

Precisely identifying and mitigating shallow reading behaviors through online reading data: exploring quantitative reading behavior methods and precise behavioral intervention

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Precisely Identifying and Mitigating Shallow Reading Behaviors through Online Reading Data: Exploring Quantitative Reading Behavior Methods and Precise Behavioral Intervention

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ABSTRACT

Online learning has become a part of daily life. However, it has fostered a tendency to shallow reading. Notably, little attention has been paid to precisely identifying shallow reading behaviors using quantified education big data in favor of methods such as conceptual descriptions, opinions, and questionnaires, resulting in an imprecise analysis of its impact on learning and a lack of strategies to mitigate its causative factors. This study addresses the issue by introducing a behavior-identifying model grounded in measurable data to precisely identify shallow reading behaviors. Initially, three key dimensions of shallow reading behaviors were proposed, along with corresponding mathematical indicators. Subsequently, the k-means algorithm and Pearson correlation coefficient were employed to evaluate the relationship between shallow reading and learning performance, underscoring its significance. The analysis showed that shallow reading behaviors are highly associated with poor learning performance, thus hindering critical reading. These findings further validate the predominant influence of reading speed on learning performance. Consequently, a strategy was developed to intentionally decrease reading speed. Following that, an experiment was conducted to assess the effectiveness of this strategy in mitigating shallow reading. The results revealed improved learning performance and a significant reduction in shallow reading behaviors without increasing cognitive load.

KEYWORDS

Shallow reading; quantifying behavior; behavioral intervention

1. Introduction

The information available to learners has exponentially increased, primarily through online sources. Online learning has grown due to widespread Internet device adoption, advanced learning environments, and continuous pedagogical efforts (Yin & Hwang, 2018). However, challenges in online learning include distractions (Rose, 2010), comprehension interruptions, memory deficits, and cognitive stress from information overload (Schommer-Aikins & Easte, 2018). In parallel, numerous studies have assessed online learning performance by calculating its effect size compared to face-to-face learning.

Shallow reading is a significant trend in online learning, impacting strategies and performance. It may hinder text comprehension and thesis identification compared to deep reading (Shapiro & Waters, 2005). More importantly, precisely defining its behavioral features remains challenging due to intricate definitions and rationales. Primarily, the correlation of shallow reading features with complex behavioral factors such as dwell time, reading speed, and keyword reading (McLean, 2019) complicates its

delineation and impact analysis on learning. Besides, this behavior is interlinked with computer-assisted reading and reading comprehension metacognition in the digital context. Moreover, the representational bias of behavioral modeling for identifying shallow reading behaviors relies on accurate definitions supported by measurable data (Maldonado-Mahauad et al., 2018). Especially, numerous studies on shallow reading relied on conceptual descriptions, opinions, questionnaires, and reviews due to the lack of precise identification from behavioral data (Carr, 2011). Meanwhile, Riley-Tillman et al. (2009) found that the accuracy of disruptive behavior assessment for subjective data was low and affected by behavior wording.

The lack of precise identification for shallow reading and its behavioral features in large-scale online learning persists (Locher & Philipp, 2023). To address this issue, extracting measurable behavior data based on precise definitions is primary (Cooper et al., 2007). Martin & Pear (2019) suggest three behavioral features considering precise definitions: duration, rate, and intensity, describing the frequency, duration, and quantity of information involved. Besides, Khalil et al. (2022) emphasize the necessity of a behavior identification model and the required operation sequence. Consequently, without a precise behavior identification model, understanding the association of shallow reading with learning performance, class engagement, and behavioral patterns in online learning becomes challenging.

2. Literature review

2.1. *Shallow reading definition*

The existing definition of shallow reading emerges from an analysis of reading forms, encompassing methods, and mediums. It's termed power browsing, bouncing, and squirreling. Shallow reading is also described as a graphic, skipping style (Kucirkova, 2019). Features include browsing, scanning, keyword spotting, and one-time reading (Liu, 2005). These methods differ from browsing newspapers and skimming books, now ultimate reading goals rather than intermediates (Adler & Van Doren, 2014).

Shallow reading, alongside computer-assisted and metacognitive reading in digital contexts, complicates defining behavioral features. Computer-assisted reading mimics paper-based habits, using animations, sounds, and documents for improved functions (Zouaghi, 2016). However, it introduces reading attention distractions, hindering comprehension monitoring during reading and causing shallow reading (Baker & Beall, 2014). From a metacognitive standpoint, poor comprehension monitoring positively correlated with insufficient intrinsic motivation and ineffective self-regulation of reading plans and strategies (Pintrich & Zusho, 2002). Morineau et al. (2005) found that computer systems offer contextual cues through assistive technology and sensory stimulation. In that case, reduced self-regulation caused by contextual cues leads to shallow behaviors like rapid scanning and limited contemplation (Loh & Kanai, 2016). While numerous studies have investigated the reasons and mechanisms of shallow reading, along with analyzing its behavioral features, these analyses predominantly rely on logical inference, not extracting behavioral features.

2.2. *Extracting core behavioral features of shallow reading*

Distinct from abstract definitions, behavioral features are externally observable and quantifiable manifestations. Frequency, duration, and quantity are crucial for behav-

ioral modeling, offering insights into extracting precise behavior features (Martin & Pear, 2019). This entails reading speed (frequency: how often a learner can process information), reading dwell time (duration: for how long can they do it), and keyword reading (quantity: how much information can they process). Faster reading, a prominent shallow reading feature, yields extensive but superficial information acquisition (Faisal et al., 2012), avoiding overload without sacrificing basic comprehension or framework content retention (Alrizq et al., 2021). Keyword reading, another feature with high frequency, involves locating information with minimal reading (Shapiro & Waters, 2005). Moreover, shallow reading’s dwell time aspect includes page jumping, and a brief hyperlinked movement. Carroll (1976) notes jump dwell time correlates with detail level and gaze stability, and longer jump dwell times enhance focused reading.

2.3. Shallow reading identification methods and challenges

Figure 1 illustrates various studies on identifying shallow reading features. Data collection is the primary step in quantifying these features. Liu (2005) surveyed reading behavior through a questionnaire, revealing increased reliance on electronic materials, skimming, and fragmented reading. The study supported that shallow reading is a hypertext-centered trait. Currently, identifying shallow reading behaviors in large-scale settings adopted learning behavior surveys, including global questionnaire tests and reading diaries (Locher & Philipp, 2023). Unlike Questionnaire-based Data Collection (QDC), Carr (2011) used a literature review to highlight digital environment’s psychological effects, noting fragmented reading and page jumping as shallow reading traits. Delgado et al. (2018) employed meta-analysis, indicating decreased comprehension due to shallow reading tendencies.

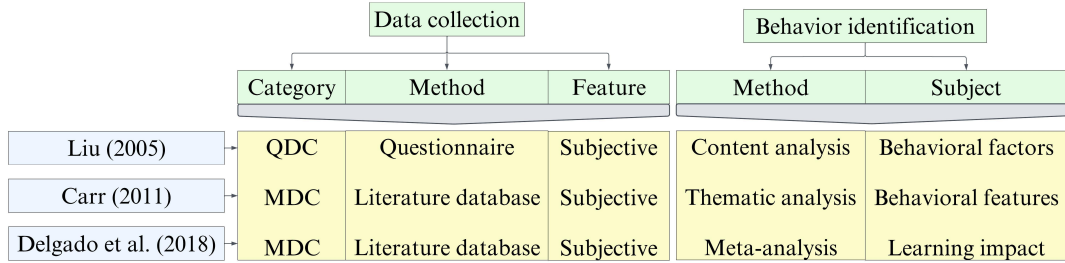


Figure 1. Data collection and behavior identification of shallow reading.

Two issues arise in prior shallow reading identification. First, subjective data, non-numerical and textual, abound. While there are methods such as QDC, Manual Data Collection (MDC) using professional tools, and Automatic Data Collection (ADC) represented by the e-book system (Yin & Hwang, 2018), objective quantification is lacking. Second, shallow reading causative factors often rely on behavior-oriented questionnaires or literature reviews, leading to variable identifications due to self-report and objective discrepancies (Kormos & Gifford, 2014). So, qualitative methods, like content, thematic, and meta-analysis, lack objectivity compared to mathematical models.

Identifying shallow reading faces challenges in behavioral feature dimensions that precisely represents behavior with measurable data (Cooper et al., 2007) and objectivity, excluding subjective factors like motivation, thoughts, or feelings (Leshner & Pfaff,

2011). A behavior identification mode encompassing three dimensions is proposed to overcome these limitations. This model contributes by examining the relationship between shallow reading and learning performance, using evidence from subjective and large-scale reading behavior data.

The study addresses the following research questions (RQs):

RQ1. How to design a behavior identification model for precise identification of shallow reading behaviors across three dimensions: Reading Speed (RS), Reading Dwell Time (RDT), and Reading Word Count (RWC)?

RQ2. Based on objective data, what kind of relationship exists between shallow reading and learning performance? What are its implications?

RQ3. Which learning strategies effectively mitigate shallow reading behaviors, enhancing learning performance?

3. The shallow reading behaviors identifying model

A behavior identification model for shallow reading behaviors was developed. It incorporates three behavior dimensions: RS (frequency: how fast), RDT (duration: how long), and RWC (quantity: how much). Figure 2 shows its structure, functions, and components. Specifically, it involves three steps: collecting reading behavior data via an e-book system, quantifying the three dimensions, and identifying behavior.

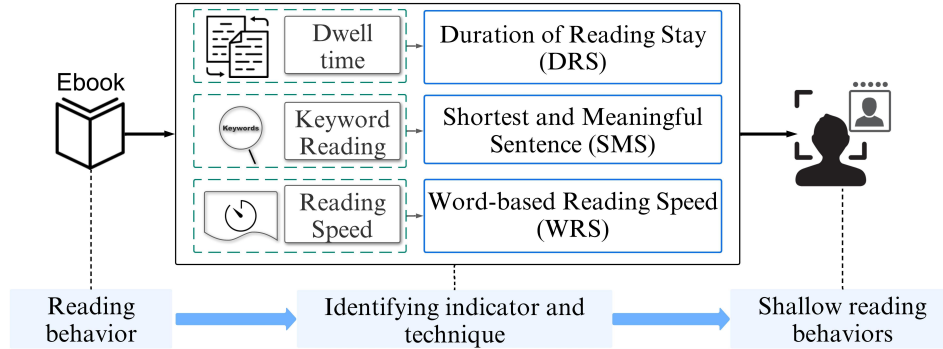


Figure 2. Shallow reading behaviors identification model.

3.1. Collecting reading behavior data via an e-book system

The e-book system (Figure 3) expands reading behavioral features through functions like Page-turning (Prev, Next), Zoom+/-, Underline, Highlight, and Memo (Zhao et al., 2023). Collected data (Table 1) includes User ID, Learning Materials (LM), Page, Reading Operation (RO), Start and End Times (ST, ET) of underlined and marked content. These data support subsequent shallow reading behavior identification.

Proficiently underlining relevant content is a prerequisite for data collection. Participants were instructed to utilize the underline function before (ST) and after (ET) reading a specified text segment, maintaining the marking effects. This strategy (Figure 4) captured ST and ET, dwell time, and text read by each participant, aiding shallow reading behavior assessment. Specifically, reading duration included time spent on

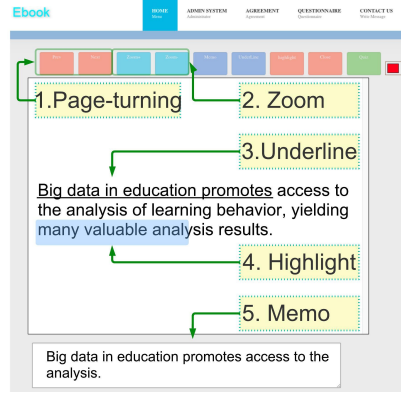


Figure 3. E-book system interface.

Table 1. Samples of reading behavior data collected by the e-book system.

ID	LM	Page	RO	ST		ET		Content
1	Game	0	Underline	2022:01:01	22:22:22	2022:01:01	22:24:22	"Education"
1	Game	1	Next	2022:01:01	22:34:22	2022:01:01	22:45:22	

the underlining button and reading text.

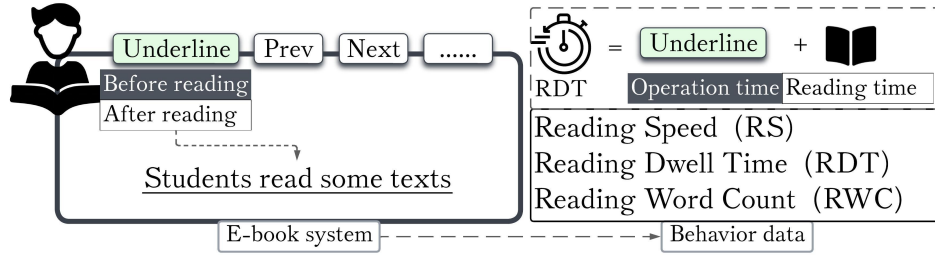


Figure 4. Three-dimensional data collection strategy.

3.2. The three dimensions of reading behavior features

The three dimensions could reflect shallow reading behaviors, offering measurable data for quantifying them. First, RS prominently reflects reading state (McGeown et al., 2015), serving as a key indicator for shallow reading quantification through an accurate correspondence between RS and state. Current RS calculation divides time to read a page by total words (Liang & Huang, 2014), assuming uniform linear reading at an average speed per page. However, this doesn't align with actual non-linear reading patterns. An innovative word-based method calculates time spent on highlighted or underlined words, avoiding unread content assumptions. The formula is as follows:

$$RS = N \div T \quad (1)$$

Shallow Reading Speed (SSR) is defined using RS, where RS signifies reading speed value, N represents the number of words read, and T is reading time. Shallow reading

is identified when RS surpasses the 400 words per minute threshold (Liang & Huang, 2014).

Another pivotal indicator is RDT, gauged by Duration of Reading Staying (DRS). In shallow reading, DRS is marked by page jumping, where learners rapidly scan a page before moving to the next. Identifying the minimum DRS for effective learning is crucial; McSpadden (2015) determined 8 seconds as the minimal time for effective memorization. The RDT dimension's key aspect in shallow reading is Page Jumping (PJ), using DRS as the PJ behavior threshold. Thus, DRS at or below this threshold defines PJ behavior as expressed below.

$$\{d \in PJ \mid d \leq DRS\} \quad (2)$$

where PJ signifies students' rapid page transitions, with d denoting DRS of a single page jump ($\leq$ DRS threshold).

Keyword Reading (KWR), or fragmented reading, involves reading fragmented words, phrases, or short sentences instead of complete sentences. Quantifying KWR involves identifying incomplete sentences, which are the shortest meaningful sentences excluding symbols, punctuation, and graphics.

$$\{n \in KWR \mid n \leq SMS\} \quad (3)$$

KWR is represented by n (Reading Word Count), and it is identified when n is less than or equal to the threshold of the shortest and most meaningful sentence (SMS).

In addition, the Content Importance of Keyword Reading (CIKR) is calculated by the TF-IDF algorithm. It is recorded along with behavior identification. Additionally, the Natural Language Toolkit (NLTK), a leading Python-based natural language processing platform, was used to implement the TF-IDF algorithm.

$$TF - IDF = TF \times IDF \quad (4)$$

$$TF = \frac{f_{td}}{N_j} \times IDF = \log\left(\frac{N}{C_t + 1}\right) \quad (5)$$

where TF and IDF are term frequency and inverse document frequency, respectively. f_{td} denotes the frequency of word t in document d; N_j represents the total number of words in document d; N signifies the total number of documents in the corpus; and C_t indicates the number of documents containing word t.

3.3. Identifying shallow reading behaviors

Shallow reading behavioral features are determined through the following steps (Figure 5): Step 1, PJ identification. Check if DRS is below the threshold. If true, identify PJ behavior. Step 2, KWR identification. If no PJ behavior is identified, assess if the sentences read are the shortest and most meaningful. Calculate the number of words read based on RS. If the word count is below the threshold, identify KWR behavior. Step 3, shallow reading behaviors identification with feature labels. If neither PJ nor KWR behavior is indicated, and sentences are not the shortest and most meaningful: Confirm if RS surpasses the set threshold. If true, characterize the behavior as shallow reading with PJ, KWR, and SSR.

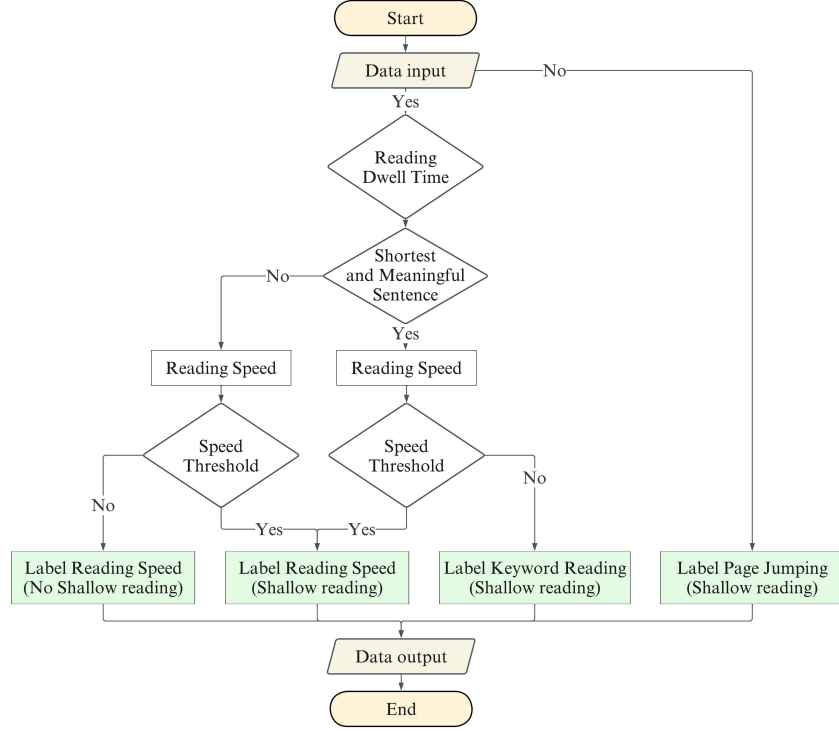


Figure 5. Identifying process of shallow reading behaviors.

4. The identification and analysis of shallow reading behaviors

4.1. Identifying shallow reading behaviors

Utilizing the e-book system for collecting data, the reading behavior of 51 graduate students was tracked during a one-week graduate course on educational technology, and reading material covered 19 pages. Students completed reading within 90 minutes based on the system operation requirements from previous training, followed by a 30-minute in-class test, including multiple-choice tests for basic knowledge and short-answer tests for application of knowledge. Finally, 10,694 valid behavioral logs remained.

Based on the proposed identifying model and process, the reading log data of 51 participants were categorized with the three core features of shallow reading (SSR, PJ, or KWR). Besides, in-course test scores and CIKR data were incorporated into the data output (Table 2).

Table 2. Examples of shallow reading behaviors identification.

ID	Page	RS	Label	RDT	Label	RWC	Label	CIKR	Score
1	1	1.342	SSR	7s	PJ	5	KWR	0.098	80

4.2. Assessing shallow reading’s influence on learning

A two-step analysis is employed to unveil shallow reading behavior patterns and their learning performance correlations. Sole reliance on user-based behavior identification data analysis might lead to bias towards users with extensive log data contributions. To reduce errors from uneven distribution and enhance analytical depth, user-level clustering and log data unit-level correlation analysis to mitigate bias were employed.

4.2.1. Analysis of shallow reading behaviors patterns

4.2.1.1. K-means clustering model. Initial step combined k-means clustering and probability density visualization to identify latent behavioral patterns. Objective function SSE measures cluster dissimilarity. The optimal cluster count (k) was determined using the elbow method. Silhouette coefficient (ranging from -1 to 1) evaluates clustering effectiveness. Based on a rule of thumb (Lovmar et al., 2005), Silhouette score >0.65 preferred, <0.25 rejected, 0.25-0.65 verified visually.

$$SSE = \sum_{i=1}^k \sum_{x \in C_i} |x - \bar{x}_i|^2 \quad (6)$$

C denotes cluster category, $\bar{x}_i$ is the average of one category. The k-means algorithm consists of three main steps. Initially, data samples are assigned to the nearest cluster center to minimize the objective function value. Subsequently, the cluster means are updated accordingly. The optimal clustering outcome is achieved when the cluster centroids attain the lowest values of the objective function. Euclidean distances serve as the measurement for data samples within the k-means algorithm.

The k-means model embedded in the Scikit-learn package in Python was applied. By combining the elbow method, k was set to 2. Finally, an acceptable accuracy of the clustering effect can be indicated by a silhouette coefficient of 0.615, which meets the reliability requirements.

4.2.1.2. Behavioral patterns and probability density distribution. Clustering results were assessed by silhouette values and features-by-clusters distribution graphics. Table 3 differentiates clusters by learning performance (Score, Number of People (NP)), behavior frequency (Number of Occurrences of Shallow Reading (NOSR)), and elements (SSR, PJ, KWR, CIKR). Also, it reveals significant disparities in clustering centroid values between the two clusters. Particularly, Cluster 1 displays significantly higher scores across behavior frequency and elements compared to Cluster 2. For PJ, Cluster 1’s score doubles, CIKR is over twice, NOSR triples, and KWR is one-fifth, revealing distinct behavioral profiles.

Table 3. Clustering results of shallow reading behaviors variables.

Cluster	Clustering centroid value						
	Score	SSR	NOSR	PJ	KWR	CIKR	NP
1	8.15	16.94	153.9	91.6	29.05	0.00076	40
2	4.0	36.16	410.5	128	104.50	0.00031	11

To thoroughly explore behavioral patterns, probability density distribution graphics were employed (Figure 6). These visual depictions portray the spectrum of values for

the five behavioral features on the x-axis, with corresponding probability density values plotted on the y-axis. Especially, greater occurrences of behavior yield higher density with elevated magnitude, while fewer occurrences result in lower density accompanied by a flattened curve. The product of these intersecting coordinates delineates the likelihood of specific behaviors transpiring.

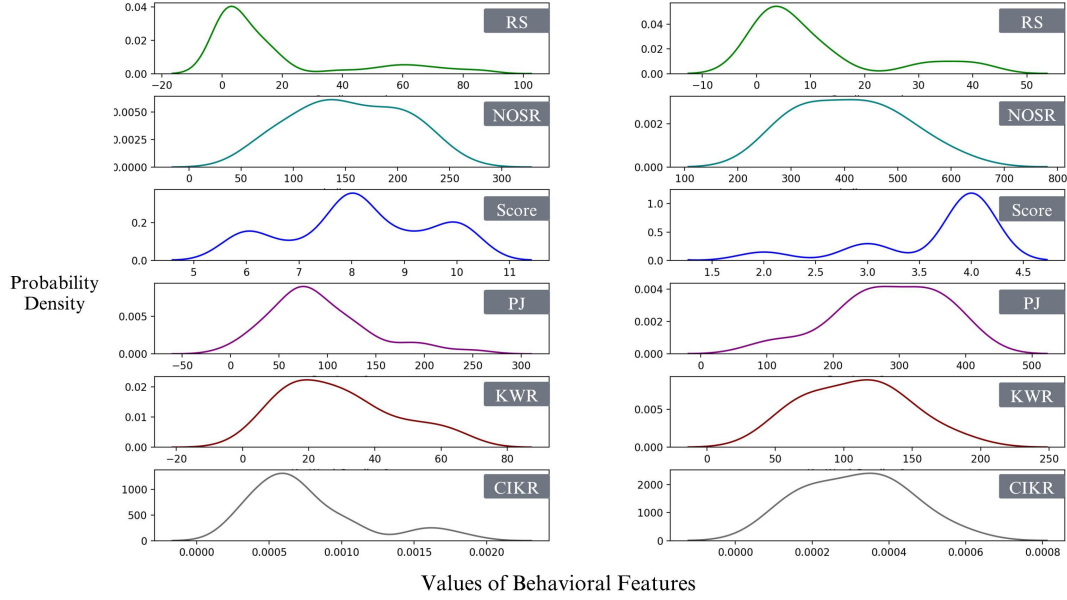


Figure 6. Probability density distribution of Reading Behavior Clusters.

According to Figure 6, distinct behavioral patterns in Cluster 1 emerged. NOSR values ranged from 100 to 200 times, with Scores concentrated between 7 to 9 points. PJ featured 50 to 100 occurrences, and KWR showed frequencies of 10 to 30 times. CIKR values spanned 0.0003 to 0.0008. In contrast, Cluster 2 displayed a different profile. NOSR ranged from 300 to 500 times, and Scores centered on 3.5 to 4.5 points. PJ occurrences spanned 200 to 400, and KWR frequencies ranged from 70 to 120. CIKR values varied from 0.00002 to 0.0004, indicating a narrower occurrence range in Cluster 2.

In summary, Cluster 1 demonstrates more favorable learning performance, with fewer instances (100 to 200 times) of shallow reading behaviors. Additionally, Cluster 1 exhibits fewer behavior elements: PJ, SSR, and KWR, while excelling in CIKR, which is twice as effective as Cluster 2. The user-based analysis dimension suggests a clear link between varying shallow reading occurrences and diverse learning performances.

4.2.2. Correlation analysis between shallow reading behaviors and learning performance

Clustering results show the frequency of shallow reading exhibited a negative correlation with learning performance. Pearson's correlation coefficient (r) was employed to quantify the extent of this correlation, ranging from -1 (negative) to 1 (positive) with categorizing correlation strength: Positively Very Strong (PSR, value $0.7 < r \leq -1$), Positively Strong (PR, value $0.5 < r \leq 0.7$), Positively Moderate (PM, value $0.3 < r \leq 0.5$), Positively Weak (PW, value $0.1 < r \leq 0.3$), None (N, value 0), Negatively Weak (NW, value $-0.3 \leq r < 0$), Negatively Moderate (NM, value $-0.5 \leq r < -0.3$), Negatively

Strong (NS, value $-0.7 \leq r < -0.5$), and Negatively Very Strong (NVS, value $-1 \leq r < -0.7$).

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (7)$$

Where r represents the correlation coefficient, x_i , y_i are values of the x-variable and y-variable within a sample, and $\bar{x}$ and $\bar{y}$ denote the means of the x-variable and y-variable values.

A z-test confirmed normality, skewness, and kurtosis, with absolute z-scores of the behavior features below 1.96, supporting Pearson’s correlation usage (Kim, 2013). Based on Pearson’s analysis between shallow reading behaviors features and learning performance, Table 4 highlights SSR and CIKR as the strongest correlations, with a noteworthy coefficient of 0.768 ($p < .01$) for CIKR, signifying improved learning performance.

Table 4. Correlation analysis between shallow reading behaviors and learning performance.

	SSR	PJ	KWR	CIKR
Score	-0.765**	-0.297*	-0.520**	0.768**

Note. ** $p < .01$ * $p < .05$

A highly significant correlation (-0.765 , $p < .01$) between SSR and in-class test scores reveals strong negative dependence of learning performance on reading speed. Student scores decrease with faster reading. KWR also significantly correlates (-0.520 , $p < .05$) with learning performance, albeit weaker than SSR and CIKR. In contrast, PJ’s correlation is weak (-0.297 , $p < .01$). Interactions among SSR, PJ, and KWR were explored (Table 5). PSR correlation (0.725 , $p < .01$) links SSR and KWR, while PM correlation (0.413 , $p < .05$) connects SSR and PJ. Slower reading speed associates with fewer PJ and KWR occurrences.

Table 5. Correlation analysis of shallow reading behaviors features.

	PJ	KWR
SSR	0.413*	0.725**

Note. ** $p < .01$ * $p < .05$

4.3. A learning strategy to precisely mitigate shallow reading behaviors

Reading strategy formulation emphasizes acceptability and suitability. Student acceptance of new strategies varies due to factors like motivation, vocabulary processing, and prior knowledge (Coiro & Dobler, 2007). Enhancing suitability for school interventions, familiar and accessible strategies should be introduced (Gresham, 2004). Clustering and correlation analysis revealed a correlation between shallow reading behaviors and learning performance, with reading speed demonstrating the most pronounced correlation and learning performance. Accordingly, a core intervention goal was established: reduce reading speed to mitigate shallow reading behaviors.

This suitability strategy adapts effective paper-based methods to the digital realm. First, reading loud as conducive to slower reading and improved memory (McCallum

et al., 2004) serves as a cornerstone. Besides, computer-assisted learning mimics paper-based reading through mouse-operated underlining and highlighting, substituting the traditional pen. Specifically, the Dots Per Inch (DPI) setting of 500 Hz, established by Microsoft research (Microsoft, n.d.), achieves optimal reading speed reduction while maintaining a user-friendly reading experience by satisfactory mouse usability. Thus, the proposed DPI and Read Loud (DRL) strategy (Figure 7) integrates elements like reading loud and low DPI to inhibit excessive reading speed.

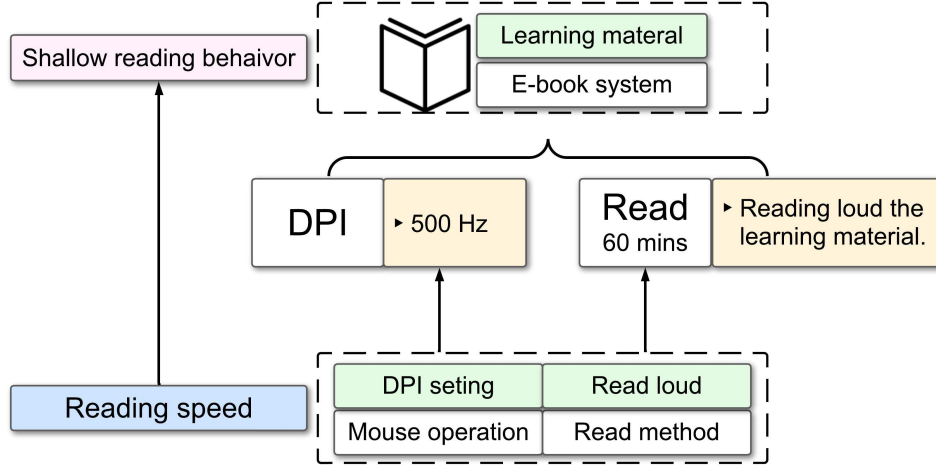


Figure 7. DRL learning strategy.

5. Experiment design for evaluating the effectiveness of DRL strategy

To evaluate the effectiveness of the DRL strategy in enhancing learning performance and mitigating shallow reading behaviors, A two-week experiment was conducted at a university to specifically evaluate its ability to effectively reduce reading speed.

5.1. Participants

71 graduate students were randomly divided into experimental and control groups. The experimental group (37 participants) utilized the DRL strategy to read the learning content of educational technology in the “Large Scale Intelligent Systems Theory” course, while the control group (34 participants) had no specific strategy assigned, allowing them to choose their preferred learning approach.

5.2. Instruments

This experiment employed a pre-test to assess prior knowledge, a post-test to evaluate learning performance, and a cognitive load questionnaire to gauge the impact of learning strategies. The experiment adapted pre-test and post-test assessments from in-class tests aligning with a specialized program. The questionnaire based on Sweller (2018) cognitive load theory featured eight questions rating mental load and effects on

a 5-point scale. The question design employs dual-task paradigms, subjective ratings, and physiological measures to gauge cognitive resource utilization during learning.

5.3. Experiment procedure

Figure 8 outlines the experimental process, encompassing introduction, pre-test, post-test, system training, and learning activities with distinct strategies. Prior to the experiment, participants were acquainted with the requirements, procedures, and the e-book system, followed by a pre-test to gauge prior knowledge within 30 minutes. Subsequently, the experimental group underwent a 60-minute DRL strategy training after one week, followed by two separate 60-minute learning activities for both groups. The groups utilized the same e-book system but different strategies. Finally, a post-test on learning performance and a post-questionnaire were conducted within 30 minutes.

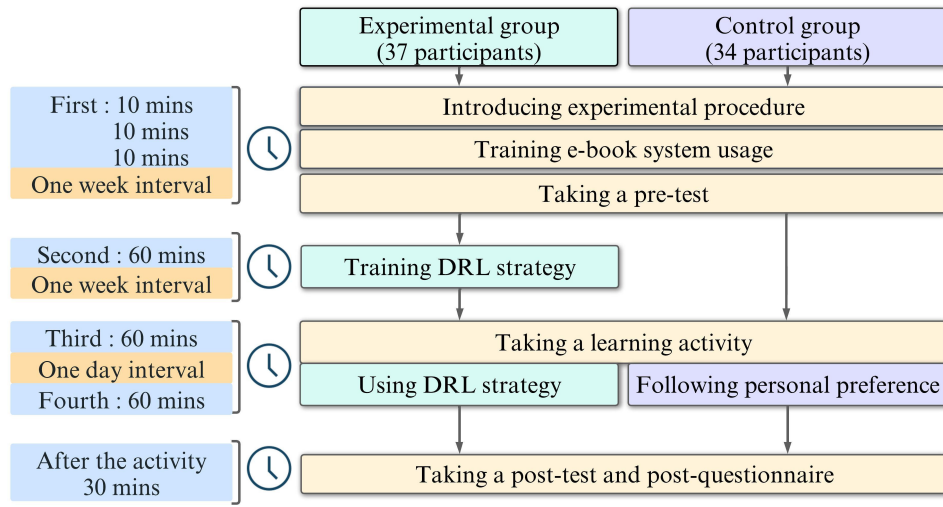


Figure 8. Experimental procedure.

6. Experimental results

6.1. Learning achievement analysis

To assess participants' comparable prior knowledge of the learning content, a pre-test was conducted before the learning activity. The assumption of variance homogeneity was upheld ($F = 1.327$, $p > .05$). Consequently, t-test results indicated no significant differences ($t = -1.176$, $p > .05$) between the independent groups. Mean and standard deviation (SD) values for the pre-test were 2.22 and 1.03 for the experimental group and 2.53 and 1.21 for the control group (Table 6).

To assess the efficacy of the DRL strategy on learning performance, a post-test was conducted in both groups. Levene's test confirmed variance homogeneity ($F = 0.490$, $p > .05$) for t-test. The t-test findings ($t = 4.103$, $p < .01$) in Table 7 indicated superior learning performance in the experimental group. Participants in this group achieved a significantly higher level of learning. Thus, the DRL strategy was deemed effective in enhancing learning performance.

Table 6. Descriptive statistics and t-test results of the learning achievement in the pre-test.

Group	Variable			
	N	Mean	SD	<i>t</i>
Experiment group	37	2.22	1.03	-1.176 *
Control group	34	2.53	1.21	

Note. * $p > .05$

Table 7. Descriptive statistics and t-test results of the learning achievement in the post-test.

Group	Variable			
	N	Mean	SD	<i>t</i>
Experiment group	37	8.03	1.69	4.103 **
Control group	34	6.29	1.89	

Note. ** $p < .01$

6.2. Analysis of occurrence and RS of shallow reading behaviors

The DRL strategy primarily constrains shallow reading behaviors, reducing occurrence and RS. Levene's test confirmed suitable use of a t-test ($F = 3.362$, $p > .05$). Initial t-test results ($t = 6.510$, $p < .05$) reveal a significant disparity in shallow reading behavior occurrences between groups. Table 8 shows experimental group's mean and SD were 123.21 and 44.29; control group had 228.18 and 86.55. Experimental group exhibited almost twice the occurrences, highlighting DRL's potential to mitigate shallow reading.

Table 8. Descriptive statistics and t-test results of occurrence of shallow reading behaviors.

Group	Variable			
	N	Mean	SD	<i>t</i>
Experiment group	37	123.21	44.29	6.510 *
Control group	34	228.18	86.55	

Note. * $p < .05$

Further investigation into intervention effect on shallow reading behaviors included analysis of RS. Subsequently, Levene's test for variance equality ($F = 66.769$, $p > .05$), one-way ANOVA analysis ($F = 53.285$, $p < .01$) in Table 9 demonstrated a noticeable reduction in reading speed for experimental group students compared to the control group. The experimental group's mean RS was 3.03 words per second, lower than the control group's mean of 5.20 words per second, highlighting the DRL strategy's effectiveness in significantly reducing RS.

6.3. Analysis of cognitive load

Cognitive load, consisting of mental load and mental effort, may influence learning performance and cognitive resource allocation during uncertain information processing (Shuell, 1986). Mental load reflects anticipated cognitive stress, while mental effort indicates the occupation of limited cognitive capacity (Zhao et al., 2023). A post-cognitive load questionnaire gauged the cognitive state of both groups. Levene's test indicated variance homogeneity ($F = 0.238$, $p > .05$). Table 10 shows no significant group differences. Regarding mental load, the t-test results ($t = -1.920$, $p > .05$) indicated similar mental load for both groups. Similarly, the t-test results ($t = -1.713$, $p > .05$) for mental effort found no significant group differences, suggesting the DRL

Table 9. Descriptive statistics and ANOVA results of reading speed of shallow reading behaviors.

Group	Variable			<i>F</i>
	N	Mean	SD	
Experiment group	37	3.03	7.52	53.285 **
Control group	34	5.20	18.56	

Note. ** $p < .01$

strategy did not raise cognitive load, consistent with mental load findings.

Table 10. Descriptive statistics and t-test results for cognitive load.

Cognitive load	Group	Variable			<i>t</i>
		N	Mean	SD	
Mental load	Experiment group	37	11.94	3.438	-1.920 *
	Control group	34	13.46	3.156	
Mental effort	Experiment group	37	11.14	3.117	-1.713 *
	Control group	34	12.66	4.200	

Note. * $p > .05$

7. Discussion

Mitigating emotional biases in behavior identification for RQ1, subjective self-assessment data encompassing motivations, thoughts, and emotions were gathered through questionnaires. Kormos & Gifford (2014) noted emotional tendencies can skew subjective assessments, inducing behavioral identification contradictions.: most truthful self-reporting and unconscious self-avoidance. To counteract this bias, objective behavioral data from the e-book system was employed—unconsciously capturing participants’ behavioral activities (Yin & Hwang, 2018). Indicators measuring behavior used in the proposed model, including RS, RDT, and RKC, were based on continuous records, sidestepping emotional influences and ensuring accurate identification.

Effective learning strategies hinge on precise behavior analysis for RQ2 and RQ3. Prior studies lack detailed intervention strategies due to complex shallow reading behaviors and limited core behavior feature analysis. For instance, Chen & Chen (2014) addressed poor comprehension in digital learning but overlooked identifying shallow reading behaviors and their core features. Besides, precise intervention requires understanding these features. This study employs two analysis dimensions: individual students (cluster analysis) and single shallow reading behaviors (correlation analysis). This approach mitigates bias from varying behavior counts, accurately exploring shallow reading’s impact on learning performance, and maximizing each behavioral feature’s influence.

Accurate data collection is pivotal for addressing RQ1. Existing methods for calculating RS lack precision due to limited high-precision behavioral capture tools (Zhao & Yin, 2022). Liang & Huang (2014) relied on RS determination, assuming linear homogeneous reading with average speed for text pages. Yet, this method does not reflect the actual non-linear reading dynamics. To overcome this, our study collects high-precision data via e-book underlining and highlighting to calculate RS, considering individual word reading speed.

8. Conclusions

The designed behavior quantification model collects measurable reading behavior using three dimensions: RS, RDT, and RKC. Objective e-book system data was utilized to enhance result accuracy and overcome self-assessment limitations and minimal subjective questionnaire data for RQ1. Shallow reading behaviors were defined based on three behavior dimensions: duration, rate, and intensity. This study established three behavioral features: SSR, PJ, and KWR by incorporating existing descriptive definitions of shallow reading.

For RQ2, the study employed k-means clustering and Pearson's correlation analysis to explore the relationship between shallow reading behaviors and learning performance. Clustering analysis showed an inverse relationship between high learning performance and shallow reading occurrences (RS, RDT, and RKC). Higher performance aligned with lower behavioral characteristics of shallow reading, indicating a proportional association. Pearson's correlation indicated SSR's stronger negative correlation with learning performance compared to RDT and RKC. Finally, Poor performance correlated with higher KWR behavior and fewer CIKR calculated via the TF-IDF algorithm.

RS emerged as a key factor impacting learning performance in RQ1 analysis. A novel strategy, DRL, was devised to mitigate shallow reading by slowing reading speed. Two inhibiting factors are involved: DPI parameter settings for reading tool operation and reading loud for content. Experimental findings indicate that the DRL, focusing on decreased reading speed, enhances learning performance, mitigates shallow reading, and reduces RS, all while avoiding additional cognitive load. To enhance behavior identification precision, integrating eye-tracking may mitigate tool interference and align better with actual educational practices and student behaviors.

Disclosure statement

No potential conflict of interest was reported by the authors

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