Quantitative Analysis of How Responsible AI Study Tools Promote Active Reading

An analysis of student usage of an AI-powered study tool reveals how generative AI can enhance, rather than diminish, engagement in reading.

Contents

Key takeaways

01

We analyzed over **79 million** interactions with a standalone eTextbook application and a courseware-embedded eTextbook within an instructor-led learning platform (MyLab & Mastering) to understand **how usage of an AI-powered study tool (AIST) was related to students' reading engagement.**

02

One-time users of the AIST in MyLab & Mastering courseware-embedded Pearson eTextbook were **23 times more likely** to be classified as an Active Reader (rather than a Passive Reader) and repeat users were **24 times more likely** to receive that designation.

Discussion of this result found on page 20.

03

A single AIST interaction increased the likelihood that a standalone Pearson eTextbook learner would be **classified as an Active Reader by 3 times** and repeat AIST usage **increased that likelihood by 3.5 times.**

Discussion of this result found on page 19.

04

Results suggest that the tool can help to maintain reading engagement or shift it toward **more active** reading modes.

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Introduction

The ability to read and comprehend text is critical to success in post-secondary education. In fact, 20 years ago, researchers estimated that more than 80% of college level tasks require students to read [1].

Though much has changed in the world since then, reading remains one of the primary modes of instructional delivery on the college campus. And reading comprehension is one of the strongest predictors of performance on complex, academic literacy tasks and of early-college grade point average [2].

Recent research suggests, however, that many students are graduating high school with poor reading comprehension. In a recent survey of college faculty, nearly half reported that their current first-year students were "much less prepared" to be successful in the skills of close reading and analysis compared to pre-pandemic student cohorts [3].

Of the 1.4 million students taking the ACT in 2025, the percentage who met ACT Reading benchmarks nationally declined, from 44% in 2021 to 39% in 2025, which translates to an increase in the number of students estimated to be unprepared for college reading by more than 31K. Over the same period, the percentage of test-takers deemed below proficient in understanding complex texts has risen from 55% to 58% [4].

For most students, formal reading instruction ends in elementary school, even though students are expected to encounter increasingly complex texts as they approach college. Young students learn to read, but older students must read to learn. Reading to learn requires students to do more than identify words and unpack syntax. Successful readers must also apply self-regulation strategies before, during, and after reading.

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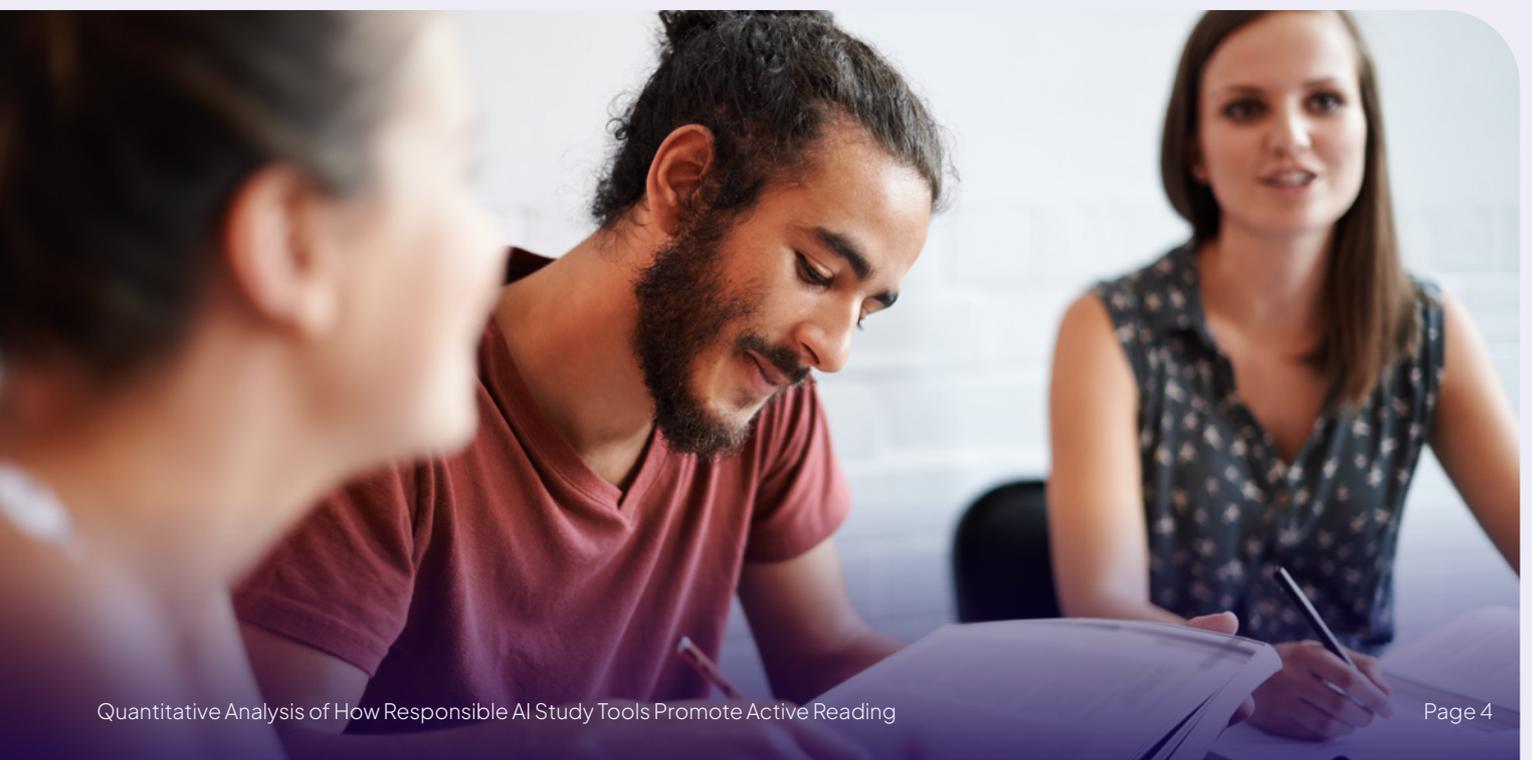
Readers play a central role in making reading happen. In addition to acquiring necessary word-reading and language comprehension knowledge and skills, readers must learn to regulate themselves, actively coordinate the various processes and text elements necessary for successful reading, deploy strategies to ensure reading processes go smoothly, maintain motivation, and actively engage with text." [8, p. S30]

Examples of such strategies include notetaking, highlighting, underlining, and asking questions during reading[9]. This type of active reading can help students better retain what they read and has been linked to improved performance on course exams[10].

Reading to learn in college can be more challenging than reading to learn in secondary education, because college-level textbooks tend to be more complex compared to the types of texts students encounter in high school.

For example, Williamson[5] estimated that a person who could read the average 11th/12th-grade text with 75% comprehension could expect to have less than 50% comprehension of the average university text. This means the types of reading and study skills that serve students well in secondary education are often insufficient for mastering college-level material[6, 7].

"Active reading" is a learning science concept that describes a set of strategies effective readers use to better comprehend what they read: highlighting, taking notes, asking clarification questions, and practicing retrieval of information. These behaviors are strongly associated with deeper comprehension, stronger retention, and improved academic performance.

The potential of Generative AI (GenAI) to support active reading

Since the mainstream launch of ChatGPT in late 2023, there has been an explosion in research examining the effectiveness of Large Language Models (LLM) for learning.

The emerging evidence base shows promising but mixed effects on performance and engagement depending on how the tools are used. A 2024 study by the Wharton School suggested that if students use these tools to procure answers to their homework, their long-term learning can be harmed [11].
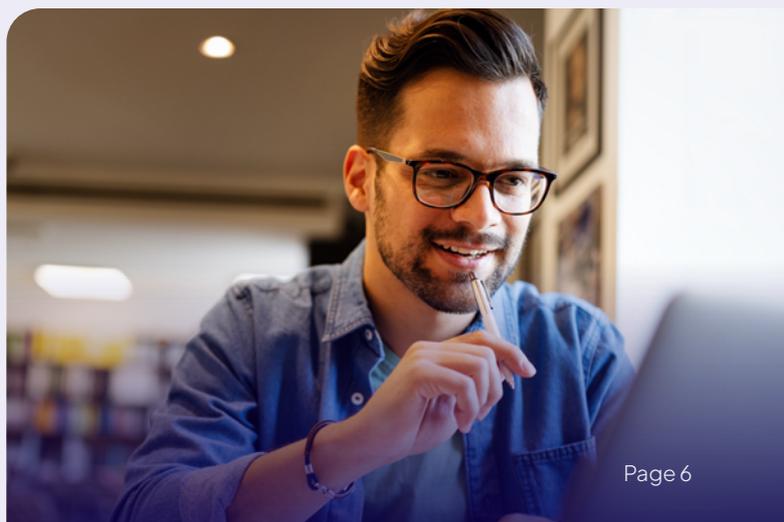
A recent analysis of anonymized student conversations with the Claude.ai platform also raised concerns about cognitive offloading [12], where students delegated higher-order processes to AI, potentially diminishing learning depth.

In their recent study of a conversational AI tool integrated with instructor-provided courseware, Maiti & Goel [13] found a statistically significant increase in higher-order questioning following sustained interaction with the tool.

As yet, little research has examined the effectiveness of GenAI tools for promoting students' active reading of college-level texts; however, one study of an AI-powered chatbot acting as a "reading companion" for university students found significant improvements in self-reported autonomous reading motivation and self-directed out-of-class reading for the group who had access to the chatbot [14].

Despite early evidence of positive impacts when used appropriately, many higher education professors [15] and students [16] have mixed feelings about the use of AI for learning, acknowledging potential opportunities for extending learning while also expressing concerns about academic integrity and the loss of creativity.

Results are more encouraging, however, where AI tools are incorporated meaningfully into the learning process.

Purpose and objectives

The present study examines the use of a Gen-AI study tool embedded in an eTextbook application that provides access to hundreds of undergraduate textbooks for millions of students. The eTextbook application itself was designed to support active reading in the following ways:

- **The table of contents** on the left-hand panel allows easy navigation within the text to preview or revisit certain pages

- **The audio (read-aloud) feature** allows students who are listening to the text to pause, rewind, and manipulate playback speed as needed to support comprehension

- **The highlighter tool** allows students to mark specific words, phrases, or sentences, just as they would in a print book

- **The notebook tool** embedded directly into the text provides a place for students to take and export notes

- **The flashcards feature** enables students to access prebuilt flashcards or convert their notes and highlights into flashcards to self-test their comprehension.
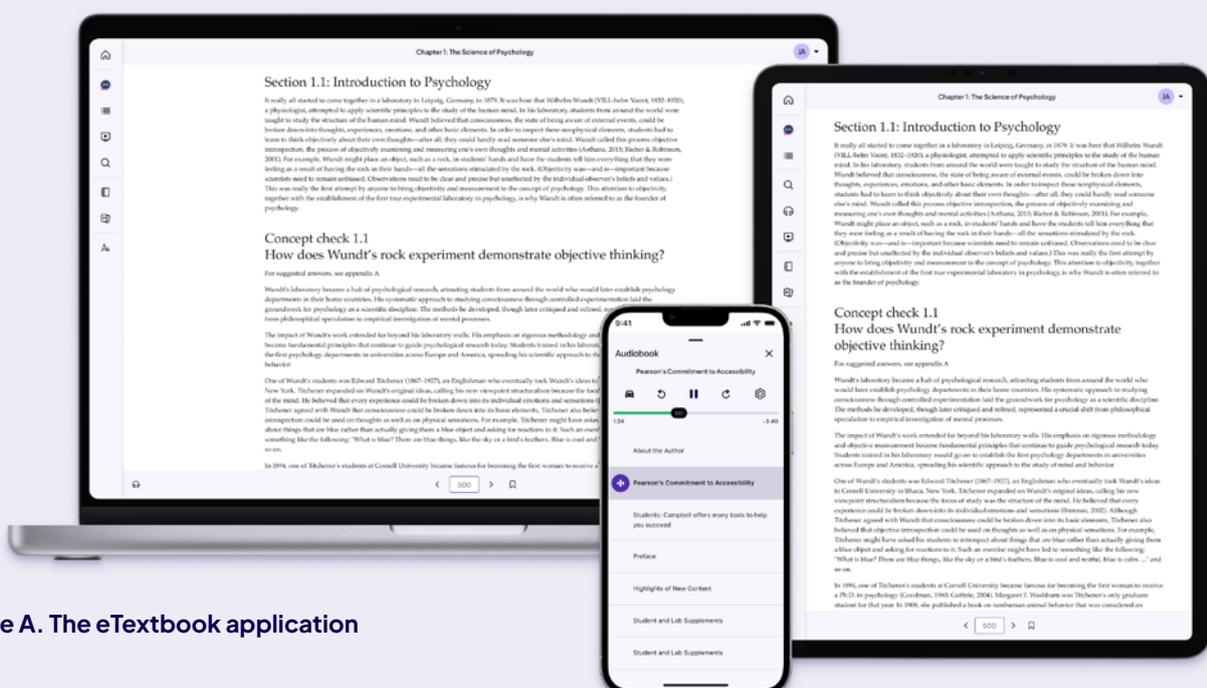

Figure A. The eTextbook application

The AI study tool (AIST) feature was first introduced into the eTextbook application in the fall of 2024. Unlike general Gen-AI platforms, the eTextbook AI study tool prioritizes publisher-approved, expert-vetted content first, using a retrieval augmented generation (RAG) process.

For example, when a student requests an explanation on a specific topic, the tool is supplied with information relevant to that topic from the textbook, promoting accuracy and ensuring its responses are tailored to the textbook. Outputs are structured in accordance with best practices from learning science, such as providing contextualized feedback that supports comprehension and retention and organizing information into short, bulleted structures.

The AIST has been designed to promote deeper engagement with the eTextbook via three main features:

- **Explain:** Invites students to formulate and pose questions about the text during reading, which can help readers monitor and repair their comprehension.

- **Summarize:** Allows students to output a short, bulleted summary of the text, which can serve as a helpful advance organizer before reading.

- **Practice:** Generates short-answer or multiple-choice practice questions specific to chapters, sections, or topics so students can self-test their comprehension after reading, which can help to promote retention [17].

Given prior research demonstrating that integration of AI tools into reading can enhance cognitive, emotional, and behavioral dimensions of engagement with text [18], we hypothesized that students who used the AIST would become more active readers. Accordingly, this research set out to answer the following research question: **How does AIST usage relate to students' reading engagement, defined in this study as active reading behaviors?**
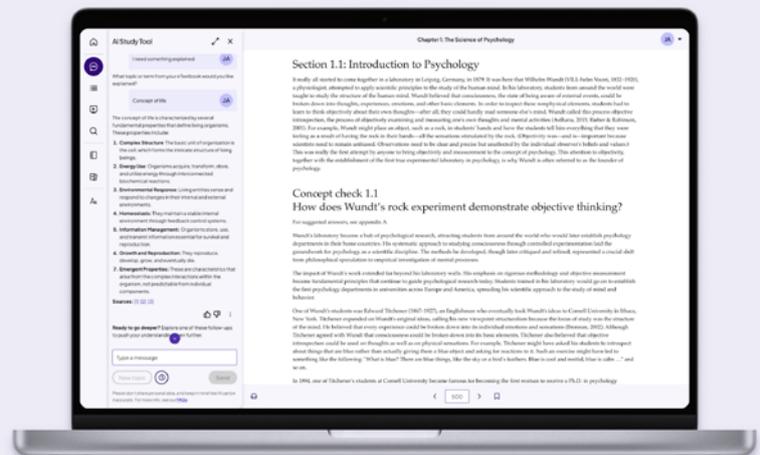

Figure B. The AI study tool within the eTextbook learning experience.

Methodology

This study analyzes student eTextbook usage data across two higher education platforms—standalone Pearson eTextbook and Pearson MyLab & Mastering (MLM) courseware-embedded Pearson eTextbook—in Fall 2024 and Spring 2025.

Although both platforms allow learners to access the same eTextbook titles, the context in which they are used is slightly different. MLM is a courseware solution featuring the eTextbook, assignable and gradable homework, and other features. It is an instructor-led learning experience, which means student activity within the platform is in the context of specific course assignments for which students may receive credit.

In contrast, Pearson+ provides access to standalone Pearson eTextbook, which is solely a student-led learning experience, meaning student activity within the platform represents students' self-motivated study behavior and students do not receive course credit for their reading and studying

Our focus on the construct of active reading rather than on the more general construct of active learning in this study is deliberate. Active reading in the standalone eTextbook may be a strong signal of active learning more generally, because in this environment, activity is self-directed and purpose-oriented toward reading.

In contrast, within the embedded courseware, students are expected to complete homework, work through study modules, and take quizzes assigned by their course instructor, and they receive course credit for doing so.

In this type of environment, a person who is an active learner in terms of assignment engagement could nonetheless appear to be more of a passive reader.

Because of these differences in the context of eTextbook use, we perform all analyses separately for standalone Pearson eTextbook and courseware-embedded Pearson eTextbook. A very small proportion of users had accounts on both platforms, constituting 8.5% of standalone eTextbook users and less than 2% ofcourseware-embedded eTextbook users.

Where users had accounts both for standalone Pearson eTextbook and on MLM, we differentiated their eTextbook activity by platform and looked at their patterns of reading engagement within each platform.

Samples

Learners were eligible for inclusion in the analysis if they were an eTextbook user during Spring 2025.

For the purposes of this analysis, eTextbook usage was defined as completing at least one eTextbook session lasting at least 3 minutes. Sessions with total durations of fewer than 3 minutes were excluded to focus on sessions long enough to permit at least a minimum level of reading engagement.

This sample comprised approximately 690 titles spanning disciplines in Humanities and Social Sciences, Business and Economics, Mathematics, Science, Engineering and Computer Science, Vocational and Professional Studies, and World Languages.

To assess effects associated with using the AIST, we filtered the samples in 3 steps:

⊙ **Step 01:** We excluded those who were not also eTextbook users during Fall 2024. We focused on returning eTextbook users so we could control for baseline reading engagement.

⊙ **Step 02:** We restricted the sample of Spring returners from step 1 to those reading titles in Spring 2025 that featured the AIST.

⊙ **Step 03:** We excluded any students who had used the AIST during the Fall semester, to ensure that Fall reading behavior could serve as a baseline.

Sampling Process

01 Identify Spring returners	Distinct Spring 2025 eTextbook users	→	Non-returners excluded
02 Screen for AIST Eligibility	Returning eTextbook users	→	Non-AIST title readers excluded
03 Exclude Fall AIST users	Returning users reading an eligible title in Spring 2025	→	Fall 2024 AIST users excluded
Final sample size	Standalone Pearson eTextbook (n=45,517) Courseware-Embedded Pearson eTextbook (n=347,097)		

The final samples comprised nearly 46k standalone Pearson eTextbook users and around 347k courseware-embedded Pearson eTextbook users.

Figure C graphically represents this three-stage sampling process, including final sample sizes.
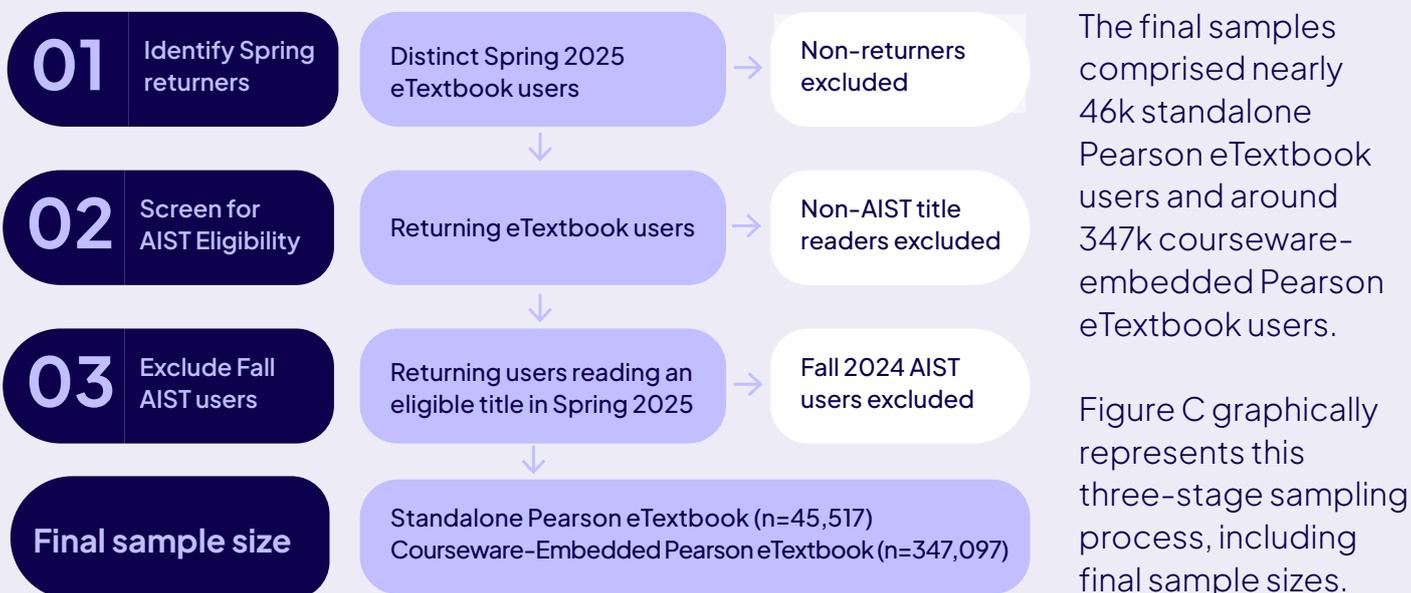
Figure C. Sampling Process

Measures

AIST Usage

For the purposes of assessing the effect of using the AIST, usage was defined in two different ways:

1. single use was operationalized as having generated exactly one output from any of the AIST features, and
2. repeat use was defined as having generated two or more outputs.

Reading Engagement

We conceptualized reading engagement as a continuum ranging from passive to active modes and mapped observable reading behaviors from clickstream data onto this continuum. As a first step, we defined combinations of raw eTextbook clickstream events in the data lake as reading-relevant behaviors (e.g., highlighting, bookmarking, notetaking, flashcards, annotation revisits).

Navigation and search-only actions without follow-on study actions were not tagged or used as analyzable reading behaviors. Importantly for this study, **AIST interactions were not included as reading behaviors** and, therefore, not used in the generation of profiles so that we could estimate the effect of AIST usage on reading profile.

We organized reading behaviors into three engagement modes:

- ⊙ **Passive reading** is consuming text (by reading or listening to audio) without any additional digital activity
- ⊙ **Intentional reading** involves manipulating information from the text in a way that signals more purposeful or intentional processing during reading or audio listening (e.g., highlighting portions of the text or creating a bookmark)
- ⊙ **Active reading** goes a step further and signals an attempt to make meaning from the text by, for example, taking notes, testing one's comprehension, or reviewing annotations.

A complete event-to-behavior crosswalk is presented in Table 1.

Table 1. Relevant Reading Behaviors in the eTextbook

Engagement Mode	Behavior	Description
Passive reading	⟩ Going to book pages and/or revisiting those pages ⟩ Interacting with the audio feature	⟩ Reading or re-reading ⟩ Listening to audio
Intentional reading	⟩ Using the highlighter feature ⟩ Using the bookmark feature	⟩ Highlighting text ⟩ Creating a bookmark
Active reading	⟩ Interacting with the notebook feature ⟩ Interacting with the flashcard and matching game features ⟩ Revisits to previously created bookmarks, highlights, or notes	⟩ Notetaking ⟩ Self-testing comprehension ⟩ Revisiting annotations

Effective readers should be engaging in all three modes over the course of the semester, but students who spend relatively more of their time in intentional or active modes would be expected to have better reading comprehension and information retention compared to someone who only engages in passive mode.

Session-level data were computed per user and semester. Along with filtering any session shorter than 3 minutes, any session exceeding 4 hours of inactivity was right censored at 4 hours to reduce distortion due to idle time. Standard preprocessing steps included deduplication of records and removal of malformed events.

Data analysis

The following analyses were conducted using R with MPlus automation in the tidyLPA package.

Reading Engagement

We modeled reading profiles separately for each semester (Fall and Spring) and by each platform (standalone Pearson eTextbook and courseware-embedded Pearson eTextbook), resulting in four total models. To determine profiles, a Latent Class Analysis was estimated using standardized indicators of reading behavior, including all behaviors from Passive, Intentional, and Active reading modes (Table 1), plus session frequency and duration. Latent Class Analysis seeks to identify distinct user profiles defined by patterns of indicators. In this case, we hypothesized that the profiles would be distinguishable from one another by the amount of reading activity, the type of activity, and the spacing of activity. Model selection was based on model fit indices (Bayesian Information Criterion, Akaike Information Criterion, entropy) and interpretability. From this process, a 3–class model was determined to be the most explanatory.

Effect of AIST usage

We applied a logistic regression, with appropriate log transformations to meet normality assumptions, to estimate the relationship between first-time usage of AIST and reading profile in Spring 2025, controlling for reading profile in Fall 2024. More specifically, the model estimated the probability of being associated with a reading profile characterized by more active reading behaviors during Spring 2025, taking into consideration the baseline reading profile. As described in Table 2, we estimated separate models for each platform type (standalone Pearson eTextbook and courseware-embedded Pearson eTextbook). Each model predicted the Spring reading profile based on different levels of AIST usage, while holding the Fall reading profile constant to control for baseline reading behavior. Interaction terms between AIST usage and Fall profile were included to test whether the effect of AIST use differed depending on a learner's prior reading behavior.

Table 2. Logistic Regression Models Estimated

Platform	Outcome	Predictors	Covariate
Standalone Pearson eTextbook	Spring profile	⟩ Single AIST use ⟩ Repeated AIST use (vs. No use)	Fall profile
MLM (Courseware–Embedded Pearson eTextbook)	Spring profile	⟩ Single AIST use ⟩ Repeated AIST use (vs. No use)	Fall profile

Results

Reading Engagement in Standalone Pearson eTextbook

Based on the results of the Latent Class Analysis, eTextbook users were probabilistically classified into each of the three profiles based on their reading behaviors. Table 3 describes the three profiles and reports the percentage of standalone Pearson eTextbook users that fell into each one in Spring 2025.

Table 3. Spring 2025 Standalone Pearson eTextbook Reading Profiles

Category	Passive Reader 35% of sample	Intentional Reader 47% of sample	Active Reader 18% of sample
Reading activity level	Across all indicators, lowest amount of reading activity (median per person reading events=9)	Moderate amount of reading activity (median per person reading events=57)	Across all indicators, highest amount of reading activity and most varied use of eTextbook features (median per person reading events=68)
Engagement mode	92% of their time is spent in Passive Mode	83% of their time is spent in Passive Mode; they are heavier users of audio and use flashcards to self-test	56% of their time is spent in Passive Mode, 17% in Intentional Mode and 30% in Active Mode
Time spent	On average, 12-minute sessions, 1.4× per week	On average, 30-minute sessions, 2.5× per week	On average, 30-minute sessions, 3× per week

Note. Reading events are defined as any instance of any of the reading behaviors in Table 1.

In Table 3, we labeled the profile (comprising 35% of the standalone eTextbook sample) the Passive Reader (column 2), since these students had the lowest absolute levels of reading activity across all indicators and almost all that activity was in passive mode.

On average, this profile also spent the least amount of time reading. The profile in the last column (comprising 18% of the standalone eTextbook sample) was named the Active Reader, since this profile had the highest absolute levels of activity across all indicators, spent a relatively larger share of their time in intentional or active mode, and tended to spend the most time in the eTextbook overall.

In the third column in Table 3, the profile (comprising 47% of the standalone eTextbook sample) showed evidence of mainly passive reading behavior.

However, these students also demonstrated moderate absolute levels of reading activity overall and were further distinguished from the Passive Readers in their use of multi-modal content and flashcards, which is considered more active behavior. Finally, they spent nearly as much time in the eTextbook as the Active Readers and spaced their reading sessions better than those in the Passive profile.

Taken together, this pattern suggests a student who is attempting to be intentional about their reading, but who could stand to inject more active strategies into their routine. For these reasons, we labeled this profile Intentional Reader and considered it to represent an intermediate level of reading engagement, between Passive and Active.
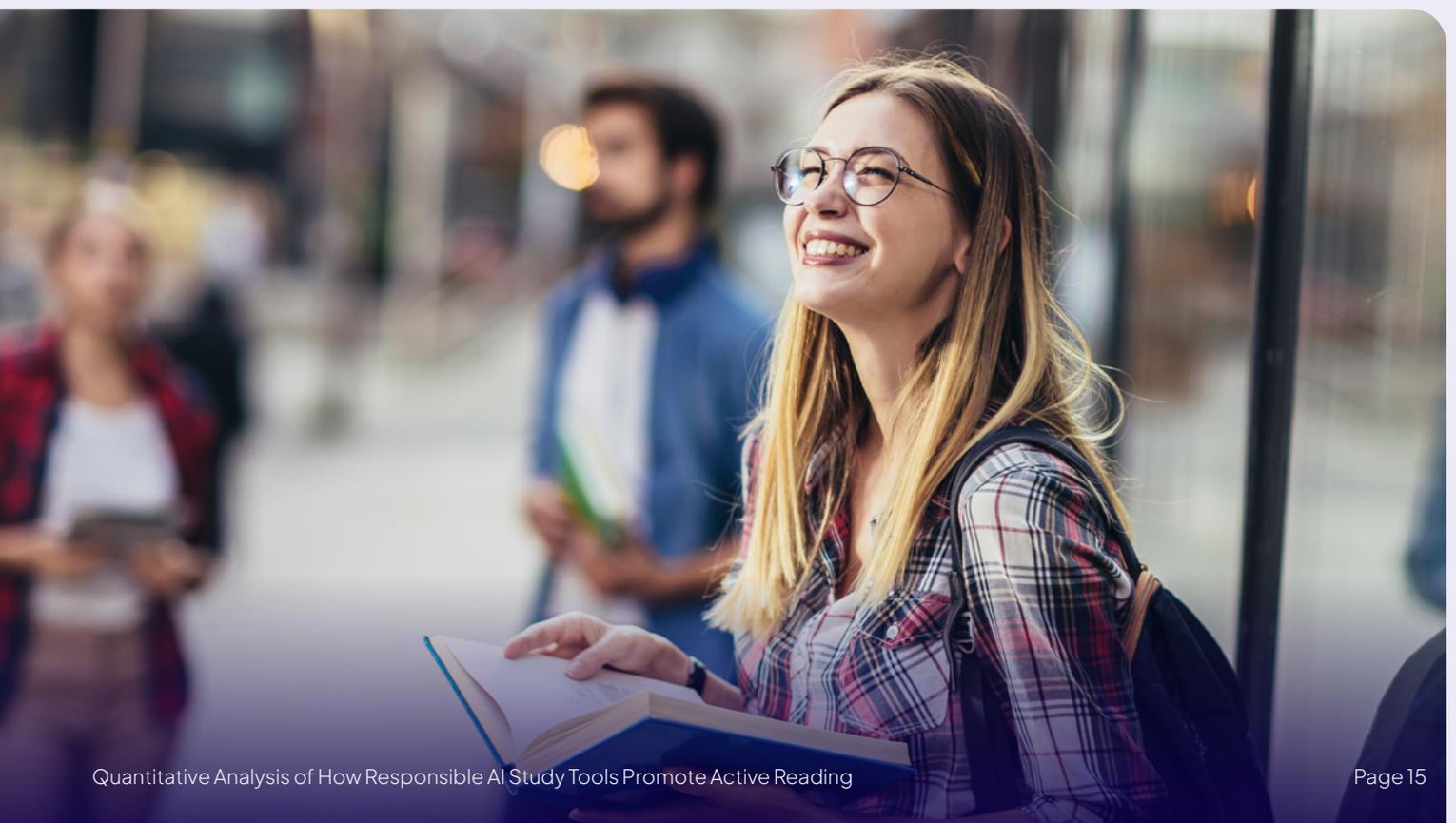
Reading Engagement in Courseware–Embedded Pearson eTextbook

Table 4 presents the corresponding profiles for the courseware-embedded Pearson eTextbook in Spring 2025. As we saw for standalone eTextbook, the Latent Class Analysis supported three profiles. These profiles look similar to those for standalone eTextbook, although overall they were less active in the eTextbook, as evidenced by their smaller median number of reading events. A smaller percentage of the courseware-embedded eTextbook sample were classified into the Active reading profile and these readers spent a smaller share of their time in active or intentional mode compared to the standalone eTextbook sample.

Table 4. Spring 2025 Courseware–Embedded Pearson eTextbook Reading Profiles

Category	Passive Reader 49% of sample	Intentional Reader 45% of sample	Active Reader 6% of sample
Reading activity level	Across all indicators, lowest amount of reading activity (median per person reading events=5)	Moderate amount of reading activity (median per person reading events=23)	Across all indicators, highest amount of reading activity and most varied use of eTextbook features (median per person reading events=25)
Engagement mode	92% of their time is spent in Passive Mode	83% of their time is spent in Passive Mode; they are heavier users of audio and use flashcards to self-test	56% of their time is spent in Passive Mode, 17% in Intentional Mode and 30% in Active Mode
Time spent	On average, 12–minute sessions, 1.4× per week	On average, 30–minute sessions, 2.5× per week	On average, 30–minute sessions, 3× per week

Notes. Reading events are defined as any instance of any of the reading behaviors in Table 1.

Effect of AIST Usage on Reading Profile

Table 5 reports the baseline distribution of reading profiles for both standalone eTextbook and courseware-embedded eTextbook samples. Comparing the percentage of students in each profile, we can see that AIST users and non-users had relatively similar reading profile distributions at baseline, with some differences favoring the AIST users among the courseware-embedded eTextbook sample. For this reason, we included Fall '24 reading profile as a covariate in the analysis to try and mitigate any self-selection bias.

Table 5. Distribution of Baseline Reading Profiles in Fall '24 by Spring '25 AIST Use

Fall '24 Profile	Standalone Pearson eTextbook Sample		Courseware-Embedded Pearson eTextbook Sample	
	No AIST Used	Used AIST	No AIST Used	Used AIST
Passive Readers	17%	17%	32%	29%
Intentional Readers	52%	49%	59%	58%
Active Readers	32%	34%	9%	13%

We used stacked bar charts to visualize the transition of reading profiles from Fall 2024 to Spring 2025 for AIST users (at least one use) and non-users. Figure D illustrates this change for the standalone eTextbook sample and Figure E shows the corresponding transition for the courseware-embedded eTextbook sample. We can see that, as a group, the non-users in both the standalone eTextbook and courseware-embedded eTextbook samples actually become less engaged over time (i.e., a larger share of readers are passive), whereas the AIST users tend to maintain or improve their reading engagement.

Figure D.
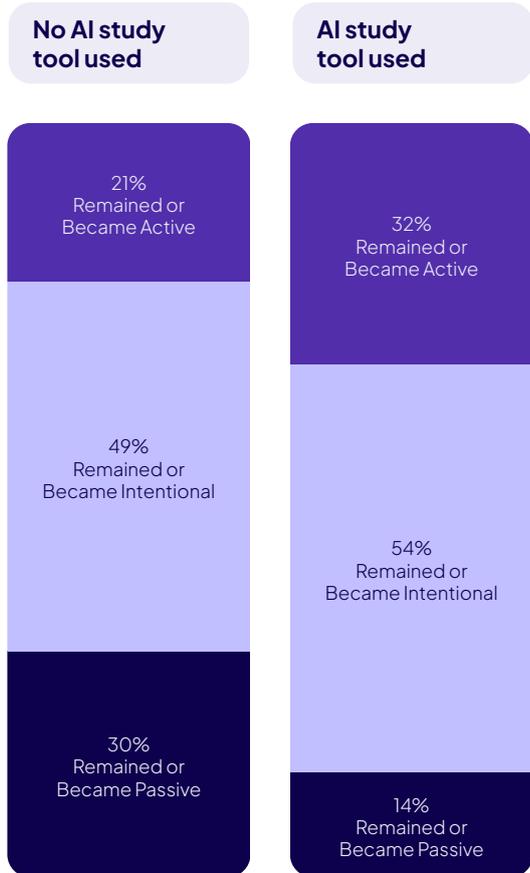Fall to Spring Transition of Reading Profiles for Standalone Pearson eTextbook Sample

| No AI study tool used | AI study tool used |

No AI study tool used
- 21% Remained or Became Active
- 49% Remained or Became Intentional
- 30% Remained or Became Passive

AI study tool used
- 32% Remained or Became Active
- 54% Remained or Became Intentional
- 14% Remained or Became Passive

Figure E.
Fall to Spring Transition of Reading Profiles for Courseware-Embedded Pearson eTextbook Sample

No AI study tool used
- 6% Remained or Became Active
- 52% Remained or Became Intentional
- 42% Remained or Became Passive

AI study tool used
- 16% Remained or Became Active
- 70% Remained or Became Intentional
- 14% Remained or Became Passive
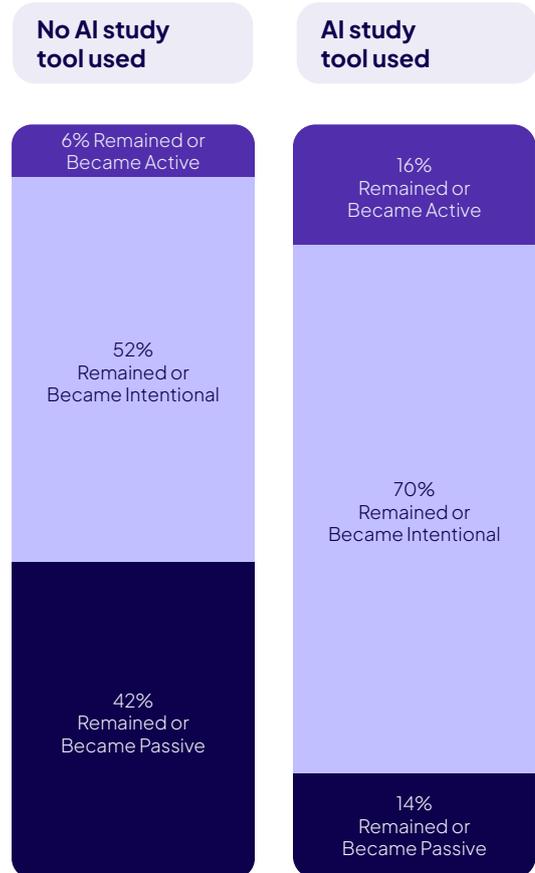
Logistic regression results (reported in Tables A1 – A4 in the Appendix) include estimates for the main effects of:

- ⟩ A single AIST use
- ⟩ Two or more AIST uses
- ⟩ Being in the Intentional profile in Fall '24
- ⟩ Being in the Active profile in Fall '24

The model also includes four interaction terms, which represent the moderating effects of Fall profile on AIST usage. To control for inflated Type I error introduced by the eight separate effects entered into the model, we used a Bonferroni correction, adopting a threshold for significance of $p < 0.00625$.

We report results separately by outcome: Intentional Reader or Active Reader in Spring '25. Parameter estimates in Tables A1–A4 are reported as odds ratios. However, for ease of interpretation, we converted those to relative probabilities to determine the change in likelihood of being classified in that profile for AIST users relative to the reference group. For usage estimates, the reference group is "no AIST use" and for Fall profile-related estimates, the reference group is the Passive profile.

Beginning with standalone Pearson eTextbook results (Tables A1 and A2), none of the interaction terms were significant (at the adjusted $p < 0.5$ level), suggesting the effect of AIST usage on Spring profile did not depend on a student's Fall profile. Turning to the main effects, we can see that the terms for AIST usage – both single use and repeated usage – were statistically significant and greater than 1, suggesting that AIST usage was associated with shifts along the reading engagement continuum toward more active study profiles.

In particular, in comparison to non-users, single AIST users were 1.4 times more likely to be classified as an Intentional Reader and **3.1 times more likely to be classified as an Active Reader**. Repeat users were 1.6 times more likely to be classified as an Intentional compared to non-users and **3.5 times more likely to be classified as an Active Reader**.

Unsurprisingly, Fall profile indicators were also significant predictors of Spring profile. If a learner was classified as an Intentional Reader in the Fall, they were more likely than a Fall Passive Reader to be an Intentional in Spring. Similarly, Active Fall Readers were much more likely than Fall Passives to be Active in Spring.

Quantitative Analysis of How Responsible AI Study Tools Promote Active Reading

A similar pattern of results holds for courseware-embedded Pearson eTextbook learners, with a few exceptions. First, unlike the standalone eTextbook results, two of the interaction terms from the Intentional Profile model and all four interaction terms from the Active Profile model were significant. The interaction terms capture the extent to which the effects of AIST usage differ according to baseline reading profile. Unlike the standalone eTextbook sample, the effect of using AIST was not the same for everyone in the courseware-embedded eTextbook sample and depended on what kind of reader a student was in the Fall. For example, in Table A3, the significant term (estimate=0.86) for the interaction between a single AIST use and being in the Intentional Reader profile in the Fall means that the effect of a single AIST use was around 1.3 times smaller for Fall Intentionals than it was for Fall Passives. The fact that all significant interaction terms are smaller than 1 generally indicates that AIST usage had a relatively larger effect on Fall Passives compared to those who were Intentional or Active Readers at baseline.

The second difference between standalone Pearson eTextbook and courseware-embedded Pearson eTextbook results is that the magnitude of the main effects for the courseware-embedded eTextbook sample was much larger compared to the standalone eTextbook sample.

Based on converting the odds ratios to relative probabilities, first-time AIST users were 2.2 times more likely to be classified as Intentional Readers and **23 times more likely to end up as Active Readers** compared to non-AIST users. Likewise, repeat AIST users were 2.4 times more likely to be Intentional Readers and **24 times more likely to be Active Readers** in Spring.

Discussion

This paper analyzes whether students' usage of an AI-powered study tool embedded in an eTextbook can shift their behavior along the reading engagement continuum toward more active reading modes.

Theoretically, improved reading engagement should translate into better comprehension of what is read and potentially into better performance in the course.

An in-depth examination of student queries to the Explain feature for one of the titles used in this study (an introductory biology text)[19] revealed that for many learners, the tool was primarily a mechanism for reinforcing foundational understanding, with most questions characterized as Remembering and Understanding Factual and Conceptual Knowledge on Bloom's Revised Taxonomy[20]. Interestingly, however, that study also found that a sizable portion of student queries were tagged at more advanced levels of Bloom's Taxonomy, with 20% tagged to Analyze or higher levels, suggesting that the Explain feature can, under certain conditions, support learners in performing higher-level cognitive tasks.

The current study shows that usage of the AIST seems to inspire more active reading engagement modes.

While adoption is not universal, even a single use significantly shifts the likelihood of active reading behavior, and repeated use compounds that effect. The effects of AIST usage were stronger for courseware-embedded eTextbook users who were Passive at baseline. We speculate that we saw this stronger effect because Passive Readers have more room to "grow." The stronger effects observed for Passive readers may, in turn, explain why we also observed larger effects overall for courseware-embedded eTextbook learners (relative to the standalone eTextbook sample), since a larger share of those users were considered Passive Readers at baseline.

It is important not to automatically extrapolate these results on active reading to active learning more generally. Differences in effects across standalone Pearson eTextbook and courseware-embedded Pearson eTextbook platforms almost certainly reflect the different contexts of usage: in a student-led eTextbook application (standalone eTextbook), reading activity may be a good signal of active learning because it is self-directed and purpose-oriented to reading. In contrast, within an instructor-led platform (courseware-embedded eTextbook), reading engagement is only one part of being an engaged learner, in addition to completing required assignments.

Discussion

This research is limited in that selection bias was not completely controlled. Learners chose whether to use the AI study tool (AIST), and those who opted to do so likely differed from non-users in important ways that we were unable to measure in this study (e.g. motivation, confidence, or overall academic engagement). The user and non-user groups were generally similar at baseline in terms of reading engagement (less so for the courseware-embedded eTextbook sample than the standalone eTextbook sample), and we included Fall reading profile as a covariate to help account for those pre-existing differences. However, due to the self-selection bias, the observed effects should be interpreted as associations rather than causal impacts.

We intend to build on this research base over time to understand how usage of the AIST and reading engagement in general relate to students' reading comprehension, and ultimately to their course outcomes, such as exam scores and final grades.

Given the increasing ubiquity of these tools in higher education, it is critical to develop a more nuanced understanding of AI-mediated learning. The findings here suggest that AI tools, when thoughtfully integrated into a learning experience, can act as an aid to active reading.

Appendix

Table A1. Standalone Pearson eTextbook Logistic Regression Estimates: Effect of AIST Use on Spring '25 Intentional Profile

Term	Odds Ratio	95% CI	SE	Wald TS	p-value
Intercept	0.91	0.86 – 0.96	0.03	3.57	<0.000
Single AIST Use	2.16	1.68 – 2.78	0.13	6.03	<0.000
Repeat AIST Use	2.92	2.35 – 3.64	0.11	9.65	<0.000
Fall '24 Intentional Profile	2.02	1.90 – 2.14	0.03	22.89	<0.000
Fall '24 Active Profile	1.85	1.73 – 1.98	0.04	17.34	<0.000
Single use x F24 Intentional	1.11	0.82 – 1.51	0.16	0.69	0.490
Repeat use x F24 Intentional	0.92	0.71 – 1.20	0.13	-0.59	0.553
Single use x F24 Active	1.07	0.74 – 1.55	0.19	0.38	0.704
Repeat use x F24 Active	0.92	0.68 – 1.26	0.16	-0.49	0.621

Table A2. Standalone Pearson eTextbook Logistic Regression Estimates: Effect of AIST Use on Spring '25 Active Profile

Term	Odds Ratio	95% CI	SE	Wald TS	p-value
Intercept	0.30	0.28 – 0.32	0.04	-31.82	<0.000
Single AIST Use	2.42	1.76 – 3.33	0.16	5.45	<0.000
Repeat AIST Use	4.37	3.40 – 5.62	0.13	11.49	<0.000
Fall '24 Intentional Profile	1.18	1.08 – 1.29	0.05	3.68	<0.000
Fall '24 Active Profile	6.12	5.61 – 6.69	0.05	40.47	<0.000
Single use x F24 Intentional	1.35	0.92 – 1.99	0.20	1.53	0.127
Repeat use x F24 Intentional	1.13	0.83 – 1.54	0.16	0.79	0.431
Single use x F24 Active	1.08	0.72 – 1.63	0.21	0.35	0.727
Repeat use x F24 Active	0.85	0.61 – 1.19	0.17	-0.94	0.346

Table A3. Courseware–Embedded Pearson eTextbook Logistic Regression Estimates: Effect of AIST Use on Spring '25 Intentional Profile

Term	Odds Ratio	95% CI	SE	Wald TS	p–value
Intercept	0.54	0.53 – 0.55	0.01	-90.88	<0.000
Single AIST Use	3.65	3.44 – 3.88	0.03	42.50	<0.000
Repeat AIST Use	5.82	5.51 – 6.14	0.03	63.47	<0.000
Fall '24 Intentional Profile	3.58	3.52 – 3.64	0.01	149.42	<0.000
Fall '24 Active Profile	4.83	4.66 – 5.01	0.02	86.66	<0.000
Single use x F24 Intentional	0.86	0.79 – 0.93	0.04	-3.60	<0.000
Repeat use x F24 Intentional	0.80	0.74 – 0.86	0.04	-5.72	<0.000
Single use x F24 Active	0.89	0.73 – 1.09	0.10	-1.13	0.26
Repeat use x F24 Active	1.04	0.86 – 1.26	0.10	0.44	0.66

Table A4. Courseware–Embedded Pearson eTextbook Logistic Regression Estimates: Effect of AIST Use on Spring '25 Active Profile

Term	Odds Ratio	95% CI	SE	Wald TS	p–value
Intercept	0.04	0.04 – 0.04	0.02	-155.23	<0.000
Single AIST Use	7.69	6.90 – 8.56	0.06	37.03	<0.000
Repeat AIST Use	19.08	17.58 – 20.71	0.04	70.50	<0.000
Fall '24 Intentional Profile	2.78	2.64 – 2.92	0.03	40.83	<0.000
Fall '24 Active Profile	48.02	45.49 – 50.69	0.03	140.29	<0.000
Single use x F24 Intentional	0.77	0.67 – 0.89	0.07	-3.60	<0.000
Repeat use x F24 Intentional	0.78	0.70 – 0.86	0.05	-4.63	<0.000
Single use x F24 Active	0.56	0.45 – 0.70	0.11	-5.11	<0.000
Repeat use x F24 Active	0.52	0.42 – 0.63	0.10	-6.44	<0.000

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