Journal of Pedagogical Sociology and Psychology
Volume 7, Issue 4, 2025
https://doi.org/10.33902/jpsp.202535544

Research Article

Dynamic adaptive algorithms in personalized literacy interventions: A data-driven analysis of vocabulary development outcomes

Hamed Ghaemi and Amirarsalan Bahrami

Department of English, Bahar Institute of Higher Education, Iran

Correspondence should be addressed to Hamed Ghaemi ghaemiacademy@gmail.com
Received 20 April 2025; Revised 8 September 2025; Accepted 10 September 2025

This study assesses the effect of dynamic adaptive algorithms on Vocabulary Acquisition in personalized literacy programs. This paper examines how adaptive systems are superior to static methods of teaching by using methods from different fields. There were 120 elementary school students in the study, half of whom use an adaptive literacy system and the other half follow a static curriculum. Participants were selected with different backgrounds and similar vocabulary skills at the start. The Structural Equation Modeling and Nonlinear Autoregressive Exogenous models were used to analyze the data. Based on the findings, adaptive systems significantly enhanced Vocabulary Acquisition, with the most tailored treatments producing the highest improvements. Variables such as text complexity and presentation time, which can be adjusted to help students learn new words, were also identified in the study. AI-assisted teaching methods and the creation of individualized learning spaces to maximize literacy outcomes have real-world consequences for educational policy.

Keywords: Adaptive learning systems, educational data mining, learning frequency, NARX, text complexity, vocabulary acquisition

1. Introduction

Particularly in literacy development, personalized learning has become a game-changer in today's classroom for improving student results. Personalized literacy interventions have become a significant focus for research and development as digital tools, artificial intelligence [AI], and Adaptive Learning technologies proliferate. These systems customize learning experiences for every student using dynamic adaptive algorithms, modifying content, difficulty levels, and pace depending on personal traits, prior knowledge, and preferences (Anderson et al., 2020; Baker & Yacef, 2009). Academic success depends on vocabulary development (Snow, 2010); hence, teachers and legislators must know how adaptive algorithms affect Vocabulary Acquisition results in their attempts to raise literacy. Both theoretical and practical aspects of education have drawn attention to how well Adaptive Learning Systems improve Vocabulary Acquisition.

These algorithms provide individualized learning routes that change in real time and are meant to constantly monitor and react to student development. This method seeks to maximize the pace and substance of education depending on the learner's particular needs, which could include reading level, vocabulary size, and comprehension skills (Johnson et al., 2014; Siemens, 2004). Though these systems are becoming increasingly popular, little data demonstrates their direct influence on language Acquisition and retention. Particularly concerning conventional, non-adaptive approaches, more study is required to grasp how these systems influence literacy development (VanLehn, 2011). This work attempts to close this gap by looking at the effectiveness of dynamic adaptive algorithms in personalized literacy interventions, with particular attention to vocabulary learning results. This work investigates how adaptive systems driven by algorithms help to improve language over time using a mix of quantitative and dynamic modeling techniques. It looks at the long-term consequences of personalized literacy interventions and the instantaneous effects of these systems on vocabulary development. By tackling these essential problems, the study seeks to offer insightful analysis of how algorithm-driven systems may be adjusted to maximize Vocabulary Acquisition and raise general literacy rates for different student populations.

The results of this study could add to the mounting body of data supporting the incorporation of Adaptive Learning technology in K–12 education, therefore providing pragmatic consequences for curriculum design, instructional practices, and policy development. Moreover, by looking at how different student traits and contextual elements interact with adaptive algorithms, this study offers direction on how to effectively customize personalized learning systems to fit the demands of many students.

2. Theoretical Framework

This study is grounded in several established educational theories that show how personalized literacy interventions, driven by dynamic adaptive algorithms, function. Key theories include constructivist learning theory, Vygotsky's Zone of Proximal Development [ZPD], cognitive load theory, dynamic systems theory, and Adaptive Learning theories. Collectively, these frameworks offer a thorough perspective on the impact of adaptive algorithms on Vocabulary Acquisition.

2.1. Constructivist Learning Theory

Constructivist learning theory, which is based on the work of Piaget (1972) and Vygotsky (1978), says that learners build knowledge by doing tasks that are meaningful, relevant to their lives, and involve other people. In Adaptive Learning environments, this philosophy shows up as personalized, changing instruction that changes based on how well a student is doing.

Constructivist-based adaptive systems put a lot of stress on learner agency, problem-solving, and scaffolded progression. These systems change the difficulty of the text, the number of words, and the type of task to make sure the content stays challenging but doable. This keeps people interested and helps them think more deeply (Brusilovsky & Millán, 2007; Schunk, 2012). For example, platforms that help people learn vocabulary may only make words harder after a learner shows that they can consistently get them right at lower levels (Miller & Baker, 2018).

Studies in the real world back up this theoretical alignment. When combined with contextual practice activities and reflective feedback, constructivist-aligned adaptive systems significantly enhanced vocabulary acquisition in elementary learners (Lipnevich et al., 2021). These results show that constructivist principles not only help shape adaptive algorithms, but they also make them more effective in K–12 classrooms.

2.2. Zone of Proximal Development and Instructional Adaptation

Vygotsky's (1978) Zone of Proximal Development is a great way to look at the teaching value of adaptive systems. ZPD shows the difference between what students can do on their own and what they can do with the right help. Adaptive Learning platforms act like digital scaffolds, changing the difficulty, speed, and support of tasks in real time. They basically become a "more knowledgeable other."

This alignment makes sure that students are always pushed just beyond what they can do now, but not so much that they get too tired or lose interest (Molenaar et al., 2014). For vocabulary lessons, this could mean introducing words that are a little more difficult after a student has shown that they know the basic words, or changing the linguistic context to help them make deeper connections between the words.

Recent studies show that ZPD-aligned adaptation works. Jansen et al. (2022) studied more than 200 middle school students and found that adaptive systems based on learners' ZPDs made it significantly easier for them to remember words and less frustrating to do tasks than static instruction. Smith and Riley (2023) also found that these kinds of systems were especially good at closing performance gaps between low-performing students by making sure they got support when they needed it and that it was tailored to their changing needs.

Adaptive literacy systems make the theoretical ideas of ZPD real by adding scaffolding to the learning algorithm. This makes differentiated instruction scalable, responsive, and effective.

2.3. Cognitive Load Theory

Cognitive Load Theory (Sweller, 1988) posits that instructional design should lower unnecessary cognitive load to maximize working memory. The learners' vocabulary levels could influence their capacity to concentrate on a task related to literacy since learners may come across material twice as challenging in terms of vocabulary knowledge or phraseologism. While vocabulary growth remains the goal in Adaptive Learning Systems, algorithms can be employed to alter the difficulty level concerning the content and the complexity of activities to attain adequate cognitive load.

By lowering the learner's excessive demands, the dynamic reordering of vocabulary texts made possible by technological aspects of adaptive systems helps to attain the desired working conditions. The system can also progressively organize the degree of new vocabulary to enable those with limited beginning levels of the language to master the words first, then the more complicated sentences (Paas et al., 2003). This helps the student function within reasonable cognitive constructions to process and recall newly acquired terminology effectively (Sweller, 1988).

2.4. Dynamic Systems Theory

Dynamic Systems Theory, as Thelen and Smith (1994) discussed, suggests an insights-packed way of understanding how learning changes and grows over time. Regarding lexicon enrichment, dynamic systems According to dynamic systems' philosophy, assimilation comes through varied interactions of the learner with the environment, constant and changing; it is not a sequential process. Through recurrent and evolutionary adaptations, adaptive educational programs can responsively support language skill acquisition—tailoring instruction to learners' evolving needs and personal contexts. As learners engage with dynamic materials, their language development can fluctuate and progress depending on situational and individual characteristics (Hang, 2024). Those who support our learning can modify their instruction depending on our actions and development. Learning delays are also significant; fast results aren't always noticeable, but speech enhancement may occur post-interaction with tailored content (Thelen & Smith, 1994). Therefore, the main focus of this research is decoding the evolution of vocabulary development over the years, particularly given increasing computational changes.

2.5. Theories of Adaptive Learning

Adaptive education theories address how learning materials should be changed to fit instantaneous learner performance criteria (Corbett & Anderson, 1995). The reformulated statement preserves the essential knowledge since it relates to the fundamental concepts of customized learning strategies - modifying instructional materials in response to the continuous achievement of a student. Adaptive Learning programs use software to monitor students' progress and change courses as necessary to offer a customized educational journey, therefore meeting every person's capacity and needs (Keller, 2010). This adaptive shift encourages more involvement since students are constantly tested without being discouraged by too challenging course materials (Brusilovsky & Millán, 2007). Applied to literacy programs, particularly those focused on word mastery, Transformative learning techniques have shown promise in increasing student participation and academic performance (Baker & Yacef, 2009). Using adaptive mechanisms helps customize the speed, challenge, and vocabulary of instructional content, improving engagement, memory, and scholastic performance (Siemens, 2004). Inspired by constructivism, Vygotsky's Zone of Proximal Development, cognitive load research, and Adaptive Learning models, this paper explores the strategies adaptive systems apply to enhance Vocabulary Acquisition. Using statistical analysis and sophisticated simulations, this study investigates important questions and generates essential knowledge of tailored reading enhancement strategies and practical recommendations for improving computer-aided teaching methods. The findings add to the growing body of research on adaptive education and how well it can raise reading rates for different student populations.

3. Research Questions

The research questions in this study aim to explore the impact of adaptive literacy algorithms on vocabulary acquisition from multiple perspectives. The investigation incorporates both quantitative analyses—conducted through SPSS and Structural Equation Modeling (SEM)—and dynamic modeling approaches utilizing Nonlinear Autoregressive with Exogenous Inputs (NARX). In this way, the study seeks not only to identify measurable differences and predictive factors among learners but also to capture how adaptive learning systems shape vocabulary development over time, in relation to dynamic changes, moderating variables, and external influences.

3.1. Quantitative Research Questions for SPSS and SEM Analysis

Under this section, the study seeks to address the following research questions through statistical analyses using SPSS and SEM.

RQ 1) Is there a statistically significant difference in Vocabulary Acquisition rates between students using adaptive literacy algorithms and those following traditional methods?

RQ 2) What demographic or baseline linguistic factors (e.g., age, initial vocabulary size, socioeconomic background) predict higher vocabulary gains in adaptive literacy interventions?

RQ 3) Do factors such as reading frequency and Text Complexity moderate the relationship between algorithm-based personalization and vocabulary development?

RQ 4) How does Vocabulary Acquisition change over time within an Adaptive Learning System compared to static interventions?

RQ 5) Are there significant differences in vocabulary retention across distinct levels of text personalization (low, medium, high) within adaptive systems?

3.2. Dynamic Modeling Questions for NARX Analysis

In this section, the research focuses on answering the following questions through dynamic modeling with NARX.

RQ 1) How accurately can adaptive algorithm usage over time predict future vocabulary scores, considering past performance as input?

RQ 2) How do changes in adaptive algorithm parameters (e.g., text difficulty, pacing) dynamically influence Vocabulary Acquisition over consecutive learning sessions?

RQ 3) What is the time-lag effect of exposure to personalized content on measurable vocabulary development outcomes?

RQ 4) How do exogenous variables (e.g., teacher intervention, parental involvement) influence the vocabulary development trajectory within a dynamic system?

RQ 5) What nonlinear relationships exist between exposure time to adaptive content and vocabulary growth, and how do these evolve across sessions?

4. Methods

The methodology applied in this work is described in this part, together with the environment, participants, data-collecting techniques, and tools used to examine the effectiveness of dynamic adaptive algorithms in personalized literacy interventions and their effect on vocabulary development results.

4.1. Setting

The study evaluated a public K–12 primary school in a suburban area of Mashhad, Iran with diverse student body in terms of socioeconomic status, academic achievement, and cultural identity. The district has a great track record of using educational technologies, and over the past two years, they have used Adaptive Learning platforms in a number of subject areas.

This study was part of the school's existing literacy instruction framework, with a special emphasis on Vocabulary Acquisition. The intervention used an Adaptive Learning System powered by AI that changed reading texts and vocabulary tasks based on how well the students were doing at the time. Students in the experimental group used the system for 30 minutes a day during their regular reading blocks for ten weeks.

4.2. Participants

The study included 120 elementary school students in all. With an eye toward a representative sample of the elementary school's student body, these youngsters were chosen from several classrooms. Two groups constituted the participants with N=60**;** the experimental group comprised students using the adaptive literacy intervention driven by dynamic algorithms. These kids were given tailored vocabulary activities that changed in complexity depending on their development, ensuring that every student received individualized teaching according to their present level of performance and learning requirements. Students who followed a conventional, non-adaptive reading program comprised the control group (N=60). Although they got the identical materials as the experimental group, the instruction was passive, using the same texts and assignments for every student regardless of their particular need.

Students were chosen to ensure a mix of gender, grade level, and baseline language ability. To enable additional study of predictive variables, demographic data—including age, gender, socioeconomic level, and initial vocabulary size—was gathered. To guarantee that all participants could interact with the digital literacy intervention, students with special education requirements or those with severe linguistic or cognitive disabilities were excluded from the study.

4.3. Data Collection Procedure

Data were gathered during the usual school year over ten weeks. Beginning at the start of the school year, the intervention period ran through the fall term in line with the typical academic reading curriculum. Attending daily reading sessions, experimental and control group participants completed vocabulary activities linked to the assigned reading materials.

To evaluate their starting vocabulary size and comprehension level, all participants finished a baseline vocabulary evaluation at the beginning of the study. Standardized vocabulary exams and reading comprehension assignments that offered a basis for tracking vocabulary improvement over time comprised these evaluations. To guarantee comparability at the start of the study, both groups had pre-tests using an identical set of vocabulary exercises.

Participants in the experimental group used an Adaptive Learning platform during the intervention period, which offered customized vocabulary exercises depending on real-time performance. Based on each student's advancement, the platform's dynamic algorithm changed the difficulty level of tasks, the frequency of new vocabulary exposure, and the kind of words presented—e.g., high-frequency vs. low-frequency terms. All students in the control group, which followed a conventional, non-adaptive curriculum, had identical vocabulary tasks regardless of their capacity.

Every participant received a post-test vocabulary assessment at the end of the ten-week intervention. This post-test matched the baseline assessment so that the two groups could be directly compared for vocabulary expansion. Participants in both groups also answered questions regarding their interaction with the resources and their apparent degree of task difficulty.

Surveys submitted to parents asked about the degree of their participation in their children's literacy development—that is, about reading at home, helping with homework, etc. Any possible moderating impact of parental involvement on language learning was evaluated using this information.

4.4. Instruments

At the beginning and end of the study, students' vocabulary size and understanding were assessed using Vocabulary Assessment (Pre-test and Post-test). The evaluation comprised multiple-choice questions, matching exercises, and sentence completion assignments testing students' grasp of common and academic terminology. The test assessed vocabulary abilities, from simple word identification to more sophisticated semantic understanding.

Apart from vocabulary assessments, a reading comprehension assessment was given to ensure that vocabulary development was linked to students' capacity to grasp and apply vocabulary in context rather than occurring separately. Short reading passages followed by questions on the primary idea, specifics, and word use within the passage comprised this evaluation.

Cognix EdTech Solutions is a private educational technology business that focuses on tailored learning environments. Their Adaptive Learning System, LexiLearn AI, was utilized in the intervention. The research team had limited institutional access to the platform for this work, however it is proprietary and not available for public or open-access use at the moment. With the use of a multi-layered adaptive algorithm, LexiLearn AI uses parameters like task accuracy, response latency, progress history, and engagement to tailor content to each learner in real time. Reading passages, vocabulary difficulty, and task complexity are all constantly adjusted by the system based on individual learner's performance trends. In addition to monitoring student behavior (such as the amount of tries or items skipped) and providing rapid feedback, it adjusts the pace and scaffolding to ensure that students are subject to an ideal cognitive load. The system automatically recorded and exported engagement data for analysis, including completion rate, duration on task, and error frequency.

All of the adaptive literacy intervention took place in a specific school computer lab and occurred during normal school hours. The experimental group made use of the school-issued tablets to access the Adaptive Learning platform. The program ran for ten weeks, with sessions held five days a week for around thirty minutes each. To guarantee consistent implementation and minimal interruptions, classroom teachers and a research assistant supervised the learning environment. The software automatically recorded all data once students performed the activities independently, so they could analyze it later. Every week, at the conclusion of class, students were asked to fill out a short survey about their experience with the adaptive system. Students were asked to rate the utility of individualized feedback, the fun of the work, and the difficulty of the task itself in these questionnaires. Furthermore, all participants' parents or guardians were asked to fill out a Parental Involvement Survey that inquired about reading habits and homework assistance at home. At the beginning of the trial, we took baseline vocabulary scores and demographic information (gender, age, and socioeconomic status). In order to evaluate the adaptive intervention's efficacy while taking into consideration any variances in learner background, these variables were utilized as covariates in the statistical models.

4.5. Data Analysis

SPSS was used to investigate vocabulary increases and to compare the results between the experimental and control groups on data gathered from the pre-and post-test assessments. Descriptive statistics (means, standard deviations) were calculated for vocabulary scores, and inferential statistical tests were conducted to determine whether significant differences existed between groups. The same research questions were also analyzed using Structural Equation Modelling [SEM] to confirm the findings of SPSS.

In addition to SPSS and SEM, dynamic modeling techniques using Nonlinear Autoregressive with Exogenous Inputs [NARX] models were employed to analyze temporal patterns and predictors of vocabulary growth across the intervention period. This analysis helped explore how adaptive algorithms impacted vocabulary development over time and whether changes in algorithmic parameters (e.g., text difficulty) influenced Vocabulary Acquisition.

5. Results and Discussion

5.1. Results of SEM Research Questions

Research Question 1: Is there a statistically significant difference in Vocabulary Acquisition rates between students using adaptive literacy algorithms and those following traditional methods?

The analysis used an independent samples t-test to compare Vocabulary Acquisition rates between two groups: those using adaptive literacy algorithms and those following traditional methods. The dependent variable was Vocabulary Acquisition rates, measured as post-test scores, while the independent variable was the group assignment (Adaptive Algorithm vs. Traditional Method). The results, as illustrated in Table 1, indicated a significant difference between the groups, with students in the adaptive literacy algorithm group ($M = 75.4$, $SD = 8.5$) showing significantly higher Vocabulary Acquisition rates than those in the traditional method group ($M = 68.2$, $SD = 10.1$), $t(198) = 4.23$, $p < .001$.

Table 1
Group Comparison of Vocabulary Acquisition Rates

Group	*Mean (M)*	*Standard Deviation (SD)*	*t*	*df*	*p*
Adaptive Algorithm	75.4	8.5	4.23	198	<.001
Traditional Method	68.2	10.1			

As shown in Table 2, a multi-group SEM model was used to compare the experimental and control groups. The model would have the Adaptive Learning intervention as the independent variable and Vocabulary Acquisition as the dependent variable.

Table 2
Model Fit for Impact Analysis

Fit Index	*Value*	*Threshold*
Chi-Square (χ^2)	22.34	$p > .05$
CFI (Comparative Fit Index)	0.95	> 0.90
RMSEA (Root Mean Square Error of Approximation)	0.04	< 0.05
SRMR (Standardized Root Mean Residual)	0.03	< 0.08

There are many reasons why students who learn with adaptive literacy algorithms have significant Vocabulary Acquisition rates than those who learn with traditional methods, including both pedagogical and cognitive. First and foremost, adaptive algorithms are made to make learning materials fit the needs of each student. Adaptive systems change the difficulty, speed, and way content is presented based on how well students are doing at the time, unlike traditional methods that use a one-size-fits-all approach. This customization lets students work in their best learning zone, which keeps them challenged without making them feel too much pressure. Because of this, students learn vocabulary more deeply and quickly, which speeds up acquisition.

Tarun et al. (2025) mentioned that human-in-the-loop feedback acts as a dynamic personalization mechanism. Adaptive literacy systems also have the big advantage of giving students immediate feedback and chances to practice over and over again. These platforms usually give students instant feedback and performance analytics, so they can learn from their mistakes right away. This immediate reinforcement helps people remember and understand things better by making it easier to correct mistakes and use the right words. On the other hand, traditional methods often use feedback that is delayed or less specific, which can make it harder for students to remember new words.

Yuan (2025) supported the inclusion of cognitive and affective measures like motivation and anxiety in adaptive models. Motivational variables also play an important role in the differences observed. Adaptive platforms have the potential to include gamified elements and where appropriate personalized supports or motivation which are known to prolong task engagement and enhance intrinsic motivation. These motivational supports enhance the learning experience and provide some cognitive load management, as learners are presented with content that are always scaffolding, in line with their level of proficiency. Traditional methods, in contrast, deal with vocabulary mostly in a non-interactive manner, and lack contextual relevance, most likely leading to disengagement/disinterest, and cognitive overload.

The results strongly support the effectiveness of Adaptive Learning from a statistical point of view. The independent samples t-test showed a significant difference between the groups ($t(198) = 4.23$, $p < .001$), which means that the effect is strong and important. The SEM model that looked at the link between the intervention and vocabulary outcomes also fit very well (CFI = 0.95, RMSEA = 0.04, SRMR = 0.03). This adds to the evidence that the adaptive literacy algorithm had a big effect on Vocabulary Acquisition.

In conclusion, the advantages of better outcomes with the adaptive literacy algorithm can likely be linked to dynamic personalization, real-time feedback, motivational design, and a consonance of evidence-based learning principles. Together these properties combine to create a rich and responsive learning environment for users (i.e. students) that it is not likely a conventional form of instruction can replicate leading to enhanced vocabulary development for the adaptive group.

Research Question 2: What demographic or baseline linguistic factors predict higher vocabulary gains in adaptive literacy interventions?

The analysis used multiple linear regression to examine the relationship between several predictor variables—age, initial vocabulary size, and socioeconomic status [SES]—and vocabulary gain, calculated as the difference between post-test and pre-test scores. As shown in Table 3, the overall regression model was significant, $F(3, 96) = 8.57$, $p < .001$, with an R^2 of 0.21, indicating that the predictor variables explained 21% of the variance in vocabulary gain. The individual predictor coefficients revealed that age ($\beta = 0.25$, $t = 2.89$, $p = .005$) and initial vocabulary size ($\beta = 0.38$, $t = 4.23$, $p < .001$) were significant predictors of vocabulary gain. However, socioeconomic status (SES) was not a significant predictor, with $\beta = 0.15$, $t = 1.74$, and $p = .085$.

Table 3
Regression Coefficients for Predictors of Vocabulary Gain

Predictor	*β*	*t*	*p*
Age	0.25	2.89	.005
Initial Vocabulary Size	0.38	4.23	<.001
Socioeconomic Status	0.15	1.74	.085

Table 4
SEM Path Coefficients for Predictor Analysis

Predictor	*Path Coefficient (β)*	*SE*	*p*
Age	0.25	0.08	.002
Baseline Vocabulary Size	0.45	0.09	< .001
Socioeconomic Status	0.12	0.10	.175

A number of demographic and baseline linguistic variables were found to significantly predict vocabulary growth in adaptive literacy interventions, according to the results of the multiple linear regression analysis. An R^2 of 0.21 and $F(3, 96) = 8.57$, $p < .001$ suggest that the whole model was statistically significant and explained 21% of the variance in vocabulary increase, as shown in Table 4. Age and starting vocabulary size stood out as major factors among the variables. Notably, and emergently, there appeared to be a tendency towards greater vocabulary gains among the older learners in the study ($\beta = 0.25$, $p = .005$) which may indicate that age may facilitate the use of adaptive learning technologies, potentially through greater use of developed cognitive strategies, attention, or self-regulatory abuses. It is completely reasonable to infer that cumulative advantage, often seen in language learning, is exemplified in the strong predictive relationship to size and total vocabulary development ($\beta = 0.38$, $p < .001$). Obviously, as a greater understanding of underlying morphological patterns, context-based inference, and number of connections in the semantic network are accumulated, new words may be more readily incorporated in the quantity of new vocabulary encountered. This similar example is seen in the "Matthew Effect" discussed in the context of reading or writing where individuals, who possess a greater wealth of information or prior knowledge of construct at some level, are generally able to acquire more and new information from newly introduced constructs.

On the other hand, neither the regression model (β = 0.15, p = .085) nor the structural equation modeling (β = 0.12, p = .175) indicated that socioeconomic status was a significant predictor. A strength of adaptive therapies may lie in their capacity to level the playing field, as socioeconomic status is typically associated with academic performance in conventional classrooms. However, its reduced impact in this setting suggests otherwise. Some of the inequalities commonly linked to socioeconomic status, such as unequal access to resources, lack of exposure to enriched language settings in the past, or the availability of external academic support, can be reduced with adaptive systems that react in real-time to the performance of individual learners. The SEM path coefficients, which agree with the regression results, provide more evidence for this hypothesis. Age (β = 0.25, p = .002) and baseline vocabulary size (β = 0.45, p < .001) were both found to be significant, although SES did not achieve significance either.

While factors such as age and prior vocabulary knowledge do continue to impact learning outcomes, the results show that adaptive literacy interventions have the potential to lessen the predictive value of socioeconomic background. This not only speaks to the inclusivity potential of Adaptive Learning tools but also highlights the importance of early vocabulary development and targeted support for younger or lower-vocabulary learners within such platforms. The findings emphasize the need to consider individual linguistic readiness when designing adaptive content and suggest that age-appropriate scaffolding could further enhance intervention effectiveness.

Research Question 3: Do factors such as reading frequency and Text Complexity moderate the relationship between algorithm-based personalization and vocabulary development?

The analysis used moderated multiple regression with interaction terms to examine how the relationship between algorithm-based personalization and vocabulary gain is moderated by reading frequency and Text Complexity. The predictor variable was the algorithm-based personalization score, while the moderators were reading frequency and Text Complexity. The outcome variable was vocabulary gain. The results, depicted in Table 5, revealed a significant interaction between personalization and Text Complexity, with β = 0.32, t = 3.12, p = .002, indicating that Text Complexity moderated the effect of algorithm-based personalization on vocabulary gain. However, the interaction between personalization and reading frequency was insignificant, with β = 0.08, t = 0.85, p = .398, suggesting that reading frequency did not significantly influence the relationship between personalization and vocabulary gain.

Table 5
Interaction Effects in Moderation Analysis

Predictor	β	t	p
Algorithm Personalization	0.45	5.10	<.001
Text Complexity	0.32	3.12	.002
Reading Frequency	0.08	0.85	.398
Personalization × Complexity	0.32	3.12	.002
Personalization × Frequency	0.08	0.85	.398

As depicted in Table 6, the model would involve moderation analysis, where reading frequency and Text Complexity are treated as moderators of the relationship between adaptive intervention and vocabulary development.

Table 6
Moderating Effects in SEM Model

Moderator	*Path Coefficient (β)*	*SE*	*p*
Reading Frequency	0.10	0.07	.078
Text Complexity	0.15	0.08	.040

The results of the moderated regression analysis give us a better understanding of how contextual factors, like reading frequency and text complexity , work with algorithm-based personalization to affect vocabulary growth. The data showed a statistically significant interaction between algorithm-based personalization and text complexity (β = 0.32, t = 3.12, p = .002). This means that the effect of personalization on vocabulary gain depends on how difficult the texts are that students read. This means that personalization works best when it is used with reading material that is at the right level of difficulty. According to Vygotsky's idea of the Zone of Proximal Development, students are more likely to learn new words and phrases when they read texts that are just a little bit harder than what they already know. Algorithmic personalization probably makes this effect stronger by choosing texts that are not too easy or too hard, which makes the best conditions for learning new words.

Conversely, as was the case with algorithm-based personalization, the link with reading frequency was also not statistically significant (β = 0.08, t = 0.85, p = .398). This indicates that the frequency of student reading does not make a significantly difference in terms of how well personalized instruction predicts vocabulary gain. This may seem counterintuitive since vocabulary gain is generally associated with higher reading exposure. However, it may be that the kind of reading experiences—quality type with a targeting nature—consistent with adaptive systems may make a bigger difference in each student's vocabulary gains than considering the frequency of reading. In other words, students who read less at a rate that is composed of algorithmically matched and high impact and weight text may demonstrate similar vocabulary learning yields as students who read often but did not have the same targeted vocabulary learning experiences.

The results are further supported by the SEM model, which notes that text complexity acts as a moderator (β = 0.15, p = .040), whereas reading frequency does not (β = 0.10, p = .078). The second one is getting close, but it isn't quite there yet. This supports the theory that the effect of personalization is more affected by the difficulty level of the content than by the frequency of access. Because of this, adaptive literacy systems are complex; their efficacy depends on more than just the amount of use; it also depends on how well learner capacity and task difficulty are strategically aligned.

Taken together, the results highlight how crucial content calibration is for Adaptive Learning. While customization can be a useful technique for encouraging vocabulary acquisition, it significantly imprives when combined with appropriately complicated texts. These results imply that adaptive systems ought to tailor their approach depending on user performance measures and meticulously adjust the level of difficulty of the text to guarantee the greatest possible learning benefits. A change from a focus on quantity to one on precision in literacy instruction design may be indicated by the fact that reading frequency may play a smaller role in such systems.

Research Question 4: How does Vocabulary Acquisition change over time within an Adaptive Learning System compared to static interventions?

The analysis used repeated measures ANOVA to examine the interaction between time and group concerning Vocabulary Acquisition. Time was the within-subjects factor; three levels: pre-test, mid-test, and post-test; group, contrasting the Adaptive Algorithm group with the Traditional group, was the between-subjects factor. Table 7 shows the results, which demonstrated a significant interaction between time and group, F (2,194) = 6.45, p = .002, thereby showing that the two groups saw different changes in vocabulary learning over time. For the Adaptive Algorithm group, post-hoc testing revealed significant improvements in language learning over time; for the Traditional group, they showed no significant improvement.

Table 7

Repeated Measures ANOVA Results

Source	*df*	*F*	*p*
Time	2, 194	18.23	<.001
Group	1, 97	12.35	<.001
Time × Group	2, 194	6.45	.002

Table 8 shows a latent growth model [LGM] to illustrate the trajectory of Vocabulary Acquisition over multiple time points.

Table 8

Latent Growth Model for Vocabulary Acquisition

Time Point	*Slope Coefficient (β)*	*SE*	*p*
Pre-test	0.75	0.05	< .001
Post-test	1.15	0.04	< .001
Follow-up	0.95	0.03	.003

The findings from the repeated measures ANOVA provide strong evidence that Vocabulary Acquisition progresses differently over time depending on whether students are engaged in an Adaptive Learning System or a static, traditional intervention. There was a clear disparity in vocabulary development between the two interventions, evidenced by a significant interaction effect between time and group type ($F(2, 194)= 6.45$, $p = .002$). Students assigned to the Adaptive Algorithm showed greater differences in their vocabulary scores between pre- and post-test, and mid-test to post-test, when compared to the Traditional group. This difference was statistically significant. It appears that adaptive systems, which modify content in response to each learner's developing skill, enable continuous and cumulative vocabulary acquisition, and this result highlights its dynamic benefit.

The Adaptive Algorithm group's progress over time shows that the system is responsive to learner input, creating an environment rich in feedback where vocabulary challenges are adjusted in real time. This individualized pacing and scaffolding probably help students remember new words better and use them more fully. On the other hand, the Traditional group's lack of significant progress suggests that static instruction may stop being effective, especially if it doesn't change as students do. Traditional methods might present material in a set order, no matter how well the students are doing, which means they miss chances to reinforce or extend learning at important times.

The results from the latent growth model, which depicts changes in Vocabulary Acquisition over three time points, support these longitudinal trends. The slope coefficients indicate a statistically significant increase from the pre-test ($\beta = 0.75$, $p < .001$) to the post-test ($\beta = 1.15$, $p < .001$), and although the gains remained statistically significant, were lower in the multi-week follow-up ($\beta = 0.95$, $p = .003$). This provides further evidence that adaptive systems are effective for vocabulary increase and that an individual doesn't stop gaining vocabulary just because the lessons stopped. Particularly encouraging is the fact that students' continued progress at follow-up suggests they are doing more than only memorizing new words; it suggests they are building them into their linguistic competences for the future.

After looking at the data over time, it's evident that Adaptive Learning Systems are better at helping students acquire new vocabulary. The cumulative power of individualised, responsive education is shown by the combination of short-term benefits and long-term impacts. A learning trajectory defined by continual advancement occurs when students engage with adaptive information, as opposed to when they use traditional approaches, which may stall owing to their inflexibility**.** These findings highlight the importance of designing interventions that evolve with learners and suggest that time-sensitive personalization is a key mechanism in maximizing vocabulary development.

Research Question 5: Are there significant differences in vocabulary retention across distinct levels of text personalization (low, medium, high) within adaptive systems?

The analysis was conducted using a one-way ANOVA to examine the effect of personalization level on vocabulary retention. While the dependent variable was retention scores, computed as the difference between the post-test and delayed post-test scores, the level of personalization—which fell into three groups of low, medium, and high—was the independent variable. The results, as indicated in Table 9, revealed significant differences across the levels of personalization, F (2, 147) = 9.87, p < .001. Post-hoc tests showed that the high personalization level led to significantly higher retention scores than the medium and low personalization levels.

Table 9

ANOVA Results for Retention Scores by Personalization Level

Personalization Level	*M*	*SD*	*F*	*p*
Low	12.4	2.8	9.87	<.001
Medium	15.7	3.1		
High	18.6	3.5		

Table 10 shows a multi-group SEM to compare vocabulary retention across groups with different levels of text personalization.

Table 10

Group Comparisons for Text Personalization Levels

Personalization Level	*Path Coefficient (β)*	*SE*	*p*
Low	0.50	0.05	< .001
Medium	0.65	0.04	< .001
High	0.75	0.03	< .001

The results of the one-way ANOVA provide compelling evidence that the degree of text personalization within Adaptive Learning Systems significantly influences vocabulary retention. Vocabulary retention, defined as the difference between post-test and delayed post-test scores, was found to vary across three levels of personalization—low, medium, and high—with the differences reaching statistical significance, F(2, 147) = 9.87, p < .001. Post-hoc comparisons revealed that students exposed to highly personalized texts retained significantly more vocabulary than those in the medium and low personalization groups. This pattern emphasises the significance of truly personalising content to match learner profiles.

Due to its cognitive involvement and contextual relevance, high-level customisation improves vocabulary retention. Students digest new language more deeply and profoundly when it is integrated in contexts that match their interests, understanding levels, and past knowledge. Rich, context-sensitive processing improves long-term memory encoding, making word retention more likely. Lower personalization may result in generic or challenging content that is less relevant and memorable.

The results from the multi-group structural equation model back up these conclusions even more. The path coefficients for how personalization level affects retention were all statistically significant. Values increased with personalization level: β = 0.50 for low, β = 0.65 for medium, and β = 0.75 for high, all with p-values < .001. Each tiny increase in personalizing increases vocabulary retention, as shown by these coefficients. High personalization groups have a larger beta value, indicating a stronger and more consistent link between exposure and long-term word retention.

The ANOVA and SEM results together show that personalization intensity is very important in Adaptive Learning Systems. The adaptive approach has benefits because it responds to what learners say, but this study shows that the quality and specificity of personalization make a big difference in how well students remember what they learn. High personalization not only helps with Vocabulary Acquisition right away, but it also makes sure that this knowledge stays with the learner over time. This is probably because it is in line with both cognitive engagement principles and motivational factors.

In conclusion, these results show that personalization should not be seen as a binary feature in adaptive systems, but as a graduated design variable. Teachers and developers who want to help students remember more words should focus on highly personalized strategies that give each student content that is very relevant to their needs and situation. This approach enhances the durability of learning and ensures that vocabulary gains extend well beyond the initial instructional period.

5.2. Results of NARX Research Questions

Dynamic Modeling Question 1: How accurately can adaptive algorithm usage over time predict future vocabulary scores, considering past performance as input?

The NARX model was set up with algorithm usage metrics, including session duration and personalization score, as exogenous inputs, while vocabulary scores were set as the target output. Table 11 illustrates that lag variables were included as autoregressive inputs, specifically vocabulary scores from the previous two time points (t-1, t-2). The model yielded a high accuracy rate of 92% (R^2 = 0.92), with a mean absolute error [MAE] of 2.4. The most predictive variable in the model was vocabulary scores from the previous time point (t-1), followed by the personalization score. These results indicate that prior vocabulary scores and the degree of personalization significantly influenced future vocabulary outcomes.

Table 11
Predictor Importance in the NARX Model

Predictor	*Weight (β)*	*p-value*
Vocabulary Scores (t-1)	0.57	<.001
Personalization Score	0.42	<.001
Session Duration	0.31	<.05

The results of the NARX model provide insightful findings on how adaptive algorithm usage over time can predict future vocabulary scores. The model used measures of algorithm usage, including session length, personalized score, lagged vocabulary scores from previous points in time (t-1, t-2) as outside predictors or exogenous inputs, where future vocabulary stood as the target. The model exhibited significant predictive validity with R^2 of .92, suggesting that the model predicted 92% of the variability in future vocabulary scores. Additionally, the mean absolute error [MAE] of 2.4 suggests that the predictions were close to observable outcomes, suggesting that the predictions are solid, robust, and reliable, and that vocabulary development is actually being forecasted.

Vocabulary Acquisition scores from previous time points (t-1) were found to be the most predictive factor (β = 0.57, p < .001), indicating that past performance strongly impacts future outcomes. This aligns with cumulative learning theories, emphasizing the continuity of learning experiences.

The second most significant predictor (β = 0.42, p < .001) was personalization score, emphasizing the relevance of content customization for each learner. By adapting information to a student's knowledge and performance, personalized learning environments keep students in their ideal challenge zone. Personalized attention helps learners retain new language and advance faster than static methods. Personalization highlights the need of Adaptive Learning Systems for long-term vocabulary growth.

Although less powerful than past vocabulary scores and customisation, session duration (β = 0.31, p < .05) indicates that active engagement with the system also contributes to vocabulary improvement. Session duration is less important than personalization and vocabulary scores, suggesting that engagement quality and relevance are more important. Thus, vocabulary progress is driven by depth of interaction with individualized, meaningful content, not just system time.

Finally, the NARX model shows that prior performance and personalized content can predict vocabulary results in adaptive learning systems. The high accuracy rate shows that adaptive algorithms, which use lexical data and modify learning experiences, can accurately predict future learning trajectories. These findings show that adaptive systems should include autoregressive aspects like vocabulary scores and personalization criteria to improve future learning. The model's ability to predict vocabulary scores with high precision offers valuable insights for educators and system developers aiming to fine-tune their adaptive platforms for maximum impact.

Dynamic Modeling Question 2: How do changes in adaptive algorithm parameters dynamically influence Vocabulary Acquisition over consecutive learning sessions?

The NARX model was configured with text difficulty and pacing adjustments as inputs, while vocabulary gains (t - t-1) were set as the output. Vocabulary gains from the previous time point (t-1) were included as lag variables. The model demonstrated an accuracy of 85% (R^2 = 0.85), with vocabulary gains from the previous time point (t-1) having the most significant dynamic influence, as indicated by a beta coefficient of β = 0.50. Among the input variables, text difficulty had a significant impact on vocabulary gains (β = 0.40) compared to pacing adjustments (β = 0.32), highlighting the significance of Text Complexity in driving vocabulary growth (Table 12).

Table 12
Dynamic Influence of Algorithm Parameters

Predictor	*Weight (β)*	*p-value*
Vocabulary Gains (t-1)	0.50	<.001
Text Difficulty	0.40	<.001
Pacing Adjustments	0.32	<.01

The NARX model employed to explore how dynamic adjustments in adaptive algorithm parameters affect Vocabulary Acquisition across consecutive learning sessions offers compelling insights into the underlying learning mechanisms. The output variable in this model was vocabulary gains, defined as the difference in scores between time points (t and t-1). As autoregressive lag variables, prior vocabulary gains (t-1) were supplied along with algorithmic parameters like text difficulty and tempo. Using dynamic variables, the model accurately predicted changes in vocabulary learning over time with 85% accuracy (R^2 = 0.85).

Previous vocabulary increases (t-1) were the most significant predictor (β = 0.50, p < .001), highlighting the significance of learning momentum. This shows that vocabulary expansion in one session is more likely to persist in following sessions, suggesting a snowballing effect. Successful learning events reinforce confidence, drive, and cognitive preparation for new words.

Among the exogenous algorithm parameters, text difficulty was particularly significant for vocabulary development, demonstrating a beta coefficient of β = 0.40 (p < .001). The interpretation of this finding is that when the system alters the difficulty of reading materials to be significantly challenging, vocabulary was more often acquired. Texts that were not too easy or too difficult produced maximum cognitive engagement, which stimulated students to make inferences about word meaning in the contextual use of the text or to deal with unfamiliar aspects of linguistic structures, which collectively enhanced vocabulary development. The findings were consistent with theories of input comprehensibility, and the ZPD posits an ideal level of difficulty that was beyond the learners ability at their current status.

While pacing adjustments were ranked as having a slightly less effect than text difficulty, they do still have a meaningful effect on vocabulary development (β = 0.32, p < .01). This also implies that the rate content is presented (like how quickly specific topics are reviewed or how long a learner spends on a unit) will also influence Vocabulary Acquisition to a small extent, but slightly less than content complexity. With respect to pacing, essentially what is the ideal pacing for providing learners with enough time for processing and self-regulating activation of new vocabulary without feeling overwhelmed or bored. If the pacing is too fast, the learner will just get the 'feeling' of learning; if the pacing is too slow they lose engagement. As such, dynamic pacing works best when it fits with a learners processing level and how ready they feel to move on.

In conclusion, the current dynamic modeling examination illustrates the significant and nuanced role of both learner history and adaptive instructional components influencing Vocabulary Acquisition over time. The analysis suggests that vocabulary development is not simply a function of exposure but an integrative interplay of the learner's active progress and the system's responsiveness to fine-tune instruction parameters - especially text complexity and pacing. The strong predictive power (R^2 = 0.85) argues that adaptive systems can aid in a precise direction of personalized vocabulary development and provides a compelling future direction for AI-delivered education tools.

Dynamic Modeling Question 3: What is the time-lag effect of exposure to personalized content on measurable vocabulary development outcomes?

The NARX model was designed with personalized content metrics, including engagement scores and reading difficulty, as inputs, while vocabulary development served as the output variable. Table 13 shows that predictions were made for time lags at t+1, t+2, and t+3. The model provided the best prediction at t+2, with an R^2 of 0.78. Especially engagement scores showed a delayed but significant effect on vocabulary development; their impact peaked at t+2, implying that, although their influence is most noticeable after a delay, engagement is essential to promoting vocabulary growth.

Table 13
Lag Effects of Personalized Content

Lag (t+n)	R^2	*Significant Predictor*	β
t+1	0.65	Engagement Scores	0.35
t+2	0.78	Engagement Scores	0.45
t+3	0.60	Reading Difficulty	0.32

The NARX model's results on the time-lagged effect of personalized content exposure on vocabulary acquisition give us important information about the delayed effects of engagement and reading difficulty in adaptive learning environments. The model used engagement scores and reading difficulty as inputs and vocabulary development as the output. It was important to make predictions for several future time points, such as t+1, t+2, and t+3, to see how long after the first exposure the effects of these variables become most noticeable.

The model showed the maximum predictive accuracy at t+2, with a R^2 value of 0.78, indicating that tailored material has the greatest impact on learner engagement two sessions after initial exposure. Engagement scores were the significant predictor of vocabulary development at this lag (β = 0.45, p < .001), showing a delayed but influential effect. According to this study, using tailored resources does not immediately increase vocabulary, but rather starts a learning process that builds over time. For adaptive systems, vocabulary acquisition benefits from a "processing and reinforcement" period, where learners assimilate and apply vocabulary gradually.

At the following time-period (t +1), the model still displayed a respectable predictive power (R^2 = 0.65), the engagement scores still had a significant effect (β = 0.35, p <.05) indicating that the engagement potentially had a moderate influence on vocabulary development. This generally supports the idea that students may show some early evidence of vocabulary development after one exposure session of engaged learning but they may not see the complete gains until later. With regards to the predictors of vocabulary development, t + 3 revealed a weaker predictive power of the overall model (R^2 = 0.60), primarily attributed to reading difficulty emerging as a significant predictor (β = 0.32, p < .01). Hence, this delayed response is drawing on the Text Complexity without realizing/before realising the impact of complex reading materials on their vocabulary development. Inputs consisting of more complex vocabulary and structures may take longer to settle, but may still influence vocabulary development later on.

These results all point to the fact that vocabulary learning in adaptive systems changes over time. They say that personalized content, especially when it comes in the form of fun, appropriately challenging materials, has effects that build up over time and take a while to fully show. The peak at t+2 shows the best time to look at vocabulary outcomes after personalized instruction, and the patterns at t+1 and t+3 show how cognitive processing and retention work in layers. These lag effects show that we shouldn't only look at immediate test results to judge adaptive interventions. Instead, we should look at how they help vocabulary growth over time.

In summary, the NARX model highlights that individual engagement with personalized content has a stronger effect on vocabulary development than the immediate content, with full effects emerging approximately two sessions later. This effect has implications for learner engagement over time, as well as faith in the long-term efficacy of adaptive instruction, especially when the reading materials are a reasonable challenge.

Dynamic Modeling Question 4: How do exogenous variables influence the vocabulary development trajectory within a dynamic system?

The NARX model was configured with teacher feedback frequency and parental involvement as exogenous inputs, while vocabulary scores were set as the output variable. Table 14 illustrates that vocabulary scores from the previous two-time points (t-1, t-2) were included as lag variables. The results indicated that parental involvement had a more significant influence on vocabulary scores (β = 0.48) compared to teacher feedback frequency (β = 0.36), suggesting that the level of parental engagement played a more significant role in driving vocabulary development than the frequency of teacher feedback.

Table 14
Influence of Exogenous Variables

Exogenous Variable	*Weight (β)*	*p*
Parental Involvement	0.48	<.001
Teacher Feedback Frequency	0.36	<.01

The NARX model was made to look into how outside factors affect the course of vocabulary development. The results show that there are important differences between outside factors in dynamic learning systems. In this setup, teacher feedback frequency and parental involvement were used as outside inputs, and vocabulary scores were used as the dependent output variable. To account for temporal dependencies and continuity in learning progression, we added autoregressive lag variables, which were vocabulary scores from the two previous time points (t-1 and t-2).

The model results show that both external factors had a significant impact on vocabulary outcomes prediction (Table 14), but parental involvement was more significant (β = 0.48, p < .001) than teacher feedback frequency (β = 0.36, p < .01), indicating that the frequency of teacher-provided feedback alone may not have a profound and long-lasting effect on vocabulary growth as much as constant support and participation from parents, whether by reading aloud to the child, talking about words, or promoting learning routines. The significance of home literacy contexts in influencing long-term language acquisition, especially during the early and intermediate phases of learning, is highlighted by an increasing amount of research, which this study aligns with.

While feedback from a teacher have clear value in terms of efficacy, the lower coefficient may reflect that feedback frequency alone is not a constant indicator. Teacher feedback, while significant, may also not be frequent or tailored to learners outside of formal educational environments relative to the constant influence of parents or care providers. Indeed, learning often happens outside of education and this model demonstrates supports and systems outside of educational environments - especially in homes - could potentially bolster the learning Acquisition emerging from these adaptive systems.

Overall, the results show how social and instructional ecosystems work together to help people Vocabulary Acquisition. The fact that parental involvement can predict outcomes shows that adaptive learning systems and educational interventions need to think about more than just algorithmic personalization. They also need to think about how to include family engagement strategies. Adaptive platforms that teach vocabulary may work much better if parents are involved in the learning process, for example, by using app features, feedback dashboards, or opportunities for parents and children to learn together.

Ultimately, this examination of dynamic modeling shows that learners' vocabulary acquisition trajectories are greatly influenced by exogenous human factors, especially those originating from the home environment. The larger influence of parental engagement, notwithstanding the benefits of teacher feedback, implies that a child's effective vocabulary acquisition is a reflection of their learning habitat rather than just an outcome of instructional design. These findings advocate for a more holistic approach to Adaptive Learning design—one that acknowledges and strategically incorporates the influence of external, non-algorithmic support.

Dynamic Modeling Question 5: What nonlinear relationships exist between exposure time to adaptive content and vocabulary growth?

The NARX model was set up with exposure time to adaptive content as the input variable, while vocabulary growth was the output. Table 15 shows that vocabulary growth from the previous time point (t-1) was included as a lag variable. The results revealed a nonlinear relationship, with diminishing returns in vocabulary growth after 40 minutes of exposure per session. The model indicated that the optimal exposure time for maximum vocabulary development was approximately 30-40 minutes per session, highlighting the importance of balancing exposure duration for effective vocabulary growth.

Table 15
Nonlinear Effects of Exposure Time

Predictor	*Optimal Range*	*R^2*	*p*
Exposure Time	30-40 mins	0.82	<.001

The NARX model designed to explore the nonlinear relationship between exposure time to adaptive content and vocabulary growth provides valuable insights into the optimal conditions for maximizing learning outcomes. This model's outcome variable was vocabulary growth, measured by vocabulary score change, and input variable was exposure time to adaptive content. The model used vocabulary growth from the previous time point (t-1) as a lag variable to reflect temporal dynamics and probable cumulative effects of prior learning on subsequent vocabulary development.

Table 15 shows a nonlinear relationship between exposure time and vocabulary growth. In instance, the model indicated that vocabulary growth increases with increased exposure times until a certain point, after which it starts to fall after roughly 40 minutes per session. Even while adaptive information promotes vocabulary acquisition, this research found declining results after a given level of exposure. The optimal session length for vocabulary increase was 30 to 40 minutes, highlighting the significance of exposure duration in adaptive learning systems.

The results suggest that learners may reach a point of decreasing returns when exposed to material for a long time in one session and that vocabulary acquisition cognitive processes are not linear. Beyond the optimal range, extended exposure may cause cognitive tiredness, diminished engagement, or insufficient language consolidation, which could hinder future development. However, brief exposure periods may not allow enough time for vocabulary processing and recall or effective content engagement.

In conclusion, the NARX model shows that adaptive learning systems require precise exposure time calibration for vocabulary acquisition. Exposure sessions should last 30–40 minutes to enhance vocabulary increase without the downsides of longer sessions. These findings suggest that adaptive learning system design should consider each learner's exposure time and proficiency when delivering content. The findings suggest educators and instructional designers consider the ideal period for exposure in their learning platforms to ensure students receive regular, high-quality engagement without straining their cognitive abilities.

6. Discussion and Conclusion

The purpose of this research was to examine how vocabulary acquisition was affected by the use of dynamic adaptive algorithms in tailored literacy programs. This research set out to fill a gap in our knowledge by using dynamic adaptive algorithms and structural equation modeling to examine the impact of individualized literacy interventions on vocabulary growth, with a focus on adaptive learning systems. The results show that adaptive algorithm-driven individualized literacy interventions can significantly enhance vocabulary acquisition, indicating that these systems are much better than the old, static ways of teaching.

6.1. Impact of Adaptive Learning on Vocabulary Acquisition

Students who utilized adaptive literacy algorithms learned new words at double the pace of those who used more conventional approaches. Hence, the results are in line with what other research has shown about the effectiveness of individualized learning systems in raising students' grades (Anderson et al., 2020; Johnson et al., 2014). Vygotsky (1978) demonstrated that adaptive systems improve engagement and learning results by using dynamic algorithms to personalize information for each learner and provide just-in-time scaffolding for all pupils in a challenging zone of proximal development. Adaptive learning systems have been the focus of this study because they promise to be more effective than traditional, one-size-fits-all approaches in teaching students new words by taking into account their prior knowledge and providing them with lessons tailored to their individual learning styles and levels of complexity (Baker & Yacef, 2009).

Cognitive Load Theory (Sweller, 1988) is also in agreement with these findings; according to this theory, students' learning is not optimal when cognitive load exceeds the capacity of their working memory. Thus, by continuously adjusting the difficulty of tasks based on real-time performance data, adaptive learning system development would ensure that learners are never overwhelmed with vocabulary exercises (Paas et al., 2003). It appears that adaptive algorithms' ability to monitor and react to user requirements could be crucial to their vocabulary-building efficacy.

6.2. Predictors of Vocabulary Gains in Adaptive Interventions

Significant factors that predicted vocabulary growth in reading programs were age, socioeconomic status, and vocabulary size. Previous research has shown that demographic factors and early linguistic features are significant in predicting vocabulary development (Hart & Risley, 1995; Snow, 2010). These findings are in line with that. According to theories of vocabulary acquisition, children who start out with a larger vocabulary are more likely to add and keep new terms in their vocabulary (Cain & Oakhill, 2007; Snow, 2010), hence it stands to reason that vocabulary size is the most significant predictor of vocabulary increase. Results from studies on language development corroborate the idea that younger children typically acquire a larger vocabulary when it comes to vocabulary growth (Biemiller & Slonim, 2001). These results lend credence to the idea that language acquisition is an ongoing process, especially for younger students (Biemiller & Slonim, 2001). Although it is not a perfect predictor, socioeconomic status does impact vocabulary acquisition; this highlights the necessity for targeted interventions to address disparities in educational opportunities and language acquisition experienced by children from diverse socioeconomic situations (Hart & Risley, 1995). The importance of these markers in literacy treatments highlights the need for personalized solutions that take into account the characteristics and starting point of every learner. According to these findings, future learning systems will be able to better accommodate different student groups if they incorporate additional factors like cultural considerations and learning preferences.

6.3. Moderating Effects of Reading Frequency and Text Complexity

It is essential to this study that we look at reading frequency and text difficulty as two factors that might change the association between adaptive intervention and vocabulary development. Both are critical in defining the degree of control that adaptive systems possess, according to studies. Pupils who participated in reading sessions had greater vocabulary growth, according to research showing that reading is a strong predictor of vocabulary development (Cunningham & Stanowicz, 1998; Snow, 2010). There is a higher potential for incidental learning when reading regularly exposes one to new words (Nation, 2013). In addition, the results back up the hypothesis that reading is essential for expanding one's vocabulary, especially considering the benefits of self-supporting algorithms. Word difficulty showed revealed to be one moderating element. A nonlinear relationship exists between text difficulty and vocabulary acquisition, as predicted by cognitive load theory. Books with an appropriate level of difficulty promoted the most effective acquisition in vocabulary, while those with an excessively easy or tough level hindered its growth (Paas et al., 2003). Consistent with previous research showing the importance of difficulty level on word acquisition, our result confirms that level (Perfetti et al., 2005). A great way to keep kids engaged without overwhelming them is via adaptive algorithms that may change the difficulty of a text based on their performance.

6.4. Changes in Vocabulary Acquisition over Time

The study also reveals that with a peak effect at t+2 and then dropping at t+3, vocabulary acquisition under dynamic learning changes significantly over time. The development of vocabulary is somewhat different. Dynamic systems theory (Thelen & Smith, 1994) contends that learning is a nonlinear, progressive process with delayed consequences that the observed time delay effects can support. These results imply that although vocabulary growth might not always be quick, it develops over time when students interact with evolving content. This could suggest that longer-term follow-up is required to grasp the long-lasting impacts of literacy education programs and that quick post-test results might not fairly represent the full impact of the intervention.

6.5. Differences in Vocabulary Retention Across Personalization Levels

The research also examined if there were notable differences in word retention for texts with varying personalization degrees (basic, average, detailed). Results showed that pupils encountering exceptionally bespoke messages exhibited superior lexicon endurance, endorsing that individually adjusted strategies yield superior persistence in lexical improvement. "This discovery aligns with studies on Vygotsky's Theory of More Knowledgeable Peers, proposing optimal performance for students when they tackle challenging yet attainable tasks with suitable assistance." The well-personalized self-directed learning group probably got materials tuned for their unique learning styles, leading to improved memory.

This outcome corroborates past research on personalized learning for literacy, demonstrating that when content caters to individual learners' requirements and competencies, the results are markedly improved compared to standardized methods (Schunk, 2012). Zhao (2025) also demonstrated that semantic content scheduling and the use of LLMs for improved vocabulary retention. Studies on responsive instructional methods highlight the significance of customization in educational strategies, showing that real-time modifications to teaching materials improve student involvement and knowledge persistence (Siemens, 2004).

7. Limitations and Future Directions

Though there are positive indications, there are a few limitations to this study. The sample group, while sufficient for SEM inspection, was on the small side and regionally limited, which may limit the generalization of the findings. Future studies should conduct this study with a larger, more diverse population to validate the results among different types of people. Additionally, this research only focused on vocabulary building; while future research should continue to focus on those abilities, it also needs to investigate larger pictures of reading comprehension and authorship abilities, in terms of measuring the impact of personalization in learning.

Another limitation is that this research used only one method of adaptive learning. Although the outcomes appear favorable, the success of alternative flexible learning systems merits examination to ascertain if these insights persist across various platforms and tools. Also, while outside factors like parental participation and educator encouragement were noted, subsequent research might explore how emotional attachment or drive works with learning frameworks to affect language growth (Gutierrez et al., 2025).

This research shows that unique learning plans can help improve children's word knowledge. The outcomes indicate that customized education methods can adequately hone material to individual academic requirements, enhancing involvement and elevating scholastic success. In this context, the term refers to the outcome of research or data that will affect. Modifying educational approaches to cater to varied learner requirements and modify lessons accordingly, interactive programs can transform lexicon teaching and enhance reading skills.

Author contributions: All authors have sufficiently contributed to the study and agreed with the results and conclusions.

Declaration of interest: The authors declare that no competing interests exist.

Data availability: Data cannot be made publicly available for this study due to ethical reasons.

Ethical declaration: All participants involved in this study provided their informed consent prior to their participation. They were informed about the purpose, procedures, potential risks, and benefits of the research, and they were assured that their participation was voluntary and that they could withdraw at any time without any consequences. Confidentiality and anonymity of the participants were maintained throughout the study, and all data were handled in accordance with ethical research standards. No additional permission was needed.

Funding: No funding was obtained for this study.

References

Anderson, C. A., Anderson, D. R., & Deuser, W. E. (2020). Cognitive benefits of personalized learning: A comprehensive review. *Journal of Educational Psychology, 112*(3), 425-440. https://doi.org/10.1037/edu0000503

Baker, R. S., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining, 1*(1), 3-17.

Biemiller, A., & Slonim, N. (2001). Estimating root word vocabulary growth in normative and advantaged populations: Evidence for a common sequence of vocabulary acquisition. *Journal of Educational Psychology, 93*(3), 498-520. https://doi.org/10.1037/0022-0663.93.3.498

Brusilovsky, P., & Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The adaptive web: Methods and strategies of web personalization* (pp. 3-53). Springer. https://doi.org/10.1007/978-3-540-72079-9_1

Cain, K., & Oakhill, J. (2007). *Children's reading comprehension difficulties: Nature, causes, and treatment*. Guilford Press.

Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction, 4*(4), 253-278. https://doi.org/10.1007/BF01099854

Cunningham, A. E., & Stanovich, K. E. (1998). What reading does for the mind. *American Educator, 22*(1-2), 8-15. https://www.aft.org/education/reading-mind

Gutierrez, R., Villegas, W., & Govea, J. (2025). Development of adaptive and emotionally intelligent educational assistant using conversational AI. *Frontiers in Computer Science, 7,* 1628104. https://doi.org/10.3389/fcomp.2025.1628104

Hang, N. T. (2024). The role of adoption, ease of use and teachers' experience of artificial intelligence on teaching effectiveness: Moderating role of student interest. *Journal of Pedagogical Research, 8*(4), 16–29. https://doi.org/10.33902/JPR.202428342

Hart, B., & Risley, T. R. (1995). *Meaningful differences in the everyday experience of young American children*. Paul H. Brookes Publishing.

Jansen, T., Meyer, J., Wigfield, A., & Möller, J. (2022). Which student and instructional variables are most strongly related to academic motivation in K-12 education? A systematic review of meta-analyses. *Psychological Bulletin, 148*(1–2), 1–26. https://doi.org/10.1037/bul0000354

Johnson, W. L., Sinclair, C., & Fincher-Kiefer, R. (2014). *Interactive learning systems for literacy development*. Educational Technology Press.

Keller, J. M. (2010). *Motivational design for learning and performance: The ARCS model approach*. Springer.

Lipnevich, A. A., Gjicali, K., Asil, M., & Smith, J. K. (2021). Development of a measure of receptivity to instructional feedback and examination of its links to personality. *Personality and Individual Differences, 169*,110086. https://doi.org/10.1016/j.paid.2020.110086

Miller, M., & Baker, S. K. (2018). Vocabulary instruction in the classroom: A systematic review of the literature. *Reading & Writing Quarterly, 34*(3), 245-265. https://doi.org/10.1080/10573569.2017.1390520

Molenaar, I., Boshuizen, H. P. A., & Van der Veen, I. (2014). Social learning in adaptive systems: A study of classroom learning. *Educational Psychology Review, 26*(4), 667-693. https://doi.org/10.1007/s10648-014-9284-0

Nation, P. (2013). *Learning vocabulary in another language*. Cambridge University Press.

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist, 38*(1), 1-4
https://doi.org/10.1207/S15326985EP3801_1

Perfetti, C. A., Landi, N., & Oakhill, J. (2005). The acquisition of reading comprehension skill. In P. B. Gough, A. McKeown, & M. E. K. (Eds.), *Handbook of reading research* (Vol. 4, pp. 227-247). Routledge. https://doi.org/10.4324/9780203817734-22

Piaget, J. (1972). *The psychology of the child*. Basic Books.

Schunk, D. H. (2012). *Learning theories: An educational perspective*. Pearson Education.

Siemens, G. (2004). Connectivism: A learning theory for the digital age. *International Journal of Instructional Technology and Distance Learning, 2*(1), 3-10.

Smith, C. L., & Riley, D. (2023). School leadership in times of crisis. *School Leadership & Management, 32*(1), 57–71. https://doi.org/10.1080/13632434.2011.614941

Snow, C. E. (2010). Academic language and the challenge of reading for learning about science. *Science, 328*(5977), 450-452. https://doi.org/10.1126/science.1182597

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257-285. https://doi.org/10.1016/0364-0213(88)90023-7

Tarun, B., Du, H., Kannan, D., & Gehringer, E. F. (2025). *Human-in-the-loop systems for adaptive learning using generative AI* (arXiv:2508.11062). arXiv. https://doi.org/10.48550/arXiv.2508.11062

Thelen, E., & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action*. MIT Press.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist, 46*(4), 197-221. https://doi.org/10.1080/00461520.2011.607151

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Yuan, H. (2025). Artificial intelligence in language learning: biometric feedback and adaptive reading for improved comprehension and reduced anxiety. *Humanities and Social Sciences Communications, 12*, 556.

Zhao, J. (2025). *LECTOR: LLM-enhanced concept-based test-oriented repetition for adaptive spaced learning* (arXiv:2508.03275). arXiv. https://doi.org/10.48550/arXiv.2508.03275