

# Considering AI for Generating Mnemonics to Support Learning in Introductory Business Statistics\*

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## Abstract

We present results from using a three-part, multiday SMART (Statistics Mnemonics Assembled with Reflection and Technology) activity designed to help students in an introductory business statistics course explore mnemonic use with and without large language models (LLMs), to support memory retention, and conceptual understanding. Preliminary findings (from analysis of  $n = 70$  student reflections) suggest that mnemonics created without the aid of LLMs felt more personal to students, while LLM-supported efforts helped students work more efficiently. Seventy five percent of 108 sentences in the reflections about anxiety reported feeling a reduction in anxiety including having more confidence, feeling better prepared, and improved recall when the mnemonic exit ticket structure was used.

**Keywords:** mnemonics, LLMs, introductory statistics, exit tickets

## 1 Introduction

### 1.1 Motivation for the SMART Activity

“Study a little each day rather than cramming for the exam.” This familiar advice is echoed across disciplines with good reason. Spaced learning has been shown to improve recall and long-term retention. Evidence suggests that having students revisit learning material a second time improves their knowledge of the material, as it helps them elucidate misunderstandings and build on learning from the first engagement (Ausubel & Youseef, 1965).

To help students adopt this habit, we created a SMART activity — Statistics Mnemonics Assembled with Reflection and Technology — that encourages frequent, low-stakes review through the use of mnemonics. By modeling reflective practices at the end of each class, we aim to support students in developing stronger study strategies for mathematics and statistics. The activity design was informed by awareness that student learning deepens through dialogue with peers and instructors, “in the individual-in-social interaction” (Duffy & Cunningham, 1996, p. 6).

### 1.2 Activity Overview and Pedagogical Framing

At the end of each of the SMART activity’s three days, students complete an **exit ticket**—a short written prompt designed to reinforce the day’s content, identify difficult concepts, and encourage memory-building strategies.

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Central to the activity is the creation of **mnemonics**— memory aids that support retention and conceptual understanding by having students reflect on what was taught, identify components, and connect to prior knowledge. Active learning practices have been shown to improve students' performance in STEM courses (Freeman et al., 2014; Theobald et al., 2020) and are highly recommended in mathematics education (Braun et al., 2017) and statistics education (ASA, 2016).

By embedding this process into multiple class meetings, the SMART activity discourages last-minute cramming and encourages habits of metacognitive self-regulation. Students complete the exit ticket both with and without the support of large language models (LLMs), allowing comparison across contexts. The SMART activity (see Section 2) is informed by research (see Section 3) and can be adapted to any high school or college-level course.

### 1.3 Course Context and Implementation

The SMART activity was implemented during the face-to-face component of a business school's flipped introductory statistics course. The course enrolled both undergraduate and graduate students and met for 100-minute sessions twice a week during an 8-week term. Two sections participated: one with 60 students, the other with 47. The activity was embedded as a recurring reflection task at the end of each in-person class session.

Using University of Florida Institutional Review Board protocol #202302020, data were collected from two sections (with 60 and 47 students). For institutional context, we note that in Fall 2023, the college's student body was approximately 55% White, 20% Hispanic/Latino, 8% Asian, 4% Black/African American, and 3% multiracial, with a gender composition of 56% male and 44% female (University of Florida Website, 2025).

### 1.4 Goals of the SMART Activity

This SMART activity is designed to:

- Encourage students to reflect on course content at the end of each class session,
- Reinforce the learning strategy of creating mnemonics,
- Introduce students to large language models (LLMs), such as Microsoft Copilot (<https://copilot.microsoft.com>),
- Support student reflection on the process of generating mnemonics both without and with the aid of LLMs.

### 1.5 Overview of the Paper

After describing and illustrating the SMART activity, we then briefly review related literature and analysis of student reflections. We close by discussing possible extensions of the activity and suggesting directions for future research. The conclusion summarizes key takeaways for both instructors and researchers.

## 2 The SMART Activity

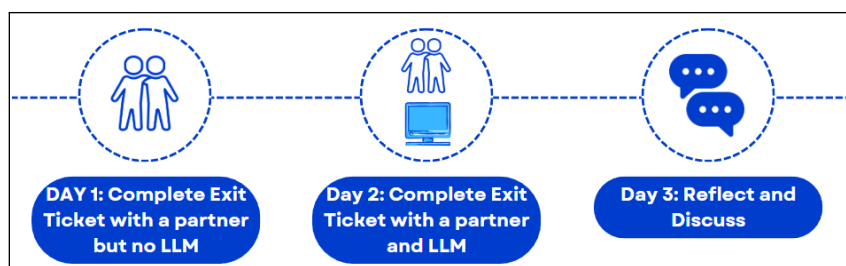
The SMART activity integrates the affordances of exit tickets, mnemonics, and LLMs. This activity was designed to help students assess their learning early in the course, identify areas of struggle, and create mnemonics to help recall, explain, and apply the challenging material, and gain critical literacy for the world in which LLMs now exist by comparing mnemonic creation without and with their use (see Figure 1).



## 2.1 Flow of the Activity

**Figure 1**

*Trajectory of the SMART Activity*



In our study, the instructor made it a point to have the activity's three days close together, lest students forget the process between the exit tickets. The first exit ticket occurred on the first day of class after discussion of the first topic covered in the course, to let students gain learning strategies they could apply throughout the rest of the course.

When this activity was first implemented, exit tickets were implemented on every meeting day of the course, assuming a dose-response relationship, and to ensure that students received sufficient practice with both variations. A drawback of this frequency was that its 15 minutes per class meeting impacted covering all course material. Additionally, it was difficult for the instructor to read all the exit tickets for more than 100 students before the next class meeting. However, if grading were the only challenge, an instructor could select a sample of exit tickets to read thoroughly and then grade them as a completion exercise. Another option would be to have a TA grade the exit tickets.

## 2.2 Day 1: Exit Ticket Without LLMs

This section outlines the activity's first day, during which students completed a structured, four-part exit ticket without LLM support. The steps for Days 1 and 2 are shown in Figure 2.

### 2.2.1 Step 1: Group Formation and Exit Ticket Setup

During the first day of the SMART activity, students completed a multi-part exit ticket in small groups (two or three people each). In our case (because of our assigned classroom's fixed "stadium seating"), we let students choose their partner. The activity took place during the final 15 minutes of class and consisted of four structured prompts: identifying declarative knowledge, identifying process knowledge, reflecting on difficult material, and creating a mnemonic.

### 2.2.2 Step 2: Identifying Declarative Knowledge

Students begin by identifying two pieces of declarative knowledge from that day's lesson. Declarative knowledge includes definitions, facts, and formulas (Anderson & Lebiere, 2014).

*Prompt from Day 1 Exit Ticket (in Appendix A):*

"Please list two declarative knowledge items that you encountered in this module. Declarative knowledge would be definitions and simple relationships. (Example from Right Triangle Trigonometry:  $\sin \theta$  equals the opposite side over the hypotenuse...)"

This step encouraged students to recall factual content, grounding their reflection in specific concepts addressed during the session. Additionally, the instructions reminded students not to use technology and to submit their responses individually via the learning management system (LMS).

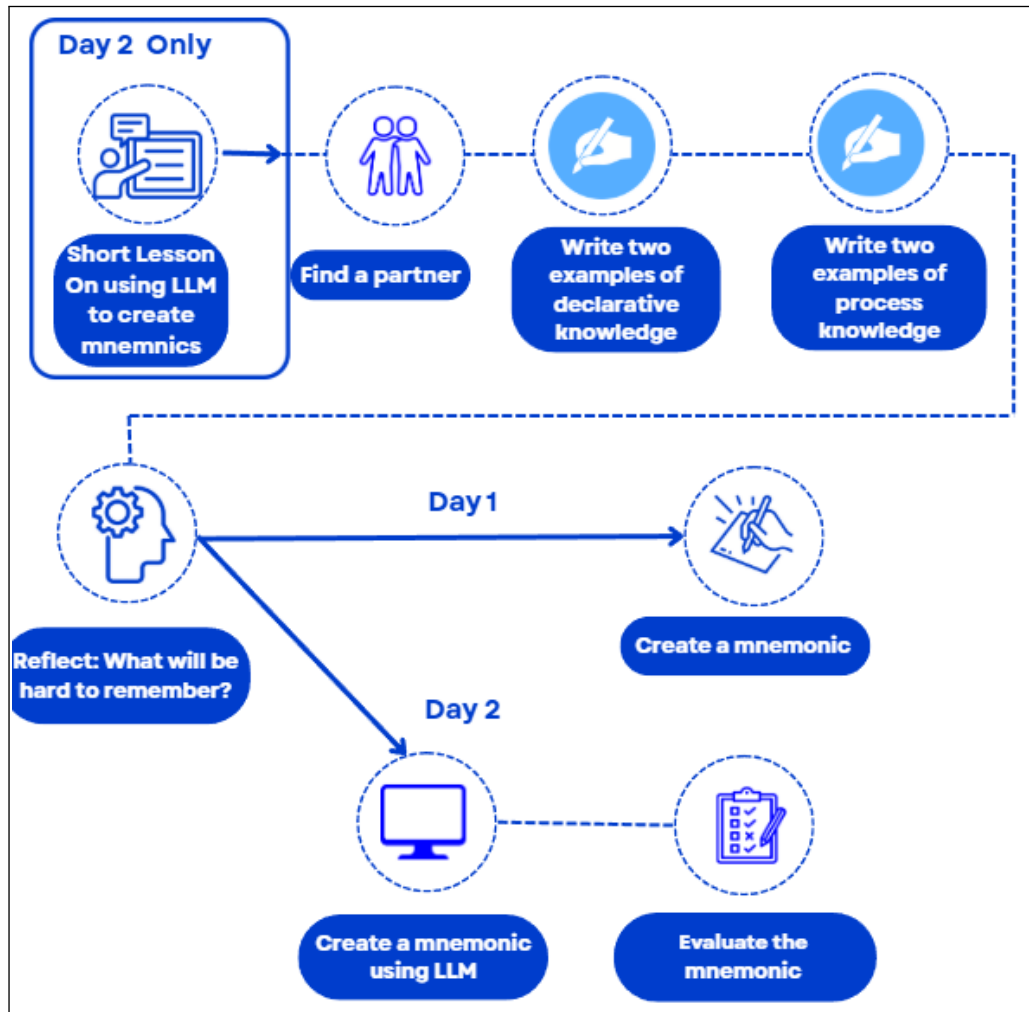
**Figure 2***Flow of SMART Activity Days 1 and 2*

Figure 3 shows how students connected statistical inference procedures with corresponding hypotheses. The instructor used responses like these to gauge whether students are retaining key facts essential for subsequent learning.

**Figure 3***Example of Students' Work—Declarative Knowledge*

1. When making inferences about the difference between two population means, the parameter is  $\mu_2 - \mu_1$
2. Our  $H_0$  hypothesis is  $\mu_2 - \mu_1 = 0$  when discussing the difference between two population means

### 2.2.3 Step 3: Identifying Process Knowledge

Next, students identified two examples of process knowledge— that is, a sequence of steps or procedures used to complete a task. The following exit ticket prompt builds on students' declarative knowledge by helping them next articulate what it takes to carry out a method or solve a problem (Anderson & Lebiere, 2014).

“Now, think about the process knowledge that you worked on in this module. Please list two processes that you encountered in this module. Processes would be completing a series of steps to solve a problem. (Example from algebra: To multiply binomials, you use the distributive property to add up all the product-pairs of terms: first(leftmost), outer, inner, and last(rightmost))”

The examples in Figures 4 and 5 show two different ways students articulate multi-step procedures. Figure 4 shows the needed steps to use the statistical software package (JMP) used in class and Figure 5 reflects a strong command of the broader modeling framework.

**Figure 4**

*Example from Student Pair 1*

To do a classical two-means test, go to JMP > Analyze > Fit X by Y > Quantitative variable is Y and groups are X > click OK > click red triangle > if pooled, click means/ANOVA/pooled; if not pooled, click t-test.

**Figure 5**

*Example from Student Pair 2*

The breakdown of the two means significance test follows as 1. Question/problem being addressed. 2. Plan— Asking the questions of who, what, when, where, and about the data being analyzed. 3. Data— identify variables in context, such as the quantitative/qualitative data, any missing pieces from the population, and define a parameter for the data. 4. Analysis — Are the necessary conditions met for the model to be valid? (Randomization, nearly normal, independent groups)

#### 2.2.4 Step 4: Reflecting on What Is Hard to Remember

Next, the exit ticket prompts students to reflect on what lesson content is hardest for them to remember: “What topics in statistics from today’s module do you think would be hard to remember? Explain your reasoning.” Figure 6 shares a sample response from a student pair. This reflection highlights how students are not just struggling with definitions but also with interpreting nuanced aspects of statistical reasoning.

**Figure 6**

*Example Student Response*

Interpreting  $P$ -values: Understanding the subtleties of  $p$ -values, especially their limitations and how they don’t necessarily imply practical significance, can be complex.

#### 2.2.5 Step 5: Mnemonic Construction (without LLMs)

Finally, students created a mnemonic to help them remember something they identified as challenging. The prompt activated prior knowledge by reminding students of well-known math mnemonics.

“Create a mnemonic to help you remember something from this module. (Examples: For example, SOHCAHTOA would help you remember trig function definitions and FOIL would help you remember the process of multiplying algebraic binomials.)”

**Table 1.** Examples of Student-Created Mnemonics from Day 1 Exit Ticket (Without LLMs)

Mnemonic	Meaning
PGA Fairway	$p$ -value greater than or equal to alpha: fail to reject
PLAYR	$p$ -value less than alpha: you reject
NONOO	No Order Nominal, Order Ordinal – types of categorical data
C+B+	Bigger Confidence Level = Bigger Basket (wider interval)

These examples show creativity and conceptual alignment. Some draw from personal interests (e.g., golf) or patterns in language (e.g., acronyms) to encode ideas in memorable ways.

The instructor used this step not only to assess conceptual understanding but also to help students engage in elaborative encoding which has been summarized as “the process of encoding more features or attributes to the representation of an event” (Karpicke & Smith, 2012, p. 18). Elaborative encoding strengthens their ability to retrieve and apply the concept later.

## 2.3 Day 2: Complete the Exit Ticket with a Partner and LLMs

On a later class day, the students repeated the Day 1 steps, but with three changes: having a demonstration of the LLMs to create mnemonics, having students create mnemonics assisted by using LLMs such as Microsoft Copilot, Google Bard (Gemini), or ChatGPT, and then adding a step of critically evaluating the mnemonic obtained. The entire Day 2 exit ticket can be found in Appendix B; however, activity parts not included on Day 1 are provided in this section, along with examples of student work.

### 2.3.1 Step 0: Demonstration of the Use of LLMs to Create Mnemonics


To help students prepare to use LLMs to create mnemonics, the instructor modeled this process for them on a topic from a previous class day. The instructor opened an LLM and entered a prompt. The instructor modeled a curious and playful attitude about using LLMs (e.g., if a prompt does not yield something useful, try writing another one or amending the previous prompt). Also, the instructor mentioned that students will get different responses from each other and each time they make a request.

*Instructor Prompt for LLMs:*

“I am a student in a statistics class, and I am having trouble remembering the assumptions for simple linear regression. Can you create a mnemonic to help me remember this?”

**Figure 7**

*Example Response from Microsoft Copilot on July 18, 2025*

 <b>Mnemonic: "LINE"</b> Each letter stands for one of the key assumptions:		
Letter	Assumption	Meaning
L	Linearity	The relationship between the independent and dependent variable is linear.
I	Independence	Observations are independent of each other.
N	Normality of errors	The residuals (errors) are normally distributed.
E	Equal variance (Homoscedasticity)	The residuals have constant variance across all levels of the independent variable.
You can remember it like this: <i>“The regression must walk a straight LINE to be valid!”</i> 🎯 If you want a sillier or more vivid version, I can whip one up that involves characters, rhymes, or even a mini story. Would you like something like that?		

The instructor modeled correcting the LLMs if its first response is not as helpful as hoped. For example, this response in Figure 7 uses the terms “independent variable” and “dependent variable” rather than “explanatory variable” and “predictor variable.” It also used the term “homoscedasticity,” which is more likely to be unfamiliar; even the phrase “equal variance” may not be enough to make the assumption clear in a student’s mind. The instructor used this opportunity to have the LLMs create a new response (see Figure 9) by using a prompt such as the following:

*Prompt for LLM:*

“I am unfamiliar with the terms independent, dependent variables, and homoscedasticity. Can you re-create this information without these terms?”

On July 18, 2025, Microsoft Copilot removed those terms from the response.


**Figure 8**

*Microsoft Copilot Second Response*

Of course, Megan! Let’s build a version of the mnemonic that’s more beginner-friendly and skips the jargon. We’ll still use **LINE** as our guide, but I’ll reshape each piece so it’s easy to grasp:

 **L.I.N.E.** stands for:

- **L — Looks like a line:** When you plot your data, the pattern between your x-values (what you’re using to predict) and y-values (what you’re trying to understand) should follow a straight-ish line—not a curve, loop, or zigzag.
- **I — Each point plays fair:** Each data point should be doing its own thing—not copying its neighbors or following a strange pattern. That way, the overall result isn’t tilted or biased by unusual clumps or patterns.
- **N — No strange surprises:** The little “misses” your prediction makes—the differences between what you guessed and what actually happened—should follow a nice, smooth pattern. Think of them as small, random hiccups rather than wild jumps.
- **E — Even spread of misses:** Whether your guesses are way off or pretty close, those little “misses” should be roughly the same size across all x-values. You don’t want them to start small and then suddenly balloon bigger as you go.

 You’re essentially checking:

- Does your data follow a straight path?
- Are all the points behaving nicely?
- Are the prediction errors not too wild?
- Is everything fairly balanced across the board?

If you’d like, I can pair this with a visual or create a short activity to help you spot these in real data. Want to explore that?

### 2.3.2 Step 5: Mnemonic Construction with LLMs

Now, the students were asked to create a mnemonic to help with the day’s material, but this time using LLM.

Using LLMs, the student pairs created numerous mnemonics (see Figure 9) to help them remember the definition of R-squared, the Box-Cox transformation, and that a variance inflation factor (VIF) greater than 5 indicates multicollinearity.

**Figure 9***Examples of Mnemonics Students Created with the Help of LLMs***Example 1:****“IVs Unite, R-squared Takes Flight”***Explanation:*

- **IVs:** Stands for Independent Variables.
- **Unite:** Imagine all your independent variables coming together for a mission.
- **R-squared:** Represents the percentage of variance explained by these IVs when regressed against another IV.

*Now, let’s break it down further:*

1. **IVs Unite:** Picture your independent variables (IVs) gathering in a team. They’re ready to tackle multicollinearity!
2. **R-squared Takes Flight:** Each IV takes turns being the hero. They regress against the remaining IVs (except one) using multiple regression. The resulting R-squared values indicate how well they explain the variance in that IV.

**Example 2:**

Box-Cox Lambda Normalizes, Deciding Transformation: Be Logical, Not Dizzy, Try!

**Example 3:***“VIF higher than 5, multicollinearity’s alive!”**This mnemonic uses the association between “VIF” and multicollinearity and emphasizes that when VIF values exceed 5, multicollinearity is present.***2.3.3 Step 6: Evaluation of LLMs-generated Mnemonics**

Since information from LLMs can be inaccurate (Cossio, 2025), the next step was for students to evaluate the obtained mnemonic. To help students navigate this evaluation process, the next portion of the exit ticket contained four statements for them to reflect on and explain their thinking and Table 2 summarizes results.

Meanwhile, Figure 10 provides an example of the reasoning behind these responses from a pair of students. Students had both positive and negative experiences using AI to create mnemonics. Notice that the students are using words to describe why the mnemonic is valuable (“very creative”, “easy-to-remember”, “elaborated”, and “helpful”) and not valuable (“doesn’t exactly help me remember”).

**Figure 10***Student Written Responses to Experiences of Using LLMs to Create Mnemonics***Example 1:**

This was a very creative and easy-to-remember mnemonic and I think that I too could’ve made one but not one as elaborated and as helpful.

**Example 2:**

The generative AI output has some useful information, but I will probably not remember the mnemonic, and it doesn’t exactly help me remember the ladder of powers.



## 2.4 Day 3: Reflection on the SMART Activity

After students experience doing the exit tickets with and without LLMs, the instructor engaged them in reflecting on the benefits and disadvantages of each method.

After completing the activity, students were asked to complete a 10-question reflection (see Appendix C) on the process. To streamline our reporting, we selected these four reflection questions that best represent the goals of this series of activities:

4. Which method did you prefer in creating mnemonics with your partner(s) — without technology or with generative AI such as ChatGPT? Explain.
6. Did the creating and compiling of mnemonics increase or decrease your anxiety about the upcoming exams? Explain.
8. Is the creation and compilation of mnemonics something that you would do in a future class? Why or why not?
10. What did you find more helpful: mnemonics for declarative knowledge or for process knowledge?

The final reflection assigned by the instructor enables students to reflect on the two processes they used to create mnemonics and consider how these processes impacted their learning. The process of understanding how LLMs affect thinking, creating, and problem-solving helped students navigate the new world where LLMs are so prevalent. This also aligns with the affordance of LLMs to personalize learning, as articulated in the NCTM (2024) position statement on AI.

## 3 Review of Literature

This section overviews the literature (on exit tickets, mnemonics, and LLMs in higher education) that informs, supports, and contextualizes the SMART activity. Readers wanting a deeper dive may follow up with the cited references.

### 3.1 Exit Ticket

This multi-day SMART activity involves two versions of an exit ticket, a type of formative assessment administered at the end of a class meeting to determine where students are in their learning process (Danley et al., 2016). Exit tickets can be implemented in many ways such as asking students to identify areas of the day's lesson that are still unclear, rate their level of comfort with a topic, or reflect on their level of attention or focus during that day's class meeting (Marzano, 2012). They allow instructors to responsively tailor subsequent class lectures and provide feedback (Paliwal, 2023). The exit tickets provided me (the instructor and first author) with information on what students found most challenging. For example, I found students struggled to recall the formulas and complete ANOVA table calculations, so I added more examples during class time to support that learning.

In a study conducted in an undergraduate marketing course in the midwestern United States, the use of exit tickets was associated with more utilization of resources provided in class and a brief review of content, but had little impact on motivation and extended study time (MacDermott et al., 2024). In their comments in the reflections, students stated that they probably should have spent more time reviewing when they completed the exit tickets (MacDermott et al., 2024).

### 3.2 Mnemonics

Searle and Gruber (2017, p. xxiii) deemphasize memory's role by comparing statisticians to lawyers: "They do not need to remember every technique exactly, but must know where to locate it when needed and be able to understand it once found." It is important to note that the preceding quote refers to consulting statisticians, who already have a solid foundation and are working on a more advanced, applied level. Students still trying to build a foundation, however, need basic statistical facts, definitions, processes, and connections readily mentally accessible to be able to take a timed and/or closed-book exam or follow a lecture in real time.

In a recent study of a large-enrollment introductory statistics course on mnemonics, a disconnect was found between students' ability to recall a statistical mnemonic and their ability to explain or use it (Mocko et al., 2024). The SMART activity bridges this disconnect by having students create or choose mnemonics, rather than having them provided. Since students created the mnemonic, they are likely more able to recall, explain, and apply it. For example, many students struggle with remembering how to determine whether to reject the null hypothesis. To create the PLAYR (" $p$ -value Less than Alpha: You Reject") mnemonic, students dialogued about the wording and concept. They had to break the concept into components that could be turned into a mnemonic, thus creating deeper, memorable understanding.

We learned from classroom testing and our prior research the value of discussing with students properties (e.g., correctness, brevity, memorability, and connection to the material) of a helpful mnemonic. For example, in a large-enrollment introductory statistics course, students rated the usefulness of 19 mnemonics (Mocko et al., 2017), of which the item with the highest rate (63.7%) of reported usage and usefulness was "Population and Parameters both start with  $p$ . Sample and statistics both start with  $s$ ."

### 3.3 LLMs in Education

By 2024, LLMs had become common in education (Ellis & Slade, 2023; Frick, 2024; Young, 2023). This SMART activity was designed to have students explore the benefits of creating mnemonics themselves or with help from LLMs. Due to the structured use and non-use of LLMs in these activities, students also begin to develop their skill set in relation to the tradeoffs of LLMs. Ellis and Slade (2023) propose that having students interact with LLM output to discuss incorrect information produced can help build critical thinking in the statistics classroom.

Day 2's exit ticket involves using LLMs to create mnemonics. LLMs have sometimes been discussed as a way to discuss a topic with something that talks back. The computer science technique of rubber-ducking helps programmers formulate initial ideas when no other human is present (Drosos et al., 2024) by discussing the code with an actual toy rubber duck to better understand the issues at hand. Likewise, in our SMART activity, students use a similar approach to create a mnemonic on statistical topics they are still learning and then reflect on the mnemonic's usefulness. The LLM becomes the rubber duck that can be used to bounce ideas off and to problem-solve together.

The preceding usage is similar to how teachers can utilize LLMs to create and refine lesson plans (Hu et al., 2025) or how students can employ LLMs for tutoring (Ramanathan & Palaniappan, 2024). The use of LLMs for tutoring follows a similar process to the SMART activity, where the student reviews the material, determines where help is needed, and then queries LLMs accordingly. The student and the LLM tutor ("rubber duck") can then dialogue until the student has mastered the topic.

Section 3's strands of literature support the SMART activity's design: exit tickets provide structure, mnemonics foster retention, and LLMs offer dialogue, reflection, and support. The SMART activity

helped students review the material and create a mnemonic personalized to their learning and context. AI-created mnemonics have been used in the (personalized) learning of other subjects, such as medicine (Elabd et al., 2025). That said, the importance of the SMART activity's Day 2 step of evaluating the mnemonic is supported by some research (Ali et al., 2025) that suggests students may not connect with LLM-generated content as well as they do with human-generated content.

## 4 Analysis of Student Reflections and Exit Tickets

In Spring 2024, exit tickets and responses to reflection questions were collected from the first author's students in a combined graduate and undergraduate-level introductory statistics course. The four Likert response statements and a brief explanation prompt were included in exit tickets #9-12 (see Appendix B and Section 4.1) because these were the class sessions in which students first practiced using LLMs. After completing exit ticket 12, students answered ten longer-response questions (see Appendix C) to reflect on the entire SMART activity (see Section 4.2).

### 4.1 Analysis of Exit Tickets that Used LLMs

**Table 2.** Means (and Standard Deviations) of Likert Responses<sup>a</sup> to the Exit Tickets (ET) with LLM usage

Statement	ET #9 <i>n</i> = 38	ET #10 <i>n</i> = 38	ET #11 <i>n</i> = 39	ET #12 <i>n</i> = 33
I am confident that the mnemonic from the generative AI output is correct.	1.79 (0.87)	1.84 (1.00)	1.59 (0.91)	1.64 (0.99)
I am confident that the mnemonic from the generative AI output is useful as is.	2.05 (0.87)	2.13 (0.93)	2.05 (0.89)	1.85 (0.87)
I am confident that the mnemonic from the generative AI output will be useful after I make a small change.	2.13 (1.02)	1.97 (0.82)	2.00 (0.95)	1.97 (0.95)
I am confident that I could have created a better mnemonic on my own without using generative AI at all.	2.26 (1.08)	2.37 (1.05)	2.34 (1.07)	2.52 (1.28)

<sup>a</sup>1 = Strongly Agree, 2 = Somewhat Agree, 3 = Somewhat Disagree, 4 = Strongly Disagree

Table 2 shows the mean level of agreement among students regarding the correctness and usefulness of the mnemonic provided by LLMs. Thus, these results suggest that students mostly agreed that the AI output was accurate and useful.

In terms of the AI output being accurate, over 81.5% of the responses from each of the four relevant exit tickets agreed or strongly agreed. There was a lower minimum fraction (66.7%) of responses by exit ticket that expressed some level of agreement that the AI output was useful. Students however seemed likely to want to make a small change to the generative AI output, with a minimum of 68.4% agreeing or strongly agreeing. Finally, for the statement of being confident that they could have created a better mnemonic without AI, only about half (48.5% or more for each of the 4 exit tickets) agreed or strongly agreed.

The standard deviations were relatively constant (near 1) across statements. Most students also stated

that they did have to make a small change to improve the mnemonic, with means ranging from 1.88 to 2.08. Students only somewhat agreed that they could have created a better one on their own. For the last exit ticket, students were neutral (i.e., mean near 2.5) on being able to create their own without the use of generative AI. We did not compute effect sizes because exit ticket averages were not monotonic within items.

## 4.2 Analysis of Reflection Questions

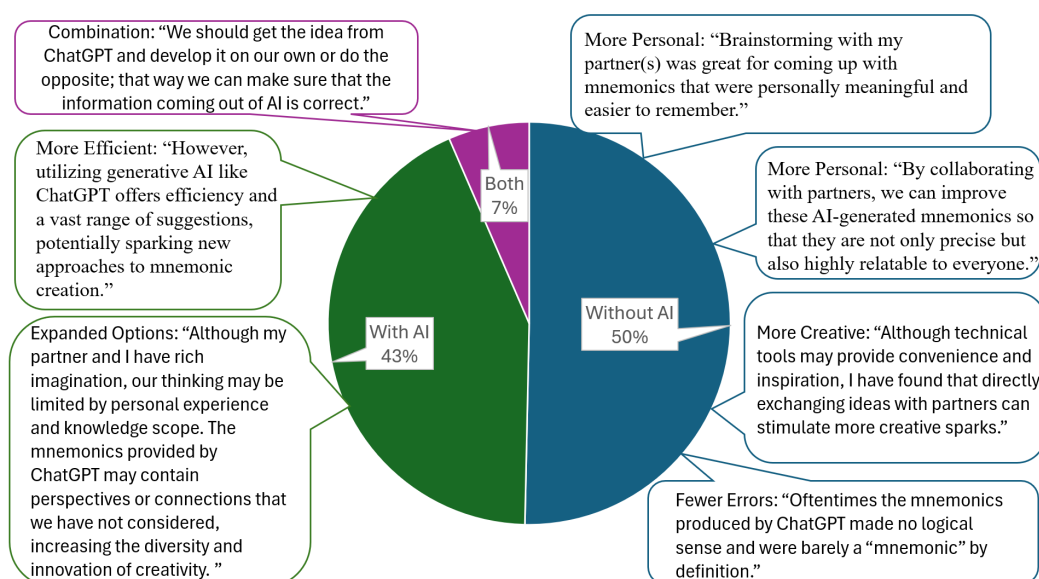
The reflection responses were disaggregated by question and then by sentence. Two researchers independently coded the data, obtaining initial per-question agreement ranging from 64.5% to 88.2%. A partial agreement between the codes, was recorded as a half-agreement. After discussing the codes, the researchers were able to reach 100% agreement. We now share an analysis of the four representative questions mentioned in Section 2.4.

### 4.2.1 Creation by Humans vs. AI

We now look at student responses to the student reflection question (SRQ) 4: “Did the creation and compilation of mnemonics increase or decrease your anxiety about the upcoming exams? Explain.” Figure 11 summarizes these responses. In this research, 50.3% preferred not using AI because the process of creation by collaborating with a human was more personal, and/or did not result in possible hallucinations. In their reflections, students commented that they liked the more personal aspect of creating their own because it allowed them to relate it more to their own context. This aligns with other authors’ observation that “Students today, the Generation Z population cohort is looking for content that is short, authentic and can be enjoyed immediately” (Smith & McMurray, 2025, p. 23). The lack of authenticity (see end of Section 3) and connection to their own lived experiences made the AI content less optimal.

**Figure 11**

*Responses to SRQ 4: “Which method did you prefer in creating mnemonics with your partner(s) without technology or with generative AI, such as ChatGPT? Explain.” (n = 292 sentences)*



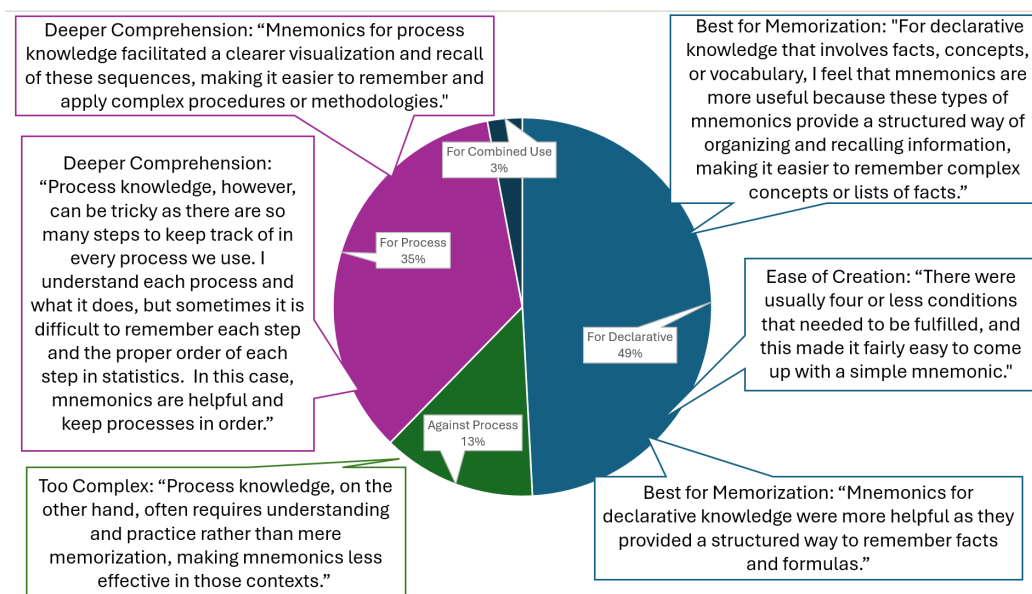
However, almost half (43.2%) of the student statements preferred to use LLMs and preferred many options, and that LLMs might quickly provide a mnemonic needing only minor edits. The remaining 6.5% preferred a combination of LLMs and human-generated mnemonics. Two statements (0.7%) were categorized as irrelevant.

### 4.2.2 Process Knowledge versus Declarative Knowledge

SRQ 10 asked students to reflect on whether they thought that process or declarative knowledge was better for mnemonics. The reflection questions were given at semester's end, after all exit tickets were completed. The 236 sentences (see representative examples in Figure 12) broke down as: 116 for declarative knowledge, 31 against process knowledge, 82 for process knowledge, and 7 for process and declarative combined.

**Figure 12**

*Responses to SRQ 10: What did you find more helpful: mnemonics for declarative knowledge or for process knowledge? (n = 236 sentences)*



Students stating preference for declarative knowledge cited its memorability or simplicity. Reflection statements about preference for process knowledge cited its structure to remember complex steps. While some students emphasized how mnemonics for process knowledge facilitated deeper comprehension of material and its steps, others wrote that this complexity was also why process knowledge was not a good fit for mnemonics.

Overall, students showed a preference for declarative knowledge over process knowledge for mnemonics; however, the requirement for students to break down information into small chunks for process knowledge was identified as a potential advantage. To create the mnemonic, the students had to break large concepts into discrete parts and identify interconnections. Thus, the process of creating mnemonics shows promise for supporting students' statistical conceptual understanding, as reflected in this student's statement: "Mnemonics helped me to break down and simplify concepts, making them more accessible and easier to recall."

### 4.2.3 Anxiety

SRQ 6 (Figure 13) addresses understanding how students perceive the use of creating and compiling mnemonics to alleviate anxiety about the upcoming exam. Of the 108 statements related to anxiety, 75 (about 7/10) mentioned a decrease, 16 mentioned an increase, and 17 were neutral.

Out of the 93 sentences coded as indicating decreased anxiety, 28% were just general statements, 20% were about improved memory, 19% stated more confidence, 18% liked the structure of the process, 6% felt more prepared, 4% were about the collaborative nature of the activity, and 3% stated that generative AI helped. For example, one student said, "The active participation much reduced my anxiety about

studying for the exam in creating mnemonics, which improved the study material's comprehension and memorability of the study material."

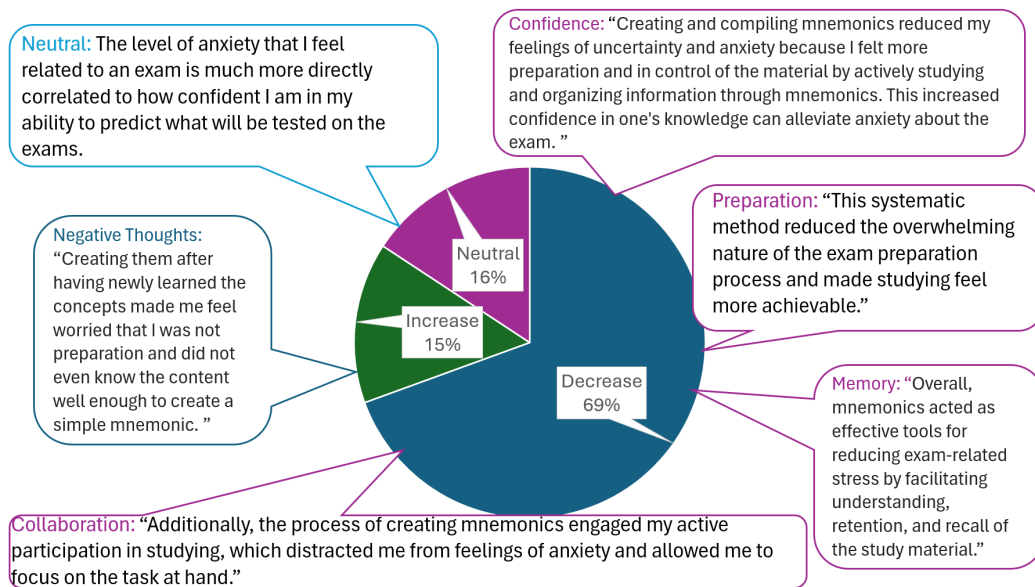
The most-cited source (9 times) of increased anxiety was the creation of the mnemonic in class. Four sentences were about how the creation of the mnemonics inspired negative thinking, one was skeptical, and one was just a general statement. The students who discussed an increase in anxiety were focused mainly on the anxiety of creating a mnemonic from a topic, stating that it "added an additional layer of responsibility" or "it was sometimes stressful at the beginning when I did not come up with good ideas for the mnemonics and I was spending more time than what I would like to, but ...definitely didn't feel more anxious about exams due to that."

While some students felt more work was involved in the course due to the exit tickets and mnemonics creation, this additional work seems to be related to a reduction in anxiety. Perhaps the process of examining the facts and processes more closely leads to increased statistical self-efficacy, which correlates negatively with statistical anxiety (Azzarello et al., 2025; Chiesi et al., 2011; Hoegler & Nelson, 2018; Trassi et al., 2022).

Because student reflection responses occurred at the end of the course, it was not possible to make a longitudinal assessment of the change in anxiety over the course of the semester. Also, comparison across majors was beyond the scope of this study.

**Figure 13**

*Responses to SRQ 6: "Did the creating and compiling of mnemonics increase or decrease your anxiety about the upcoming exams? Explain." (n = 108 sentences)*



#### 4.2.4 Future Use of Mnemonic Creation

SRQ 8 (see Figure 14) was "Is the creation and compilation of mnemonics something that you would do in a future class? Why or why not?". The most common code was "Helps my Studying," with 30.1% of the responses having a positive outlook on the use of mnemonics. A student expressed, "This experience has taught me that while mnemonics can be helpful, they might not be necessary for every topic or at such a high frequency." "I would still do the creation of mnemonics in class, but maybe in a different way." Interestingly, the second most common response, with 24.0%, was that mnemonics were "not usable/not applicable," including responses stating they "might" use them or knew that they were not going to implement them past the exit tickets. "Type of academic area" was a factor used to

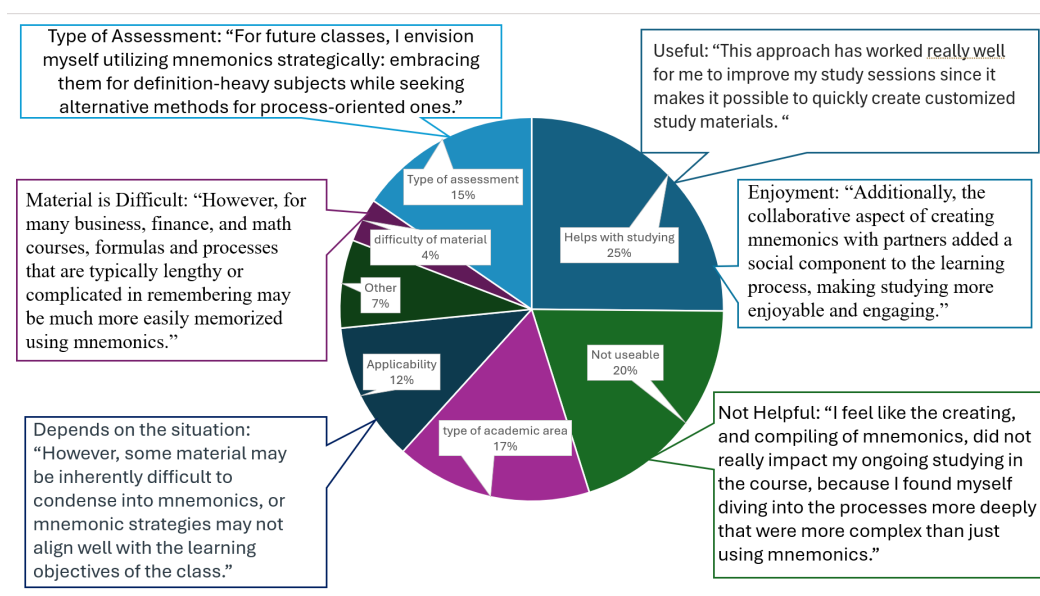


determine whether they would create or compile mnemonics in the future. Eighteen of them described which classes they saw mnemonics more helpful with: 8 said language or creativity-related subjects, and 10 said numbers-based courses, such as mathematics or statistics. It is interesting to note these are almost equally split. An example of mnemonic usage in a non-math-based course, “I think if I were to use a mnemonic for another class, I would only do so in a different subject that is more creative and not so much math-based.” From another perspective, here is a student stating that it would indeed be helpful for mathematical content: “I think I could have used them in the past in a mathematics class where there were a lot of formulas involved.”

A representative quote for the 18.5% of statements coded as “type of academic area” is: “However, the decision to use mnemonics in future classes would depend on factors such as the nature of the material, personal learning preferences, and the specific requirements of the course.” It really did depend on the course or type of information that needed to be memorized. The type of assessment could have been an exam, an essay, or any moment in class where they had to recall information. This leads to “Applicability” with 11.7% of the responses. Unlike past codes, this one has a variety of reasons why someone would use the memory aids, not just for classes or assessments. For example, “By associating course material with personal experiences, mnemonics provide a structured and memorable approach to studying.” Fourteen stated mnemonics can be useful in various subjects as a study tool or to improve study habits; however, nine admitted that although helpful, it depends on the situation and only in certain aspects. Thirteen of the 41 statements pertained to the creativity, engagement, and personable qualities required to devise effective memory aids, as this helps deepen their understanding. The difficulty of the material was the least common code, with 13 responses in SRQ 8. These responses mentioned the words “difficult” or “challenging,” with most referring to the material covered, rather than a few that mentioned the course itself being difficult. Five of them stated they used mnemonics strategically depending on the material, while one person said, “regardless of the class”.

**Figure 14**

*Responses to SRQ 8: “Is the creation and compilation of mnemonics something that you would do in a future class? Why or why not?” (n = 350 sentences)*



## 5 Potential Extensions for the Activity

This SMART activity can be easily adapted for different age levels and courses or extended to allow for more discussion about memory aids and different prompting styles for LLMs.

## 5.1 Discussion about Mnemonic Recall

Another option is to extend this activity to a date later in the semester, in which students are asked to recall the mnemonic that they created, explain how it works, and apply it to a statistical problem. This exercise encourages students to revisit previously discussed material.

## 5.2 Other Learning Strategies

To help students develop good study habits, learning strategies other than mnemonics could also be used, such as a mind map (Edwards & Cooper, 2010), metaphors, or summarizing. The same three-step process could be used, where students complete the first part of the SMART activity without technology, then use LLMs in the second part. They can then reflect on how that learning strategy and technology worked for them.

## 5.3 Discussion about LLMs Use

Another extension is to discuss in class or via online discussion board the usefulness of AI to create mnemonics, seeded by questions such as:

1. What did this activity inform you about your learning processes?
2. How might you utilize or not utilize LLMs in your future studying and learning?

## 5.4 Prompting Styles

Additionally, this SMART activity can be extended to explore different prompting styles. The basic input-output prompt modeled in Section 2 is simply one of seven classic prompting styles. This style was used because it is the simplest prompting style to write, resembling a question that you might pose in an email to an instructor. For example, a student could just ask, “What is a  $p$ -value?”. This prompting style would be a simple input–output method. We now illustrate the use of role-play prompting style and chain-of-thought with the resulting LLM feedback from Microsoft Copilot (see Section 5.4.1). These are just two of the seven classic prompting styles shown in Table 3.

### 5.4.1 Prompt Style Example: Role-Playing

A role-playing prompt encourages the LLM to take on a particular role. In the following example, the user asks the LLM to act as a tutor helping a struggling student, and Figure 15 shows the resulting mnemonics for the students. The results from Copilot show three possible examples that primarily use the same letters, but in different orders.

**LLM Prompt:** Imagine that you are a tutor helping a student who is struggling with assumptions for simple linear regression. You want to help the students by having them review several mnemonics generated for this topic and select one that is helpful for them.

**Figure 15***Response to Role-Playing Prompt in Copilot on July 21, 2025*

Absolutely! Helping students grasp the assumptions of simple linear regression can be a game-changer in how they interpret models and results. Here's a set of creative mnemonics tailored to make each assumption memorable and approachable. You can share these with students and have them choose the one that clicks best for them:

### **Mnemonic Set: Understanding Regression Assumptions**

#### **1. LINE**

Each letter stands for one of the key assumptions:

- **L — Linearity:** The relationship between X and Y is linear.
- **I — Independence:** Observations are independent of one another.
- **N — Normality:** Residuals are normally distributed.
- **E — Equal Variance (Homoscedasticity):** The spread of residuals is consistent across values of X.

💡 Use: "Draw a straight LINE through your data assumptions."

#### **2. I LOVE RAIN**

A quirky and visual take:

- **I — Independence**
- **L — Linearity**
- **O — Outliers avoided**
- **V — Variance is equal**
- **E — Errors follow a normal distribution**
- **R — Residuals matter**
- **A — All assumptions checked**
- **I — Influential points assessed**
- **N — No multicollinearity** (mostly for multiple regression, but still useful context)

💡 Use: "If you LOVE RAIN, your regression's on solid ground."

#### **3. CHER**

Quick and memorable, like the pop icon!

- **C — Constant variance**
- **H — Histogram of residuals** (check normality)
- **E — Errors are independent**
- **R — Relationship is linear**

💡 Use: "Sing with CHER—your model's in harmony!"

#### **4. NEIL**

Playfully personified:

- **N — Normality of residuals**
- **E — Equal variance**
- **I — Independence**
- **L — Linearity**

💡 Use: "NEIL checks your data before regression begins."

Each of these captures the essential assumptions but varies in style—some are straightforward, others playful. You could ask students:

- Which one helps you visualize the assumptions best?
- Do you prefer humor, structure, or characters?
- Could you create your own version using examples from class?

Would you like me to turn one into a teaching graphic or build an example where a violation becomes visible using R code?

### 5.4.2 Prompt Style Example: Chain-of-Thought

The chain-of-thought prompting style (Figure 16) requests that the LLMs show every step of the process to create the mnemonic.

**LLM Prompt:** Provide a mnemonic for the assumptions for simple linear regression, but show me each step of the way why you chose the mnemonic and the steps that you did.

**Figure 16**

*Response to Chain-of-Thought Prompt in Copilot on July 7, 2025*

Great question, Megan! Let's walk through how to build a mnemonic for the assumptions of simple linear regression step by step. This will not only help you remember the assumptions but also give you a method you can apply when creating mnemonics for other statistical concepts.

#### **Step 1: Identify the Core Assumptions**

Simple linear regression has four key assumptions. These are similar to multiple regression but tailored to a single predictor:

1. **Linearity** — The relationship between the predictor (X) and the outcome (Y) is linear.
2. **Independence** — Observations (and residuals) are independent of each other.
3. **Normality** — The residuals (errors) are normally distributed.
4. **Equal Variance (Homoscedasticity)** — The residuals have constant variance across all levels of X.

So we're working with: Linearity, Independence, Normality, Equal variance

#### **Step 2: Look for a Pattern or Acronym**

Let's take the first letter of each assumption:

- **L** — Linearity
- **I** — Independence
- **N** — Normality
- **E** — Equal variance

That spells **LINE** — a perfect fit for simple linear regression! It's intuitive because it literally reminds you of a line, which is the foundation of linear regression.

#### **Step 3: Build the Mnemonic Around the Word**

Now let's give each letter a vivid, memorable phrase that reinforces the concept:

Letter	Assumption	Memory Hook
L	Linearity	"The data follows a straight line."
I	Independence	"Each point stands on its own island."
N	Normality	"The errors form a normal bell curve."
E	Equal Variance	"The spread of errors is even everywhere."

#### **Final Mnemonic: LINE**

Here's how you might explain it to a student:

"To remember the assumptions of simple linear regression, just think of the word **LINE** — because that's what we're trying to fit!

- **L** is for Linearity: the relationship should look like a straight line.
- **I** is for Independence: each observation should be independent.
- **N** is for Normality: the residuals should be normally distributed.
- **E** is for Equal variance: the spread of residuals should be consistent across the line."

This LLM output provides a good opportunity to discuss the process as described by the LLM. Follow-up questions might include:

1. Is your process of developing mnemonics similar or different? In what way?
2. The LLM states that a good mnemonic is simple and memorable. Do you think that the qualities of simple and memorable are necessary and sufficient qualities for a mnemonic to be effective? Explain. If not, what other qualities would you suggest?

**Table 3.** *Examples of prompts in different styles*

Prompt Styles (Walter, 2024)	Example Prompts
Input-Output	Provide a mnemonic for the assumptions for simple linear regression.
Chain-of-Thought	Provide a mnemonic for the assumptions for simple linear regression, but show me each step of the way why you chose the mnemonic and the steps that you took.
Role-Play or Expert	Imagine you are a tutor helping a student who is struggling with assumptions for simple linear regression. You want to help the students by having them review several mnemonics generated for this topic and select one that is helpful for them.
Self-Consistency	Create five mnemonics to remember the assumptions for simple linear regression. Of these five, pick the best and list reasons why it is best.
Automatic Prompt Engineering	<p>For this type of prompt, there is a two-prompt structure. The first prompt asks the LLMs to generate its prompt. Then, the user enters this prompt into the LLMs.</p> <p><b>First prompt:</b> Here are examples of a few good mnemonics for assumptions for simple linear regression. Define good as a mnemonic that is simple, memorable, has a logical order, comprehensive, and consistent with common terminology in statistics.            LINE: L is for linearity, I is for independence, N is for Normality, and E is for equal variance.            DINNER: Data is linear, independent, normal, no outliers, with equal variances, and residuals are normal.            Use these to create a prompt to find other good mnemonics for this situation.</p> <p><b>Guidance for second prompt:</b> After the LLM creates the prompt, feel free to tweak if needed and then re-enter the LLM-created prompt.</p>
General Knowledge	Describe the process of checking assumptions in linear regression. Use this information to create a mnemonic about this topic.
Tree-of-Thought	[Not applicable, as this relies on inconsistencies in the output, which may not be present.]

## 6 Future Directions for Research

Implementing the SMART activity with students and analyzing the exit tickets and reflections yielded new questions regarding students' use of LLMs and mnemonics strategies.

### 6.1 Student Interaction with LLMs

We saw there was more to learn about how students utilize LLMs, including prompting styles and persistence. Future research could benefit from individual interviews using a think-aloud protocol, where students are asked to explain their process when prompting LLMs, especially when the initial prompt was ineffective. What other prompts do they use, or do they give up?

### 6.2 Mnemonic Creation and Adoption

Concurrently, the research could also explore at what point students determine that they feel sufficiently able to create a mnemonic on their own, with or without the use of LLMs. Is this accomplished with one 3-day SMART activity? Secondly, at what point are students able to articulate whether it helps them as a learning strategy, and adopt if desired? This information could help instructors determine optimal SMART activities to foster metacognition and personalized learning.

### 6.3 Preference for Knowledge Type

Since 49% of the statements responding to SRQ 10 expressed preferences for declarative knowledge in the context of mnemonics, research interviews could unpack the reason for that preference. Is it because students feel that creating a mnemonic for declarative knowledge is safer, because it would be more likely to be correct? Did they think that this was the type of knowledge more likely to be tested? Or is it that students have a preconception that mnemonics can be used only for facts?

### 6.4 Mnemonics for Learning Differences or Emerging Bilinguals

Mnemonics might also be particularly useful for emerging bilingual learners. In alphabet-based languages, LLMs can generate mnemonics in a student's home language (such as the following ones in English, where the three common measures of location in alphabetical order happen to align with a rule of thumb that is usually true for unimodal distributions). Students with learning differences can be encouraged to use LLMs to help them navigate difficulties such as dyslexia (confusing left and right).

**Right-Skewed:** "The tail is on the RIGHT."

- Imagine the longer tail stretching toward the larger numbers — to the right.
- Mean > Median > Mode

**Left-Skewed:** "The tail is on the LEFT."

- The longer tail is on the smaller-number side — to the left.
- Mean < Median < Mode

Understanding the use of mnemonics and LLMs separately and in combination can help instructors plan adequate support for learners by providing potential learning strategies.

## 7 Conclusions

Instructors often focus their efforts on ensuring students understand core course content. Yet as students transition into more independent academic or professional settings, the ability to regulate one's own learning, through strategies such as reflection, planning, and strategic review, becomes just as critical. The SMART activity supports that shift. Through a structured, multi-day experience, students not only created mnemonics but also reflected on their utility, iteratively refining their learning strategies as they engaged with emerging technologies, such as generative AI.

Findings from student reflections suggest that generating mnemonics, particularly in collaboration



with a partner, can be personally meaningful and effective in supporting learning. While mnemonics generated by LLMs were appreciated for their efficiency and novelty, students also commented on the lack of personal connection in the LLM output. This tension between efficiency and authenticity also manifests in the fashion design industry, where the availability of data to create new, personalized designs with generative AI can significantly accelerate the design process; however, consumers tend to respond more favorably to human-designed clothing (Lee & Kim, 2024). Similarly, in a recent article on writing haikus (Smith & McMurray, 2025), the authors noted how younger students preferred the authenticity of the human-created haikus. Perhaps most notably, most students reported that using mnemonics, especially as part of the structured exit ticket process, reduced their anxiety around upcoming exams. This supports previous findings on the benefits of formative assessment and retrieval-based reflection as tools for both retention and emotional regulation (Danley et al., 2016; Marzano, 2012).

In this context, AI becomes not just a content generator but also a tool for metacognitive contrast, giving something to work against, reflect alongside, or refine. Following Ellis and Slade's (2023) suggestion that students engage critically with LLM output to strengthen their reasoning, the SMART activity positions learners not just as recipients of AI-generated ideas, but as active editors and evaluators. Similarly, Lozano and Strayer (2025) describe how students can use LLMs to help critically think about central concepts and definitions.

As generative technologies continue evolving, students will require structured opportunities to test, reflect on, and refine their use of LLMs to support their learning. Reflecting on the benefits and limitations of using AI in their learning process can benefit students' ability to decide when and where LLMs should be used in their learning process. The process of creating mnemonics in this SMART activity should also provide students with confidence to use mnemonics or other learning strategies when they are struggling. The SMART activity offers a flexible, low-stakes approach to do just that. By encouraging students to contrast AI- and self-generated strategies and reflect meaningfully on those experiences, we not only support their real-time learning but also help equip them for a future where tools like LLMs are prevalent. In this way, the activity supports not only comprehension and confidence gains in the course at hand but also the development of lifelong learning strategies useful beyond the statistics classroom.

### **AI statement**

Grammarly was used throughout the writing process. LLMs were prompted to help with clarity on section 6 during the revision process. Also, the original draft was submitted to LLMs for feedback from four reviewer profiles on three areas (Originality / Significance, Style / Length, Mathematics / Content Accuracy) and this yielded the suggestion of an activity extension and an acknowledgment of learning differences.

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**Megan Shein** is an accounting major at the University of Florida whose research interests include using AI to generate mnemonics and studying its classroom impact. Mentored by Megan Mocko, she explores how generative tools can support students' memory and confidence in statistics learning.

## APPENDIX A: Day 1 Exit Ticket (without LLMs)

**Partners:** (Please include first and last names.)

**Instructions:**

- Do not use technology of any kind, other than the Canvas that you are using to submit.
- Each person must submit this assignment to Canvas.

**Purpose:** This opportunity is for you to think about and consolidate what you have learned in this module so far. We require that you not use technology for this assignment so that you can create a deeper connection and understanding of the content.

**Declarative Knowledge**

Think back to what we have worked on in this module. Please list two declarative knowledge items that you encountered in this module. Declarative knowledge would be definitions and simple relationships. (Example from Right Triangle Trigonometry: sine  $\theta$  equals the opposite side over the hypotenuse, cosine  $\theta$  equals the adjacent over the hypotenuse, or tangent  $\theta$  equals the opposite side over the adjacent side.)

**Process Knowledge**

Now, think about the process knowledge that you worked on in this module. Please list two processes that you encountered in this module. Processes would be completing a series of steps to solve a problem. (Example from Algebra: To multiply binomials, you use the distributive property to add up all the product-pairs of terms: first(leftmost), outer, inner, and last(rightmost) )

What topics in statistics from today's module material do you think would be hard to remember? Explain your answer.

Create a mnemonic to help you remember something from this module. (For example, SOHCAHTOA would help you remember trig function definitions and FOIL would help you remember the process of multiplying algebraic binomials.)

## APPENDIX B: Day 2 Exit Ticket with the use of LLMs

**Partners** (please include first and last names):

**Instructions:** Unlike the previous Exit Ticket, you are required to use generative AI tools, such as ChatGPT, to help you generate mnemonics.

**Purpose:** This opportunity is for you to think about and consolidate what you have learned in this module so far. We recognize that we now live in a world of generative AI and we want you to build skills on how to use this as well in your study process. In this section of the material, you are required to use a generative AI program. The instructor will give a short introduction to using a generative AI product.

### Declarative Knowledge

Think back to what we have worked on today. Please list two declarative knowledge items that you learned today. (Declarative knowledge would be definitions and simple relationships.)

### Process Knowledge

Now, think about the process knowledge that you learned today. Please list two processes that you learned today. Processes would be completing a series of steps to solve a problem.

What topics in statistics from today's module do you think would be hard to remember? Explain your reasoning.

Create a mnemonic to help you remember something from today's material, using generative AI.

Express your level of agreement with these statements. (1 Strongly Agree, 2 Somewhat Agree, 3 Somewhat Disagree, 4 Strongly Disagree)

\_\_\_\_\_ I am confident that the mnemonic from the generative AI output is correct.

\_\_\_\_\_ I am confident that the mnemonic from the generative AI output is useful as is.

\_\_\_\_\_ I am confident that the mnemonic from the generative AI output will be useful after I make a small change.

\_\_\_\_\_ I am confident that I could have created a better mnemonic on my own without using generative AI at all.

Explain.



## APPENDIX C: Student Reflection Questions

Items in boldface (4, 6, 8, 10) are higher priority and can suffice if the instructor is short on time. The reflection assignment was completed at the end of the term and it was done individually by each student.

**Reflection Assignment** — Each response needs to be more than 100 words for each question

1. Describe the process that you and your partner(s) used to create mnemonics.
2. Did you find that the process felt creative and fun, or did it feel stressful? Please elaborate on your answer.
3. Think about your typical learning and studying process. In what ways, if any, did the creation of the mnemonics in the class have you focus on the learning process differently? If it did not, why do you think it did not?
4. **Which method did you prefer in creating the mnemonics with your partner(s) without technology or with generative AI, such as ChatGPT? Explain.**
5. Explain how the creating and compiling of mnemonics helped or did not help you prepare for the exams. Do you think that the use of generative AI had any influence on this?
6. **Did the creating and compiling of mnemonics increase or decrease your anxiety about the upcoming exams? Explain.**
7. How did the creating and compiling of mnemonics impact your ongoing studying in the course?
8. **Is the creation and compilation of mnemonics something that you would do in a future class? Why or why not?**
9. If you weren't able to find a mnemonic right away, did you feel that you wanted to give up or did you want to keep trying? Explain.
10. **What did you find more helpful: mnemonics for declarative knowledge or for process knowledge?**