The impact of AI on note taking in higher education

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Introduction

As the pace of life accelerates, it is vital to equip both students and educators to become **friction architects.** This involves intentionally designing opportunities for productive friction, the desirable difficulties essential for deep learning.

Effortless learning is a deceptive shortcut that leads to poor retention. **(Bjork & Bjork, 2011)** This truth was apparent long before the rise of generative AI and is even more critical now in an era of instant gratification. We are currently witnessing the rise of metacognitive laziness, where learners offload the very self-regulatory processes of monitoring, evaluating, and synthesizing that are required for mastery. **(Fan et al., 2024)**

Traditional students are no longer the majority in institutions. We have a New Majority. They are time poor, navigating college without familial knowledge or support and financially struggling. It is no wonder in an age where the productive friction of learning can be avoided students are choosing to cognitively offload **(Bjork & Bjork, 2011)**. However, when current AI tools prioritize frictionless outputs, they deny learners of the encoding opportunities required to reach mastery. **(Grinschgl et al., 2021)**

The current landscape of automated AI does not merely save time, it creates a pedagogical debt **(Kosmyna et al., 2025)**, where the tool handles the synthesis and leaves the student as a passive observer of their own education. **(Chen et al., 2025)**

This is nothing new. For example, in the 1970s, the spiral-bound notebook arrived as a disruptor **(Palmatier & Bennett, 1974, as cited in Morehead et al., 2019)**. While it solved the unproductive friction of disorganised loose-leaf paper, it removed the productive friction of the extra study sessions previously required to organise those notes **(Morehead et al., 2019)**. AI poses a parallel, yet far more profound, challenge. Students now have the opportunity to offload the entire process of synthesis to receive neat, effortless outputs **(Fan et al., 2024; Risko & Gilbert, 2016)**. Yet we know that to achieve mastery, the brain requires the struggle of encoding, decoding and synthesis **(Bjork & Bjork, 2011; Kiewra et al., 2018)**. Therefore, we must guide students to become friction architects, empowering them to use AI as a scaffold that supports deep learning rather than a crutch that replaces it **(Luo et al., 2025)**.

How does cognitive offloading lead to "digital amnesia"?

When a student chooses to cognitively offload, they are often making a strategic decision triggered by the intrinsic load of the material **(Dong et al., 2022; Risko & Gilbert, 2016)**. When this load feels insurmountable, the temptation to remove extraneous load through automation becomes highly attractive **(Skulmowski, 2023)**. Humans have long used external mechanisms to store information and offload tasks, think writing reminders down on paper or posting reminders in your calendar app **(Gilbert, 2015a; Risko & Gilbert, 2016)**. Yet, every offloading decision carries a pedagogical debt that must be accounted for **(Kosmyna et al., 2025; Rohilla, 2025)**. With the rise of AI-driven automation, that debt is increasing at an unprecedented rate **(Kosmyna et al., 2025)**.

To understand the long-term impact of AI on the New Majority learner, we must distinguish between cognitive debt and pedagogical debt. Cognitive debt is the immediate neural deficit incurred when a student uses AI to bypass the struggle of synthesis, leading to what researchers call digital amnesia **(Kosmyna et al., 2025; Krsmanović & Deek, 2025)**. However, when this behaviour becomes the default mode of engagement, it aggregates into a broader pedagogical debt **(Kosmyna et al., 2025; Rohilla, 2025).** This systemic debt is not just a personal lack of retention, but an institutional crisis where the efficiency of task completion is prioritised over the development of cognitive resilience and intellectual agency **(Chen et al., 2025; Selwyn, 2024)**.

When students move their extraneous load to external tools, they undoubtedly increase their speed of task completion **(Grinschgl et al., 2021; Risko & Gilbert, 2016)**. However, this efficiency creates a storage vs. encoding paradox **(Jiang et al., 2018; Kiewra et al., 2018; Skulmowski, 2023)**. The decision to offload leads to the creation of biological pointers where the brain remembers where to find information rather than the knowledge itself **(Skulmowski, 2023; Sparrow et al., 2011)**. It is the cognitive equivalent of remembering which shelf a book is on without ever having read the pages. Studies into cognitive offloading show that while immediate recall is improved, it comes with significant pedagogical debt in long-term memory **(Grinschgl et al., 2021; Kelly & Risko, 2019)**. While this paradox affects all learners, it is particularly damaging for the New Majority learner **(McGee et al., 2024)**. For these students, frictionless AI is not acting as an equalizer but is instead widening existing achievement gaps by denying them the opportunity to encode material that is crucial for achieving mastery **(Chen et al., 2025; Skulmowski, 2023)**.

Does AI widen the achievement gap for **New Majority Learners?**

Learning is a **personal process,** the methods we use vary widely as we each try to synthesize information to ensure retention.

This friction is deeply personal. Applying a gendered lens reveals a significant disparity in how students value and engage in the productive friction of manual synthesis. Research shows that female students are more likely to take notes in class **(97%)** and believe note taking is essential for learning **(93%)** compared to their male counterparts **(79%) (Morehead et al., 2019)**. However, the intersectionality of the New Majority learner means gender is only one lens. When we apply a neurodiversity lens, we reveal a population that has traditionally struggled with the mechanical burden of note taking, often leading to reduced engagement with the process **(Kruger & Doherty, 2016; Bui & Myerson, 2014)**. With the evolution of AI-powered tools, there is a systemic risk that students who already take fewer notes will rely even more heavily on full automation **(Chen et al., 2025)**. This reduced participation could lessen the productive friction necessary for critical encoding and deep learning, being further disadvantageous to those who most need active schema construction to reach mastery **(Chen et al., 2025; Fan et al., 2024)**.

The temptation for students who are struggling to expand their potential by offloading tasks is powerful **(Skulmowski, 2023)**. Yet, these are the very learners who must be supported to become friction architects by choosing intentionally when and where to offload **(Skulmowski, 2023; Risko & Gilbert, 2016)**. While AI is often positioned as a tool for equity, it can, in fact, widen existing gaps for those already struggling by denying them the desirable difficulties of the encoding process **(Bjork & Bjork, 2011; Rohilla, 2025)**. When we add the intersectionality lens of the New Majority learner, the time poor working parent, it becomes critical that institutions move beyond frictionless shortcuts and instead provide the active scaffolding required for students to become the architects of their own learning **(Chen et al., 2025; Stanford Accelerator for Learning, 2024)**.

How does the **"fluency illusion"** affect AI-assisted learning?

In increasingly digital environments, we have already witnessed a reduction in active note taking and engagement **(Chen et al., 2025; Morehead et al., 2019)**. Students frequently bypass the effortful work of encoding, wrongly assuming that because information has been stored externally, it has been encoded internally **(Kiewra et al., 2018; Skulmowski, 2023)**. This belief is a deceptive indicator of mastery, creating the fluency illusion **(Bjork, Dunlosky, & Kornell, 2013)**. When we apply empirical research to AI-assisted learning, we see a strong negative correlation between high-frequency AI offloading and critical thinking scores of a reduction of 17% **(Rohilla, 2025)**. When the "struggle" of productive friction and reflective processing is removed, the cognitive resilience required for deep analysis begins to atrophy **(Fan et al., 2024; Rohilla, 2025)**.

Students using AI need to be clear about when it is helpful in reducing extraneous load and when it is affecting and inhibiting their learning **(Chen et al., 2025; Skulmowski, 2023)**. When students fully outsource the writing of assignments to AI they receive a higher performing essay but no increase in transfer of knowledge or retention of the content **(Fan et al., 2024)**. Those who face challenges with task initiation may look to this shortcut without understanding the widening gap of pedagogical debt it will create **(Kosmyna et al., 2025; Rohilla, 2025)**.

AI usage levels generally fall into three categories: low-level, mid-level, and full task offloading **(Chen et al., 2025)**. Low-level AI, such as transcription, is a known feature that offers multiple means of material representation. Transcription along with captions enable New Majority learners to re-engage with lectures refocussing or relieving the capture panic knowing low-level AI is available to help **(Kruger & Doherty, 2016; McGee et al., 2025)**. This use of AI can be seen as equalising **(Kruger & Doherty, 2016)**.

However, studies evaluating the impact of fully offloading tasks show significant negative consequences **(Chen et al., 2025; Rohilla, 2025)**. Students who delegated note taking to AI experienced substantial score reductions, 35% in one study **(Chen et al., 2025)** and 24% in another **(Kreijkes et al., 2026)**. Overall, learning outcomes were observed to be reduced by 22% **(Rohilla, 2025)**. The pedagogical debt of offloading note taking to AI has to be evaluated **(Kosmyna et al., 2025)**. Studies showing that the lack of productive friction is impacting student outcomes highlight the importance of EdTech tools to be friction architects removing extraneous load for students but encouraging the productive friction necessary for effective learning **(Chen et al., 2025; Skulmowski, 2023)**.

Just as students historically preferred passive strategies like re-reading, mistaking fluency for mastery **(Bjork et al., 2013; Dunlosky et al., 2013)**, the same behavior is appearing with AI **(Chen et al., 2025)**. Students prefer the passive consumption of offloaded notes because it feels "easier" **(Kreijkes et al., 2026)**. However, this ease is a deceptive indicator of learning **(Bjork et al., 2013; Chen et al., 2025)**.

The lack of productive friction within educational environments directly impacts student achievement and necessitates a fundamental shift in how we design and select edtech **(Chen et al., 2025; Rohilla, 2025)**. Tools must act as friction architects by removing the extraneous load of mechanical capture while fiercely protecting the productive friction of synthesis necessary for learning **(Kruger & Doherty, 2016)**.

While AI is frequently positioned as a tool for equity, and can afford New Majority learners some benefit, it can in fact widen existing gaps **(McGee et al., 2025; Rohilla, 2025)**. The time poor working student can be forgiven for falling for the allure of a frictionless shortcut **(Fan et al., 2024)**. Yet these shortcuts often act as a barrier to true academic social mobility **(Rohilla, 2025)**. It is therefore critical that institutions move beyond the trap of frictionless automation and instead provide the active scaffolding required for students to become the architects of their own learning **(Chen et al., 2025)**. By intentionally preserving the struggle of synthesis, we ensure that technology serves as an equalizer of capability rather than just an equalizer of task completion **(Fan et al., 2024)**.

What are the ethical implications of AI, and how do they contribute to **pedagogical debt?**

Alongside the three levels of AI, how students position AI in their learning approach is also key. The trust they place in this additional thought partner can be problematic **(Gerlich, 2025)**. Even when students are aware that AI can hallucinate, they tend to still rely on its outputs **(Gao et al., 2022; Li & Little, 2023)**. This misplaced trust is compounded by the reliability gap. In academic writing, for instance, AI often generates persuasive arguments supported by 'hallucinated' citations, where the tool fabricates sources and evidence that do not exist. When students accept these descriptions without understanding the underlying logic, they accrue significant pedagogical debt **(Kosmyna et al., 2025)**.

The sophisticated, authoritative tone of AI language often bypasses a student's critical filters **(Petricini, 2025)**. Doubts about accuracy and authenticity are frequently silenced by the fluency of the output **(Bjork et al., 2013; Skulmowski, 2023)**. Drawing on Bjork & Bjork's (2011) concept of desirable difficulties, we propose students must become friction architects, intentionally reintroducing the productive friction of learning as they conduct synthesis and verification **(Chen et al., 2025; Kosmyna et al., 2025)**. The risks of passive acceptance of AI outputs are quantifiable. In a study evaluating AI-generated medical references, 39% lacked a Digital Object Identifier (DOI), and 16% were entirely non-existent **(Athaluri et al., 2023)**. Students cannot treat AI as a frictionless search engine, they must engage in the productive friction of auditing every claim **(Chen et al., 2025; McGee et al., 2025)**.

AI is biased by design, reflecting the data on which it was trained **(McGee et al., 2025; Zhai et al., 2024)**. This doesn't just result in factual errors, it risks perpetuating harmful stereotypes **(Grassini, 2023; Mbalaka, 2023)**. With 94% of studies into AI learning tools happening in Western industrialised countries, global populations are not represented nor being supported by the biases in AI. AI datasets are sourced from economically advanced countries so therefore it is no surprise that in a systematic review of AI-based learning tools it was found that only 4 out of 63 studies were conducted in countries with low or medium Human Development Index (HDI) rankings **(Luo et al., 2025)**. The pervasive use of these datasets leads to a form of semantic imperialism, as western-centric viewpoints dominate the global AI discourse, thereby obscuring alternative narratives and marginalizing non-western perspectives **(Petricini, 2025)**.

To protect the New Majority learner and prevent them from passively inheriting systemic biases and linguistic prejudices embedded in AI outputs, we must avoid a "frictionless" experience **(McGee et al., 2025; Petricini, 2025)**. It is critical to acknowledge that to create equity in the age of AI we all need to become friction architects validating AI outputs to avoid amplifying existing disparities **(Chen et al., 2025; Luo et al., 2025)**.

Why does **AI dependence** stifle curiosity and critical thinking?

Skill atrophy occurs like muscle atrophy when skills are not used, stretched or developed **(Fan et al., 2024; Niloy et al., 2024)**. As learners increasingly become tempted to offload tasks in whole new ways they risk increasing pedagogical debt that may not be ever rebalanced **(Kosmyna et al., 2025)**. When tasks are repeatedly offloaded skills become degraded **(Risko & Gilbert, 2016)**. The decreased expenditure of mental effort when using AI causes significant degradation of basic cognitive abilities **(Krsmanović & Deek, 2025)**. Beyond this, curiosity is stifled. As students rely on AI, their interest in validation dwindles as does their inquisitiveness **(Rohilla, 2025)**. Most significantly, empirical research indicates that high dependence on AI tools correlates with a 17.3% reduction in critical thinking scores compared to low-frequency users **(Rohilla, 2025)**.

Task initiation skills are being degraded as increased AI usage develops **(Lee et al., 2026)**. Students struggle to begin tasks without technological assistance **(Rohilla, 2025)**. Many New Majority learners already struggled to begin tasks, meaning the intended equalizer of AI, in providing scaffolded support to start, has created a new problem in the degradation of limited skills **(McGee et al., 2025)**. In test environments, students enter a state of inertia without the familiar AI tools they rely on for support **(Krsmanović & Deek, 2025; Rohilla, 2025)**. What was intended to be a scaffold and an equalizer has become a crutch. Without it, the student cannot function with almost 50% of students saying they are reliant now on this AI crutch **(Krsmanović & Deek, 2025)**.

The skill of recalling information is diminished as students rely on offloaded external storage meaning over a fifth of concepts are immediately forgotten when compared to manual note taking **(Rohilla, 2025)**. This creates a digital amnesia where students recall the memory traces but not the knowledge needed **(Grinschgl et al., 2021; Krsmanović & Deek, 2025; Sparrow et al., 2011)**. While students prefer the fluency and ease of automated AI note taking, their test scores indicate mid-level AI or no AI usage are the only way to ensure knowledge is retained and synthesised **(Chen et al., 2025)**.

To ensure neurocognitive health, institutions must empower both educators and students to become friction architects **(Firth et al., 2019)**. Rather than accepting the path of least resistance, friction architects intentionally design learning interactions that prioritize strategic scaffolding over total automation **(Chen et al., 2025)**. By requiring students to attempt a task independently before consulting AI, friction architects ensure that the neural pathways associated with active reasoning are fully activated before external support is introduced **(Kapur, 2023; Rohilla, 2025)**.

Conclusion

In conclusion, it is clear that the integration of AI into the educational landscape represents a definitive crossroads for the New Majority learner **(McGee et al., 2025)**.

While the promise of frictionless automation offers an attractive solution to the time poverty and mechanical burdens faced by many students, we must recognize it for what it truly is, a deceptive shortcut that trades long-term capability for short-term efficiency **(Chen et al., 2025; Rohilla, 2025)**. By bypassing the essential struggle of encoding, decoding, and synthesis, we risk graduating a generation of students who possess the biological pointers to find information but lack the cognitive architecture to understand or apply it **(Jiang et al., 2018; Skulmowski, 2023)**. This is powerfully illustrated by neurophysiological data demonstrating that frictionless AI bypasses internal encoding entirely. When 83% of students had difficulty quoting their own work immediately after writing and none could provide an accurate quote, we must take action and create opportunities for students to become friction architects. **(Kosmyna et al., 2025)**

The rise of metacognitive laziness and the subsequent accumulation of pedagogical debt are not inevitable consequences of technology, but rather the results of how we choose to deploy it **(Fan et al., 2024)**. To protect the intellectual agency of our students, especially New Majority learners, institutions must pivot away from the pursuit of a frictionless experience **(Selwyn, 2024)**. We must instead embrace the role of the friction architect, intentionally designing tools and curricula that preserve the desirable difficulties necessary for deep learning **(Bjork & Bjork, 2011; Chen et al., 2025)**. By moving from a model of AI dependency to one of cognitive augmentation, we transform technology from a crutch into a powerful scaffold **(Rohilla, 2025)**.

Ultimately, true equity in the age of AI is not found in making the path to an answer easier, it is found in ensuring every student has the opportunity to engage in the productive friction that leads to mastery **(McGee et al., 2025; Rohilla, 2025)**. As friction architects, our goal is to empower learners to audit, verify, and synthesise, ensuring they are not passive observers of their own education but rigorous critics and active creators **(Petricini, 2025; Zhai et al., 2024)**. By fiercely protecting the internal struggle of the mind, we ensure that the New Majority learner achieves more than just task completion, they achieve the academic social mobility and critical resilience required to thrive in a complex, automated world **(Selwyn, 2024)**.

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