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The impact of Productive Friction on Learning, Engagement, and Decision-Making: A Quantitative Experimental Study

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Abstract

This experimental study examined how productive friction — low, moderate, and high levels of task difficulty — shapes learning, engagement, and decision-making in an AI-supported environment. Grounded in Cognitive Load Theory and the concept of desirable difficulties, the study tested 188 undergraduate participants (131 female, 57 male; ages 18–24) who were randomly assigned to one of three friction conditions and completed a multiple-choice knowledge task followed by a 5-point Likert-scale questionnaire measuring engagement, cognitive load, persistence, confidence, and perceived understanding. A one-way ANOVA found no statistically significant difference between the three friction groups, $F(2, 185) = 0.869$, $p = .421$. Descriptively, the High Friction group showed the highest mean performance ($M = 5.00$, $SD = 1.56$), followed by Low Friction ($M = 4.82$, $SD = 1.36$) and Moderate Friction ($M = 4.65$, $SD = 1.55$), and cognitive load remained comparable across conditions, suggesting that increased task difficulty did not produce overload. However, because the omnibus ANOVA was not significant, these between-group patterns should be interpreted as descriptive trends rather than confirmed effects. The findings are discussed in relation to the proposed Adaptive Productive Friction Model (APFM), and implications for future research — including the need for adequately powered samples and post-hoc comparisons — are outlined.

Introduction

The fast growth and advancement of artificial intelligence (AI) has changed educational and professional environments. This happened by making it more efficient, personalizing learning, and scalable instructional delivery. Contemporary AI systems, has adaptive learning platforms and generative tools, which can directly provide real-time feedback, and enhance accessibility. Recent empirical research says that Places with AI-assisted learning system has shown improved engagement and influenced cognitive processing by adapting instructional pathways (Feng, 2024; Qi, 2024; Guo et al., 2024). From a perspective of Cognitive Load Theory, this systems have the capacity to make better learning by reducing undesirable cognitive difficulties and supporting information processing system that's efficient (Sweller, 2011).

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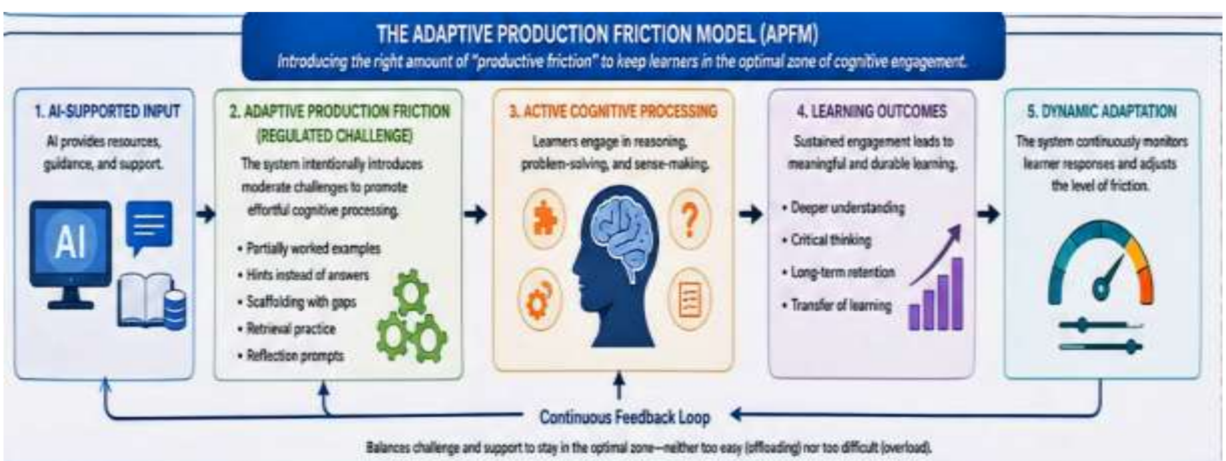
However, recent evidence suggests that the cognitive implications of AI is not only about performance enhancement rather it's alarming as it raised critical concerns regarding the quality of learning. While AI systems provide fast responses for task completion, at the same timethey also reduce effortful cognitive processing because solutions are readily available. This phenomenon is termed as cognitive offloading, where individuals extremely rely on external systems rather than engaging themselves in internal reasoning processes. Studies also predict that AI-supported environments can end up encouraging passive interaction and as a result under high automation there will be significant reduction in active engagement (Qi, 2024; Adewale et al., 2024). Systematic analyses throws light on increasing personalisation by AI, his tension reflects a broader paradox in AI-supported learning: systems which are structured to improve efficiency may hinder the cognitive effort which is very important for deep learning, critical thinking, and long-term memory retention and this can also contribute to over-reliance and superficial processing if cognitive effort is not maintained deliberately.(Halkiopoulos, C. and Gkintoni, E. 2024).

This constant conflict shows a broader picture in AI-supported learning that these systems are made to improve efficiency but that can eventually hinder the cognitive effort. Cognitive Effort is also very important for deep learning, critical thinking, and long-term memory retention. The frameworks that are present today, including Cognitive Load Theory, primarily emphasize on reducing unnecessary difficulty, while complementary perspectives such as desirable difficulties shows the benefits of controlled challenge. However, these perspectives remain insufficiently integrated in the context of AI-mediated environments, where both under-engagement and overload can occur dynamically.

To address this gap, the present study proposes the Adaptive Productive Friction Model (APFM). The most traditional approaches prioritize efficiency but APFM sees cognitive challenge as a extremely regulated mechanism that retains engagement without creating overload. By introducing regulated “productive friction” into AI-supported systems, the model aims to maintain active cognitive processing along with leveraging the benefits of automation. In the process of doing so, this study contributes to the growing discourse on AI and cognition by offering a theoretically grounded and practically applicable framework for increasing engagement, learning, and decision-making in complex, technology oriented environment.



Literature Review

All the latest research on artificial intelligence in education mainly focuses on it has the capacity to increase learning through mechanisms like personalization, automation, and adaptive feedback mechanisms. All the studies explains that systems that are assisted by AI can increase engagement and influence cognitive load by creating instructional pathways for each individual learners (Feng, 2024; Guo et al., 2024; Qi, 2024). These findings tells that AI has the potential to increase learning efficiency by combining instructional support with cognitive capacity. Still this efficiency-oriented perspective brings a difficult questions about how cognitive effort is disrupted when tasks become extremely automated (Adewale et al., 2024).

The new interdisciplinary perspectives says that AI can not only improve performance but also analyse how individuals engage with information. In extremely automated environments, the possibility of the learners relying on AI-generated outputs is extremely high rather than actively constructing knowledge. This outcome can lead to reduced cognitive engagement. This sort of phenomenon is similar with the concept of cognitive offloading, where any external tools can replace internal processing. Such offloading can significantly reduce cognitive burden, as a result it can also limit deeper learning if overused. Systematic reviews shows that environments with AI supported machines can promote over-reliance and diminish learner agency when cognitive effort is absolutely not intentionally structured (Halkiopoulos & Gkintoni, 2024; Adewale et al., 2024). These outcomes says that the effectiveness of AI depends on main factors like how it supports learning and also how it retain meaningful cognitive engagement.

The cognitive engagement in human and AI has been always linked to automation bias. The individuals rely more on system outputs without verifying (Parasuraman & Riley, 1997), which actually leads to errors of omission and commission. This problem mainly in high-stakes contexts (Goddard et al., 2012). Research now a days comes up with indication like complex digital systems can increase cognitive workload while on the other hand there's a reduction in active oversight, shifting learners from active reasoning to passive monitoring (Carayon et al., 2015; Khairat et al., 2018; Ratwani et al., 2018). This reflects a very important limitation of current AI systems that reduced cognitive vigilance instead of increased technological capability.

A central tension lies between reducing cognitive load and introducing productive difficulty. According to Cognitive Load Theory it prioritizes on reducing unnecessary demands on working memory (Sweller, 2011; Paas et al., 2003; Kirschner et al., 2006). The frameworks created for desirable difficulties and productive failure says that there will be benefits in the long-term by effortful processing, but can impair and affect immediate performance (Bjork & Bjork, 2011; Schmidt & Bjork, 1992; Kapur, 2008, 2016).This tension says that best learning depends on balancing cognitive demands rather than reducing it.

The Yerkes–Dodson Law explains and supports this position, focusing on a particular point that performance is maximum under moderate arousal, while both underload and overload impair and affect the outcomes (Yerkes & Dodson, 1908; Lupien et al., 2009), with sustained imbalance that contribute to burnout in professional settings (West et al., 2018).

Talking about all these fragmented landscape, the Adaptive Productive Friction Model (APFM) introduces a dynamic framework that expects best cognitive engagement through the Friction Calibration Mechanism (FCM), which adaptively regulates challenge via feedback loops. This is created by integrating Cognitive Load Theory, desirable difficulties, productive failure, and automation bias. APFM mainly focuses on optimizing cognitive friction, better independent decision making and enabling deeper learning rather than minimizing effort in AI-mediated environments.

Research Objectives

1. To examine how different levels of productive friction (low, moderate, high) affect on performance (test scores) in AI-supported tasks.
2. To compare all the levels of cognitive engagement, cognitive load, and persistence in various friction conditions.
3. To analyze how productive friction on decision-making, accuracy and confidence impact the learners
4. To investigate how the understanding of concepts get influenced by productive friction.
5. To identify the most effective learning in the basis of outcomes (performance and understanding) under different level of productive friction.
6. To examine what is the practical relevance of the Adaptive Productive Friction Model (APFM) in structured learning environments.

Prerequisite Knowledge

Form A

Productive friction is a learning condition under which the students were given an extremely small amount of knowledge with guidance and support for better understanding.

Improvement in very easy tasks is very less and very difficult tasks creates confusion and repeated failure in students whereas

Moderately easy tasks with guidance support effective learning and shows optimize performance of the students Cognitive load means mental effort that is important required while learning. Learning becomes easier with support and guidance along with proper explanation of the task.

The desirable difficulties in any task performance should be manageable.

Form B

Learning effectiveness is mainly affected by the difficulty level the student is going through during the task.For better understanding the task can't be easy and without effort, for improvement the task needs to have little effort.Tasks that are very difficult can affect the learning and memory retention.Tasks with proper level of challenge can help in improving the level of understanding. Cognitive load means the amount of mental effort that is used while processing any information.

Extremely low cognitive demand can affect the engagement level of learners sufficiently. Excessively high demand can reduce the performance of the learners.The learning effectiveness depends on the distribution of the mental effort.During learning, students can face difficulty with tasks but will show better performance with little effort and with time. This concludes that some level of difficulty influences positively making it more understandable and also depends on how it is managed.

Form C

Learning outcomes depend on the interaction between task complexity, cognitive load, and the availability of support and guidance. These factors are not independent so have different effects based on their combination.

Cognitive load means mental effort that is needed to process information within limited working memory capacity. When this difficulty increases that the students capacity, performance may decline, even after repeated tries.In a complex structured learning setup, the lack of guidance can make the students wrongly interpret the information while learning. Increased task difficulty, along with limited support, can lead to situations where desirable difficulties don't improve understanding or accuracy. Although moderate amounts of difficulty can improve learning. Additional difficulty can reduce efficiency, inconsistent decision-making, and variability in outcomes.Repeated attempts of the students under high complexity conditions do not show effective learning because the performance gets constrained by cognitive limitations rather than lack of effort.

Methodology

This study used a quantitative experimental design employing a between-subjects approach. Participants were tested under three conditions to examine how they responded to different levels of friction: Group A received low friction, Group B received moderate friction, and Group C received high friction. Each participant completed a set of multiple-choice questions designed to test knowledge, followed by a five-point Likert-scale questionnaire, on which 1 indicated strong disagreement and 5 indicated strong agreement, assessing engagement, cognitive load, persistence, confidence, and perceived understanding.

The sample consisted of 188 participants (N = 188), including 131 female and 57 male respondents. The majority of participants were between 18 and 24 years of age, and the sample was predominantly undergraduate students.

The study examined one independent variable, the level of productive friction, which was operationalized across three levels: low (Group A), moderate (Group B), and high (Group C). Six dependent variables were measured: learning performance (MCQ score), engagement, cognitive workload, persistence, confidence, and perceived understanding.

DATA ANALYSIS

Effectiveness of Productive friction among study participants

Friction Condition	N	Mean	SD	t	df	p	95% CI Lower	95% CI Upper	Sig.
Low Friction	60	4.817	1.359	27.452	59	< 0.001	4.466	5.168	Significant
Moderate Friction	51	4.647	1.547	21.453	50	< 0.001	4.212	5.082	Significant
High Friction	77	5	1.564	28.046	76	< 0.001	4.645	5.355	Significant

All three friction conditions recorded mean scores significantly greater than zero ($p < 0.001$). The High Friction group demonstrated the highest mean score ($M = 5.00$, $SD = 1.56$), followed by Low Friction ($M = 4.82$, $SD = 1.36$) and Moderate Friction ($M = 4.65$, $SD = 1.55$). One-sample t-tests confirmed that all three conditions differed significantly from the null test value of zero — Low Friction [$t(59) = 27.452$, $p < 0.001$, 95% CI: 4.47–5.17], Moderate Friction [$t(50) = 21.453$, $p < 0.001$, 95% CI: 4.21–5.08], and High Friction [$t(76) = 28.046$, $p < 0.001$, 95% CI: 4.64–5.36]. Moderate Friction yielded the widest confidence interval and the smallest sample ($n = 51$), indicating comparatively greater variability in responses under that condition. Collectively, these findings suggest that regardless of the level of friction — low, moderate, or high — participants consistently demonstrated a meaningful and statistically significant response above baseline, with the High Friction condition eliciting the strongest and most consistent effect.

Table 2: One-Way ANOVA for Productive Friction across Groups

Productive Friction	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.896	2	1.948	0.869	0.421
Within Groups	414.630	185	2.241		
Total	418.527	187			

The one-way ANOVA for Productive Friction revealed no statistically significant difference between groups [$F(2, 185) = 0.869$, $p = 0.421$]. The between-groups mean square ($MS = 1.948$) was marginally lower than the within-groups mean square ($MS = 2.241$), indicating that variability within groups outweighed any variability attributable to group membership across the 188 cases examined.

These results suggest that participants across all groups perceived or experienced productive friction at comparable levels, irrespective of group assignment. Within the friction model framework, productive friction refers to the degree of optimal challenge or resistance that stimulates engagement, learning, or growth — and the non-significant finding here implies that the groups did not differ meaningfully in how they encountered or responded to this productive dimension of friction. This may indicate that productive friction, as measured, operates as a relatively stable and uniformly distributed experience across the sample, rather than one that is differentially shaped by group-level characteristics. Alternatively, the non-significance may reflect insufficient statistical power given group size distributions or a genuine absence of group-driven moderation at this friction level. Findings from the moderate and high friction ANOVA should be considered alongside this result to build a comprehensive picture of how friction intensity interacts with group membership within the broader friction model.

Discussion

The results of this study suggest that productive friction may shape different dimensions of learning, although the ANOVA result was not statistically significant, $F(2, 185) = 0.869$, $p = .421$. This means the differences observed between the three groups cannot be treated as confirmed effects; they should instead be read as descriptive trends that warrant further investigation with post-hoc comparisons and a larger sample. In terms of performance, the highest mean score was observed in the high friction condition (Group C), which is broadly consistent with the theory of desirable difficulties, where effortful processing is associated with better outcomes — though this pattern was not statistically confirmed. Descriptively, the moderate friction condition (Group B) showed the highest engagement and persistence, a pattern that would be consistent with the Yerkes–Dodson Law, which holds that performance is optimized under moderate levels of difficulty, though this too was not tested for significance. Cognitive load remained similar across all three conditions, which is consistent with the idea that increased difficulty did not produce overload in this sample, and suggests that productive friction may be tied to meaningful (germane) cognitive effort rather than harmful difficulty — bridging Cognitive Load Theory with effort-based learning. Perceived understanding did not strongly track actual accuracy, reflected in a weak correlation ($r = 0.23$) between confidence and performance, which may point to automation bias, where learners feel confident without deep understanding, particularly under low-friction conditions. Taken together, these descriptive patterns suggest, but do not statistically confirm, that low friction may be associated with more passive learning and lower engagement, moderate friction with the strongest engagement and persistence, and high friction with the highest performance outcomes.

These patterns offer preliminary, though not statistically confirmed, support for the Adaptive Productive Friction Model (APFM) and its premise that learning is most effective when cognitive challenge is balanced rather than minimized. The findings suggest that removing difficulty should not be the default goal of AI-supported learning, but rather that difficulty should be strategically designed to enhance thinking, persistence, and understanding. Given the non-significant omnibus result, future work should prioritize adequately powered samples and post-hoc group comparisons to test these patterns more rigorously.

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