 3 R*) and after controlling for time-on-page and sequence length, the RBA loop remains statistically significant (*β = 0.244, SE = 0.092, p = 0.008*), corresponding to an odds ratio of 1.28 (*95 % CI [1.07, 1.53]*). This translates to a roughly 6-percentage-point increase in predicted success probability, for example, a typical linear session's 46 % chance of a correct answer rises to about 52 % with an RBA loop. Prior English ability is the strongest predictor (*β = 0.569, OR = 1.77 per SD, 95 % CI [1.63, 1.91], p < 0.001*), reinforcing the importance of baseline proficiency. Random effects still indicate meaningful variance among students and content difficulty.

In summary, after adjusting for confounding factors, RBA loops offer about a 28% increase in quiz success odds (5-6% absolute gain), supporting our hypothesis that reviewing material before answering enhances immediate learning outcomes.

3.3 Robustness Checks: Session Definitions and Loop Size

We conducted several checks to confirm the robustness of our results: **Varying Session Gap Threshold:** We analyzed different session break definitions (5 min, 15 min, and 45 min). The prevalence of RBA patterns and their accuracy effects were consistent (*Table 1*). At 15-minute gaps, RBA loops appeared in ~38% of sequences with a ~9% accuracy difference; at 45 minutes, ~37% prevalence and ~10.5% difference. The logistic regression odds ratio for RBA remained around 1.25-1.30, indicating our conclusions are stable regardless of session definitions. **Loop Size (k) Sensitivity:** We examined how backtrack distance affects outcomes. At k = 1, RBA prevalence was nearly 0%, as most users moved forward. At k = 2, about 23% had back-jumps; at k = 3, 26%; k = 4, ~37.5%; and k = 5, ~38.6%. This indicates RBA loops tend to be around 4 pages long, capturing most instances. The accuracy benefit was ~5% points for k = 2 or 3, increasing to 9.1% at k = 4, with no further gains at k = 5. This suggests reviewing 4 pages yields optimal benefits. *Figure 4 (R)* shows that RBA advantages are consistent across session-gap definitions, with medium- and high-ability groups outperforming linear sessions by 8-12 percentage points, and low-ability learners seeing a 3-5 percentage points (pp) lift. Short backtracks (1-2 pages) had less impact, while longer backtracks (beyond 4 pages) showed no added benefit, indicating that brief reviews before quizzes are most effective (see *Figure 5*). **Model Variants**: Alternative modeling approaches were explored, showing that students who frequently used RBA had higher mean scores. A logistic model excluding sequence length or time maintained a significant RBA effect, indicating it is not confounded by these variables. A mixed-effects model on complete cases also produced a similar odds ratio for RBA (~1.26), suggesting that imputation did not introduce bias.

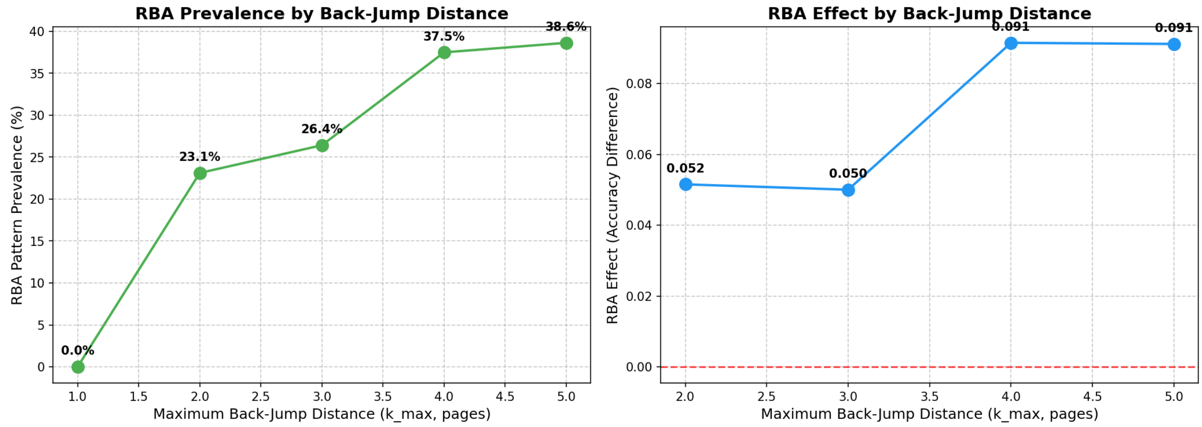


Figure 4. K-Sensitivity | Prevalence (L) & Impact (R) of RBA Loops by Back-Jump Distance

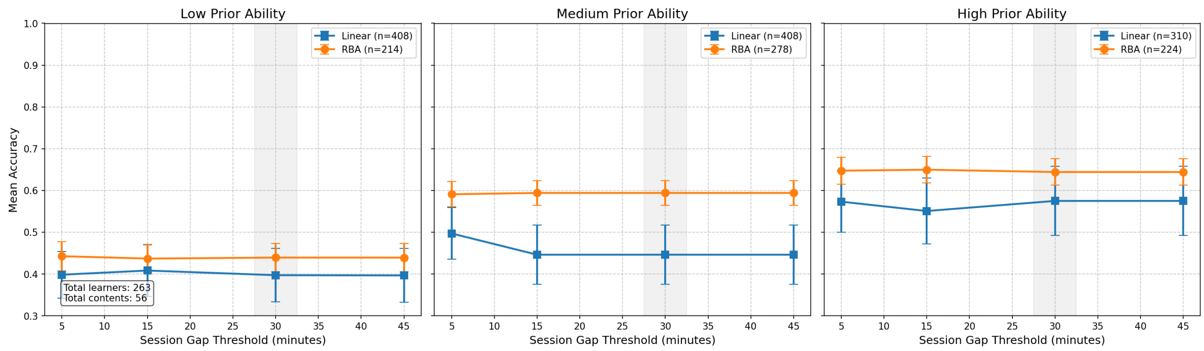


Figure 5. Accuracy by Session Gap Threshold, Navigation Type, and Prior Ability

In conclusion, students who reread content non-linearly before answering open-book quizzes performed 5-10 percentage points better in accuracy compared to those who read straight through, supporting the hypothesis that RBA loops are an effective learning strategy in this e-book context.

3.4 RQ3: Common Navigation Motifs in Top-Quartile MCQ-Accuracy Sessions

What navigation patterns characterize the most successful learners beyond RBA loops? We analyzed log sequences for frequent motifs, comparing high vs. low performing sessions. *Figure 6* shows a heatmap of the top 10 navigation patterns, with each row representing a specific sequence of page transitions (2 or 3 steps). The count at the start of each row indicates how often that pattern occurred in 500 sampled sequences. For example, "438 (87.6%): *2 → 3*" indicates this transition occurred in 438 sequences (87.6%). The second row "449 (89.8%): *1 → 2*" is even more frequent, as many sessions start at page 1. These linear patterns are common across all sessions and do not distinguish high vs. low performers. More notable are the backward transitions like "*3 → 2*," found in 326 sequences (65.2%), which indicate RBA-type loops. These backtracks, such as "*4 → 3*" and "*2 → 1*," were significantly more common in high-scoring sessions. The heatmap shows that high-accuracy sessions (left) have more purple marks in the backtrack rows, indicating these patterns are present, while lower performers (right) show more yellow, indicating their absence.

Over two-thirds of top-quartile sessions involved backward navigation (e.g., from page 3 to 2), while less than half of bottom-quartile sessions did. High performers frequently revisited pages, with notable motifs such as "*3 → 3*" (self-loop on page 3) appearing in 252 sequences (50.4%). This indicates students spent extra time on the same page, likely to re-read or take notes. Self-loops like "*1 → 1*" (92.8% of sequences) suggest many sessions involved repeated access to page 1, indicating students returned to summaries or key points. Another common motif was "*2 → 1*" (309 sequences, 61.8%), where top students often returned to page 1 for reviews, a behaviours less common among lower performers. We also examined 3-step motifs, such as "*4 → 3 → 4*" (140 sequences, 28.0%), showing thorough review loops between pages 3 and 4. These patterns were predominantly found in higher quartile sessions, indicating that successful learners engaged in back-and-forth navigation rather than linear reading.

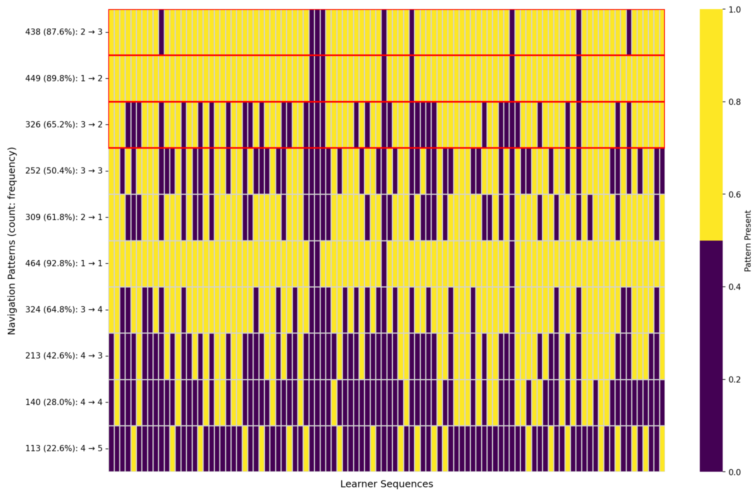


Figure 6. Top Navigation Patterns (Motifs)

In summary, the most successful sessions exhibited higher instances of review-oriented navigation motifs. While simple forward-reading (*1→2→3…*) was common, top quartile students distinguished themselves with strategic backtracking. Patterns of revisiting pages were linked to deeper engagement with content, as illustrated by an example involving English grammar, where high-performing students effectively navigated between pages to reinforce understanding, contrasting with lower performers who often missed critical details by not revisiting earlier content.

4. Discussion and Limitations

This research elucidates the relationship between digital textbook navigation and educational outcomes, with a particular focus on rereading before answering (RBA) as an advantageous pedagogical strategy. Participants who engaged in RBA cycles attained superior quiz scores, irrespective of the total duration of study or their prior capabilities (as visualized in *Figure 5*). These findings are consistent with cognitive theories that prioritize self-regulated learning and reading comprehension, which are especially pertinent in contexts of EFL (Jafarigohar & Morshedian, 2014), where learners frequently revisit previous pages to enhance their understanding of linguistic elements. Our results reinforce earlier investigations, such as those conducted by Flanagan et al. (2022), which observed enhanced performance linked to page revisits. Notably, our study emphasizes that the sequence of study, not merely the duration of study, exerts a significant impact on learning, thereby advocating for a temporal analysis within the domain of learning analytics. However, several limitations necessitate consideration:

- **Causality**: The correlational design of our study constrains the ability to make definitive assertions regarding causation. Although prior ability was controlled for, extraneous variables such as student motivation or metacognitive skills may affect the utilization of RBA. Experimental investigations that explicitly prompt RBA could yield clearer causal relationships.
- **Immediate vs. Long-term Learning**: The results of our study primarily address immediate quiz performance. The implications for long-term retention attributed to RBA remain ambiguous; subsequent research should investigate prolonged assessments to substantiate these findings.
- **Generalizability**: The specific context of this study, a high school EFL curriculum in Japan, may constrain the generalizability of the results. Outcomes could vary across different subjects or in contexts requiring closed-book assessments. Nonetheless, the efficacy of active content review is likely to persist across various settings. Future research should examine analogous patterns within diverse educational environments.
- **Data Interpretation**: Deducing strategies from log data bears the risk of mischaracterizing certain page revisits as constructive, when they may instead signify confusion or distraction. The incorporation of qualitative methodologies such as screen capture or eye-tracking could elucidate the intentions of learners more clearly.
- **Highlighting and Note-taking**: Although the act of highlighting was captured indirectly, the explicit analysis of this behaviour was limited. Given anecdotal support linking highlighting to academic success, further motif analysis encompassing annotation practices could enhance comprehension.
- **Motif Analysis Scope**: Our motif analysis was predominantly centered on prominent navigation behaviours. More nuanced actions merit comprehensive statistical scrutiny (e.g., motif enrichment testing) for a more profound understanding of navigation strategies related to performance.
- **Platform Limitations**: The reliance on BookRoll logs necessitates continuous online engagement, which may overlook offline study activities. Additionally, the imposition of a 30-minute session threshold could result in an underestimation of session continuity. Future inquiries might implement varied definitions of sessions to affirm the robustness of findings.

Despite these limitations, the persistent correlation between RBA cycles and improved educational outcomes underscores the potential significance of promoting strategic review behaviours among students.

5. Implications and Future Work

Our findings offer practical implications for students, educators, and e-learning systems. Students, particularly those who tend to rush quiz attempts, may benefit from explicit guidance on adopting a "Rereading-Before-Answer" (RBA) strategy. Our data indicate that brief review loops significantly increase quiz accuracy, notably improving lower-ability learners' performance from approximately 40% to 45%. E-book platforms could facilitate this by incorporating adaptive prompts encouraging students to review critical pages before answering quiz questions. Additionally, platforms can enhance navigation by highlighting pages frequently revisited by high-performing students, thereby implicitly sharing effective study strategies. Teacher dashboards displaying students' navigation patterns could provide early indicators of struggling learners, enabling timely pedagogical interventions. Future research can expand these findings by applying similar analyses across varied datasets, including different educational contexts or disciplines, to test RBA's broader applicability. Longitudinal studies could further examine the impact of systematically training students to adopt RBA, assessing long-term improvements and the efficacy of adaptive interventions. Additionally, employing advanced machine-learning methods, such as sequence-to-sequence modeling, could reveal nuanced navigation profiles and their correlation with learning outcomes. Integrating semantic analyses via NLP with log data might enable predictive recommendations, thereby enhancing personalized tutoring functionalities. Extending beyond e-books, exploring analogous rereading behaviours in video-based learning or interactive simulations could provide cross-media validation and further strengthen the generalizability of these insights.

In conclusion, reinforcing timely content review substantially improves student performance. Leveraging digital learning environments' analytic capabilities allows transforming passive data collection into proactive instructional support.

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