

How should high school homework change in the age of AI?

Introduction:

In the age of Artificial Intelligence (AI), online chatbots have diminished the viability of take-home homework assignments. Before the introduction of AI, teachers could generally expect students to go home and complete an assignment as a product of their own original thinking. However, generative AI has made it easier for students to submit work they did not independently produce. Many students report disliking the current format of homework (Galloway et al., 2013); AI gives them an excuse not to engage with it. At the beginning of 2025, a study found that 79% of students reported using AI for schoolwork in some form (College Board, 2025). Currently, the incentives for using AI to complete homework assignments are high, and the benefits of forgoing the ease of using AI for these tasks are low. This conflict creates a crisis point that demands the education system revisit what homework is for and what it should look like.

The purpose of this paper is to evaluate whether traditional take-home assignments remain effective in the age of AI, and if not, to establish a new methodology teachers can use to assign homework. I propose an evidence-based alternative to alleviate the negative impact AI has had on student take-home work in grades 9 to 12 (high school). Based on research, I propose that teachers eliminate the incentive to use AI for homework by 1) removing homework grades and the consequences for imperfect performance during practice, 2) increasing the agency students

have in how they spend their effort during homework assignments, and 3) communicating to students that their grade doesn't depend on a single final exam by replacing a large final exam with periodic formative evaluative assessments throughout the year. This allows teachers to move graded accountability from take-home products to brief, independently completed in-class demonstrations.

Methods:

Methodologically, I used a theory-informed narrative synthesis to reconsider the purpose and structure of homework for students in grades 9–12 in the context of generative artificial intelligence. I focused on cognitive science research and learning theories to rethink the nature of homework for the age of AI. Literature was located through searches in Google Scholar, journal databases, reference lists, and citations in relevant reviews. I generally prioritized empirical evidence and meta-analyses to support my argument and used foundational theoretical publications, practitioner guidance, and opinion pieces for context and theoretical logic.

Within the literature, I considered participant grade levels, educational setting, research design, number of participants, learning outcome measured, limitations, and relevance to assess whether a study or paper would be effective as part of my argument. In some cases, I used papers that included participants outside of grades 9-12 to support my paper, as they still provided effective evidence on how homework would change in the age of AI from a theoretical standpoint. My search did not exhaustively cover the complete applicable literature, and it was not preregistered. Source selection may reflect my judgment, and much AI research is new, short-term, and still theoretical.

Definitions and a conceptual, theory-based framework:

Before analyzing the effects of AI, it is important to define what qualifies as dangerous AI use, and there are 2 clear distinctions. The first is AI-assisted learning: The student remains responsible for the central thinking and uses AI for limited support, such as hints, explanations, feedback, practice questions, or revision suggestions (Bastani et al., 2025; Alam et al., 2026). On the other hand, detrimental AI use comes in the form of outsourcing, which is when AI performs the central cognitive work the assignment was intended to require, such as generating the analysis, reasoning, solution, or written product that is submitted as evidence of the student's understanding (Barcaui, A., 2025; Jose et al., 2025).

If applied correctly, AI can be a potent force that increases learning and understanding. AI tools can give detailed explanations and personalize learning, allowing for a deeper understanding of content (Vieriu & Petrea, 2025; De Simone et al, 2025). However, heavy AI outsourcing in youth has been shown to correlate with decreased self-monitoring and poorer metacognitive accuracy over time (Jose et al., 2025).

AI use should not be eliminated, but instead changed to supplement the learning process. AI outsourcing can be discouraged by eliminating consequential homework grades and, therefore, the incentive to complete high-quality homework.

To grasp how AI will affect homework, it is crucial to first understand the motivation mechanisms that lead students to engage with it and how they will change. This section lays out the key learning and motivation theories that ground this paper and defines them in the context of homework and AI.

The two theories I center on in this paper and favor for understanding students' motivation are expectancy-value theory and self-determination theory. Expectancy-value theory (EVT) states that an individual's motivation to complete a task is based on the value they expect to receive from completing it and their confidence in completing the task. It lays out the following equation: $\text{expectancy} \times \text{value} = \text{motivation}$ (Wigfield & Eccles, 2000). To understand the value a task brings to an individual, EVT considers 4 key components. *Intrinsic motivation* is the completion of an activity for its satisfaction instead of for a separate value (Ryan & Deci, 2000a). *Attainment value* is the private meaning of succeeding at a task because it aligns with a person's identity or image (Wigfield & Eccles, 2000). *Utility value* is the value a task contributes to one's future or external goals (Wigfield & Eccles, 2000). Lastly, *cost* is the negative factor of missed opportunities that the completion of one task over another may contribute (Wigfield & Eccles, 2000).

To calculate one's confidence in completing a task, EVT considers both a task's difficulty and the internal confidence and ability beliefs that the person has (Wigfield & Eccles, 2000). Both the value of a task and one's confidence in completing it constantly fluctuate; EVT does not classify students as inherently motivated or unmotivated and is dependent on surrounding conditions and context. EVT has become a linchpin of the educational sphere, and a recent study by Jacquelynne S. Eccles and Allan Wigfield reviewed more than four decades of research and concludes that the model has received support across multiple subjects, age groups, and achievement decisions (Eccles & Wigfield, 2024). Other studies such as Trautwein et al. (2006) and Hulleman and Harackiewicz (2009) have found that a student's confidence, along with personal relevance and intrinsic value, aligns with interest and course grades.

Applied to homework, EVT suggests students are most likely to exert effort when they believe that they can complete the work, understand how it contributes to an outcome they value, and consider its costs reasonable. Pre-AI, homework grades provided an immediate completion goal, and mastery and learning goals provided more long-term motivation.

AI affects this relationship by lessening costs. It can significantly decrease the time and effort taken to complete a task. While AI use decreases the value students receive from completing an assignment, cost benefits are extremely appealing and have been shown to overshadow ethical concerns (Schwartz & Diliberti, 2026). AI use can also provide value by providing an easier path towards higher scores in the form of a homework grade, and AI use increases a student's confidence in success.

Self-determination theory (SDT) is similar to EVT and holds that for humans to learn and engage the most effectively, they should have autonomy, competence, and relatedness (Ryan & Deci, 2000b). Autonomy is the experience of acting with personal freedom and choice, competence is the experience of being capable of succeeding through one's actions, and relatedness is the experience of being respected, cared for, and connected to others (Ryan & Deci, 2000b). SDT prioritizes the quality of motivation over quantity, and proposes that motivation ranges from an absence of intention to the end goal of intrinsic motivation. According to SDT, the least autonomous form of motivation is when actions are not personally endorsed but are completed to obtain a reward or avoid a punishment, such as completing homework solely to avoid failing a class (Ryan & Deci, 2020). This is called external regulation, which stands in contrast to intrinsic motivation, when the activity is performed because it is inherently interesting or satisfying (Pelletier & Rocchi, 2023). Part of SDT is the belief that when its conditions are met, the process of internalization can take place. External rules and values can become personal

goals and self-regulated actions to develop into intrinsic motivation (Pelletier & Rocchi, 2023). Since being first created by psychologists Edward L. Deci and Richard M. Ryan, SDT has also become widely accepted throughout academia, and studies such as Howard et al. (2021), Bureau et al. (2022), and Vansteenkiste et al. (2004) have supported the proposition that autonomy, competence, and relatedness contribute to creating the most effective form of intrinsic motivation. These studies have also shown that intrinsic motivation is positively associated with student success and well-being, supporting the argument that internal motivators rather than external pressures create sustainable motivation. This argument is only helped along by the rise of AI, because teachers have fewer external motivation tools available. AI makes it easier to not complete a task, and teachers must increase student curiosity and engagement.

Generative AI changes SDT by substituting for competence (Goh et al., 2025). A student may submit successful work without experiencing or internalizing the value of the activity. Over time, this decreases engagement with class material, and fewer students will develop the intrinsic motivations that SDT aims for by outsourcing work. The central question is therefore not whether AI is present but whether its use supports the student's agency and competence or removes the student from the learning process.

Both EVT and SDT complement the Achievement Goal Theory. Achievement goal theory concerns how students define success. Goal orientations include:

- **Mastery-approach:** trying to learn, improve, or master something.
- **Mastery-avoidance:** trying to avoid misunderstanding or losing skill.
- **Performance-approach:** trying to outperform others.
- **Performance-avoidance:** trying to avoid looking incompetent. (Ames, 1992; Elliot & McGregor, 2001)

Mastery-approach goals should be the aim of the education system, and to combine SDT and EVT, it is the environment where students feel maximum competence, relatedness, autonomy, confidence, and value in completing a task. Teachers must change homework assignments so they are not a burden, but rather an opportunity for students to learn and master a topic they are already interested in and motivated to engage with. Teachers should help students understand and internalize the assignment's value. To create mastery goals, teachers can give students feedback to build on prior knowledge. But, without proper guidance, I predict AI will spur students towards performance-based goals, as they will use AI to complete more tasks in shorter amounts of time, retreating from mastery goals and instead focusing on efficiently reaching landmarks.

In order for students to thrive with increased autonomy, it is crucial to consider Barry J. Zimmerman's model of self-regulated learning. Self-regulated learning (SRL) frames learning as student-directed rather than something that is thrust upon them (Zimmerman, 2002). Students actively manage their thoughts, motivation, behavior, and environment to reach learning goals (Zimmerman, 2002). Homework does not automatically develop self-regulated learning, and only when given sufficient freedom paired with specific goals and guidance do students receive the benefits of SRL, as they can properly discipline themselves (Ramdass & Zimmerman, 2011). AI can both support SRL by creating a more organized workflow and providing more options for how to understand content, but also harm student regulation by contributing to outsourcing, which diminishes the productive struggle that powers student development (Xu et al., 2025; Liu, 2026).

Within my solution, I encourage increased assessment, not only to hold students accountable but also for academic benefit. To understand the benefits of assessment, it is

important to know about spaced retrieval practice - the combination of distributing practice across multiple sessions and attempting to recall information during those sessions (Maddox & Balota, 2015). Spaced retrieval practice is also supported by evidence of the testing effect, which is the finding that actively retrieving information from memory improves later retention more than merely rereading or restudying it (Roediger & Karpicke, 2006). Foundational literature such as Roediger & Karpicke (2006), Karpicke & Roediger (2008), and Roediger et al. (2011) has empirically demonstrated that spaced retrieval practice leads to improved academic and learning outcomes.

A key benefit of increased assessment is to provide a more effective teacher feedback mechanism to support student development. Formative feedback evaluates learning and responds to it while it is in progress and involves ongoing, low-stakes evaluation (Shute, 2008). Summative feedback is the opposite of formative feedback and is made up of one or two large pieces of feedback at the end of a learning period (Brookhart, 2018). By including multiple spaced retrieval tests every week, students will receive a consistent source of formative feedback that they can use to develop throughout a semester and understand both their weaknesses and strengths.

Findings: Homework was already not great, but it still provided some value; AI is making it worse:

Before the introduction of AI, homework was flawed, but it still came with numerous benefits such as reinforcing learning and building academic habits (Trautwein & Köller, 2003). Across two meta-analyses covering more than three decades of studies, homework's association

with achievement changes with grade level, starting from a moderate impact in middle school and progressively growing as students age (Cooper, 1989; Cooper et al., 2006). Additionally, homework develops valuable skills such as time management, organization, problem-solving, and self-discipline (Cooper et al., 2006; Ramdass & Zimmerman, 2011). But if the primary benefit of homework is to build habits, AI has undone that benefit; if students use AI to complete their homework, assigning homework actually entrenches bad habits. There is a major difference between the habits created by a student outsourcing work to an AI tool and a student completing work through effortful engagement with the material. Using AI to complete assignments leads to cognitive offloading and damages one's ability to think critically (Darvishi et al., 2024; Bastani et al., 2025; Barcaui, 2025). This habit is dangerous for students. AI reliance may reduce both content knowledge and the skills required to acquire it. If habit building remains a primary benefit of homework, other non-academic activities may become better at achieving this goal unless homework is reformed in a way that brings both effective academic and social development.

A solution to AI use must also change students' perception of homework. When teachers assign too much work, stress and pressure can create a negative perception of school as a whole (Galloway et al., 2013). From an early age, students return home and see schoolwork as a chore (Cooper et al., 2006). Learning becomes a burden, and by the time students reach high school, where a larger amount of content needs to be learned, school may be seen in a negative light (Parker, 2014). The consistent use of AI to replace critical thinking and academic engagement will continue to create a negative perception of schoolwork (Bai et al., 2023; Klimova & Pikhart, 2025). As students put less effort into their work, their willingness to engage with the curriculum will lessen (Reeve & Lee, 2014).

This pessimistic outlook on homework means that students are willing to cheat their way out of assignments as they see little value in completing them (Murdock & Anderman, 2006). AI tools can blur the boundary between assistance and substitution, creating new academic-integrity problems. At home, students are willing to sacrifice academic honesty if it means less time required to complete an assignment (Schwartz & Diliberti, 2026; Başer et al., 2026).

The reason why homework is seen poorly by students is that many assignments consist primarily of repetitive practice that students may experience as low in value, called “busy work” (Galloway et al., 2013). Many assignments can be completed passively and don’t effectively engage students. They test one’s endurance instead of thinking power and creativity. This aligns with EVT: when students don’t see the value in an assignment or task, they put less effort into it and aim to complete it with the minimum amount of effort needed. However, before the emergence of AI, students still completed the homework that they disliked at high rates, and grade contingencies were able to increase assignment completion (Koenka et al., 2021; National Center for Education Statistics, n.d.; Cullen et al., 1975). The power of AI tools to complete homework assignments and also achieve high grades on those tasks will force educators to rethink how they can craft assignments that interest and motivate students to learn.

Homework serves many purposes, but many modern-day assignments can be grouped into two main categories: practice and learning. For many teachers, homework is a valuable opportunity for practice and repetition. After learning content in class, students return home to refine skills they developed during the day.

On the other hand, in the learning model, students learn content at home. The flipped classroom has grown in popularity recently and is an example of this framework (Bishop & Verleger, 2013). Students typically learn a lesson and then, at school, refine the content from the

night before. The flipped classroom has shown potential to enhance learning outcomes and increase engagement, as well as higher-order learning skills (Han et al., 2025).

AI will disproportionately hurt the model of practice at home, much more than the second one, learning. Think of practice as a worksheet or a mandate to write an essay, while learning comes in the form of reading a book or watching a video. Most tasks designed to be completed by a student can be completed by AI, and when AI supplies a finished answer, it can remove the retrieval, reasoning, and error correction that the assignment was intended to elicit (Darvishi et al., 2024, Kosmyrna et al., 2025; Bastani et al., 2025).

The reason many students have begun using AI for assignments is that they tend to get a short-term grade boost. A non-peer-reviewed study in the Chinese education system of 26,811 students found that AI adoption raises homework scores by 18% and reduces completion time by 30% (Stromberg et al., 2026). Yet, that same study found AI adoption *lowers monthly exam scores by 20%* within six months, entrance-exam scores by 18–24%, and that ~80% of AI users show behavior consistent with outsourcing. In prior years, not completing homework meant academic punishment. However, using AI to cheat on assignments means students can put in less time and effort and achieve higher grades. The incentive structure that has powered homework for years is now collapsing under the pressure of AI.

Without the proper guidance and regulation, in the current academic sphere, AI outsourcing may be worse than receiving no homework when it produces high assignment scores without the corresponding learning, creates an illusion of mastery, and hides students' needs from teachers. The current model of homework, by penalizing low performance and not demonstrating value to students, heavily incentivizes students to use AI rather than effortfully engage with their learning outside of school. In the remainder of the paper, I will propose an

alternative model of what homework could look like moving forward; however, if teachers, especially in younger age groups, have doubts about their ability to adapt to the rise in AI, it is safer to eliminate homework rather than continue with the pre-AI status quo.

Why common countermeasures fail

As Artificial Intelligence has become increasingly prominent in the educational sphere, it is important to discuss not only effective practices but also what techniques should be avoided in the age of AI. Many ineffective practices have been put in place to avoid the risks of AI, and have been advertised as solutions that increase learning at home. If correct steps are not taken, teachers may experience decreased levels of engagement and worsened learning outcomes as students come to rely on AI.

The first fallacy is that it will be effective to assign more long-term, multi-step projects. In the project-based learning model, assignments such as capstone projects require large amounts of creativity and research, which are skills that AI models often have trouble with. Teachers believe that because of this, students will struggle to use AI (Garcia et al., 2025; University of Chicago, n.d.).

These designs may improve learning, but they cannot by themselves verify who produced unsupervised work. It is an extremely flawed framework to rely on the flaws of AI. AI is progressing at an unprecedented rate, and according to a core dataset from the AI research institute Epoch AI, the rate of frontier AI improvement nearly doubled between 2021 and 2025 (Edelman & Lee, 2025). What AI is incapable of doing today may be possible tomorrow, as its skills and capacity change. This is relevant to the project-based model because many steps of the project are often completed at home and offline, without observation. Students may end up

submitting a final product that could contain large parts of AI-generated content. To execute the project-based model in the age of AI, important graded demonstrations should consist of a verifiable component such as an oral defense or supervised writing.

Personalized prompts are also seen as a way to force students to use their own experiences and dissuade AI use. Many teachers view a question such as, “What is your favorite childhood experience?” as a topic that only the student themselves could answer. However, this model still allows students to rely on AI chatbots to do the work for them. Students can provide personal details to a chatbot and ask it to construct a response. Educators must always ask themselves what specifically about their proposal will turn students away from AI. If it has to do with the substance of the assignment, AI models will evolve soon enough to mimic human behavior and writing. Instead of content, educators must begin to prioritize the manner in which assignments are completed. Each assignment should be set up for a student to learn as a product of their own critical thinking and curiosity.

Another way that teachers have tried to limit students' use of AI on homework assignments is through tools of AI detection. Primarily in the humanities, many developers have created software that detects AI in writing based on patterns and language. However, AI text detectors are unreliable, and their failures are well documented: OpenAI discontinued its own AI-text classifier in 2023 for low accuracy (OpenAI, 2023); Weber-Wulff et al. (2023) tested 14 detection tools and found none reliable; Liang et al. (2023, *Patterns*) showed detectors systematically flag non-native English speakers' *human* writing as AI-generated. Even if a detector becomes competent at tracking AI use, every detector improvement trains the next generation of evasion (Weber-Wulff et al., 2023). Teachers must instead use systems of learning that don't leave room for dangerous AI use in the form of outsourcing.

While beginning to become accepted, there are still too many educators who believe AI literacy alone will prevent harmful outsourcing. A recent RAND study found that 67 percent of students endorsed the statement, "The more students use AI for their schoolwork, the more it will harm their critical thinking skills." Yet the same study says 62 percent of students use AI to assist with homework assignments (Schwartz & Diliberti, 2026). Even though many students understand that, in the long term, AI use decreases their academic achievement on tests and leads to a lower quality of learning, the temptation of being able to complete an assignment after a long day of work in a matter of minutes is leading to the rapid adoption of AI in the homework routine of millions of students. While AI literacy is important to helping students and teachers understand how to work with AI in a world in which the workforce increasingly rewards those who leverage AI to their advantage, it is dangerous to assume students will be able to regulate themselves even if they understand the dangers of AI usage.

There is a similarity between the concepts I have attempted to rebut above. When educators try to outsmart AI, they fail. Students are constantly adapting, and it's even easier for them to do so with the introduction of AI. Instead of outsmarting AI, leave no room for its dangerous usage and ensure consequential grades come from verifiable demonstrations of student knowledge.

Discussion and proposed solution

The solution to outsourcing is to increase low-stakes home study, create meaningful student choice, and increase brief unassisted in-class assessments. By significantly reducing or eliminating homework grades, the incentive to use AI on assignments will be eliminated, and teachers can focus on using take-home assignments to develop mastery goals. In-class checks

can still create a controlled external reason to prepare and engage with content at home. There will be no reason to outsource work to AI because consequential grades come only from brief, unassisted, in-class demonstrations along with other teacher-chosen formats such as participation grades. This model is AI-proof rather than AI-resistant and encourages healthy AI-supplemented learning rather than outsourcing. A student can use AI at home in any way they like, and it either helps them learn or reveals itself on Thursday when they are assessed on the knowledge or skills they were supposed to learn at home. Learners who currently rely on AI will quickly learn that AI-created work can no longer replace their learning and pivot to healthier practices.

Arguably, the most important factors in creating effective homework are student autonomy (Patall et al., 2010) and creating assignments that students place value in (Trautwein et al., 2006). To increase student autonomy, I propose that teachers eliminate traditional homework assignments and give students the freedom to choose how they reach the goals educators set for them to achieve with homework, with each student later demonstrating the target independently in class. To learn the same topic, one student may watch a YouTube video and take notes while another may choose to annotate a textbook. This model allows students to choose among study strategies and evaluate which strategy improves their performance. To supplement this, teachers should explicitly teach high-utility techniques such as practice testing and distributed practice (Dunlosky et al., 2013). Additionally, teachers need to scaffold self-regulation with short plans, study logs, strategy instruction, feedback, and reflection (Zimmerman, 2002). A key benefit of this self-directed learning model will be habit creation. As students are forced into independence, skills such as self-discipline, time management, organization, and consistency will develop (Xie et al., 2026; Zimmerman, 2002).

A combination of in-class assessment, intrinsic goals, learning targets, effective feedback, and supportive teacher relationships can drive and create value and motivation to study at home. While grades stemming from supervised in-class assessment may serve as an initial reason to study at home and learn content (Planchard et al., 2015; Cullen et al., 1975; Koenka et al., v2021), the goal is to establish a baseline motivation mechanism that starts with grades but develops into intrinsic motivation, which contains a deeper valuation of skill development, aligning more strongly with SDT. By supplying a choice of study method (autonomy), attainable checks with feedback and mastery replacement (competence), and teacher communication (relatedness), internalization can proceed, and students will develop mastery goals that align with intrinsic motivation.

The largest challenge in carrying out this plan is to ensure assessment creates mastery rather than performance goals. Goal orientation isn't driven by the amount of assessment; it's driven by the structure and framing of assessment (Ames, 1992). When evaluation is high-stakes and a judgment of ability, students believe the purpose of a semester's work is to perform on the final assessment rather than to master a concept. However, when teachers use formative feedback and treat quizzes as learning events to signal the importance of knowledge over performance, grades can be seen as accountability mechanisms and landmarks of progress, but not necessarily as a performance goal that must be met (Black & Wiliam, 1998). Each assessment presents an opportunity for students to receive feedback and use it to reach a long-term learning goal.

An example of this model could include at least 2 brief retrieval checks per week, each 3-5 minutes, culminating in an overarching assessment grade, with each check counting for a small percentage of the overall score. If students struggle initially, there will be enough assessments to improve over time. The checks would count for no more than 5% of the course

grade; two scores would be dropped; later mastery could replace earlier scores; absences should not become zeroes; and written feedback would accompany results (Koenka et al., 2021).

Equally important, a high volume of assessments gives students time to understand the importance of each content check and understand the value of engaging with content at home, aligning with the expectancy-value theory. I would recommend expanding this model to include not only short writing or multiple-choice assignments but also formats such as short presentations. Use presentations only when oral explanation is part of the learning target. These checks give students and teachers evidence of what has been learned independently and where additional support is needed (Black & Wiliam, 2009). Frequent assessment will allow for spaced retrieval practice, leading to more successful long-term learning outcomes (Karpicke & Bauernschmidt, 2011).

Teachers should also be encouraged to tweak the grading breakdown and incentive structure until they see the best outcomes. In-class assessment needs to create enough expectancy-value pull that students feel motivated to engage with content at home, yet don't feel overly pressured to perform on a given assessment. This is contingent on effective teacher-student communication, and this paper should serve as a framework, not an exact description of how educators should operate. Additionally, as important as it is to create assessments that effectively test students, it is also key to produce a manageable assessment model. It is unrealistic for a teacher to consistently grade multiple projects or essays every day. Multiple-choice quizzes should be set as the baseline, and when designed effectively with multiple-choice questions built with plausible competitive alternatives — wrong answers a student must actively rule out — genuine retrieval benefits can be produced (Little & Bjork, 2015). Layered on top of multiple-choice questions should be short 1-2 question writing prompts

and other assessment formats such as short presentations, demonstrations, or any other demonstration of mastery which can be applied to a specific subject. Students should have at least 4-5 of these non-multiple-choice mastery checks per marking period, giving teachers enough time to grade while continuing to assign short writing prompts and multiple-choice questions to hold students accountable. By shifting assessment models from a summative and performance approach framing to a formative, mastery approach, teachers may be able to avoid many of the pitfalls of AI use in homework without needing to completely revolutionize our existing educational assessment model.

AI has highlighted long-existing problems with homework, and we now have an opportunity: we can either use evidence-based theories of learning and motivation to rethink how we are framing practice and assessment in secondary education, or we can let these cracks grow so wide the system breaks. By pairing the motivation frameworks of SDT and EVT to drive students, SRL to develop habits, and formative feedback and retrieval practice for academic outcomes, an effective new system of homework can be created. One that leverages the pros of AI (AI-assisted studying) and eliminates the inducement to outsource critical thinking to AI tools. Not only will students find themselves reducing their reliance on AI, but they will also find themselves chasing mastery goals, unlike how they have been taught to for much of their academic careers.

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