The self-regulated learning paradox: Or, one reason why educational interventions might fail

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Abstract

Why do large-scale field experiments in education often have muted effects? Drawing on system dynamics and self-regulated learning theory, we sought answer this question by simulating the behavior of self-regulated (discrepancy-reducing) learners over time affected by different types of educational interventions. We analyze three types of interventions: changing students' learning rates (learning strategies), intercepts (prior knowledge or teaching effectiveness), and norms of study (achievement goals). We uncover situations where educational interventions can affect achievement in the short run, but typical cross-sectional analyses do not find a measurable effect in the long run. Results indicate that highly motivated, self-regulated learners may resist external interventions, particularly those targeting learning strategies or prior knowledge. In contrast, interventions show the greatest effect on achievement when students are under time constraints and struggling to achieve their desired performance. Ultimately, self-regulated learners may be the hardest to help, a phenomenon we call the "self-regulated learning paradox."

Keywords: Self-Regulated Learning; System Dynamics; Complexity Science; Cybernetic Theory; Educational Interventions

Psychology and education researchers often dedicate their research careers to testing interventions in schools aimed at improving student performance. Despite the backing of social scientific theory, various psychological mechanisms, and years of research, the results of these interventions often show less-than-optimal results. In fact, the average intervention barely shows an effect. Kraft (2020, 2023) analyzed 3,000 randomized controlled trials in schools from a variety of sources (e.g., IES's What Works Clearinghouse). He found that the average main effect of interventions in his sample was small, around 0.05 standard deviations. Altogether, large-scale evidence indicates that the main effects of educational interventions on achievement are small, and if we do find an effect, it tends to be for at-risk students. This has led researchers to ask: How is this pattern found across a wide array of interventions with different theoretical mechanisms and psychological targets (Schwartz et al., 2016)?

In this paper, we offer one potential reason for this pattern of findings, which we term "the self-regulation paradox." We do so by introducing the concept of balancing feedback as a more formal way of describing and understanding the cyclical nature of common self-regulated learning theories. We contend that resistance to change is implicit in the concept of "self-regulation." Taken seriously, this resistance to change may explain why so many interventions or field experiments show limited effects in the field (Kraft, 2020, 2023). But it is not all bad news. The results of the present study can inform research designs to better capture effects of educational interventions. To foreshadow these recommendations, we may benefit from using longitudinal designs and measuring the efficiency of time usage (not just achievement) as a primary dependent variable of interest.

To begin, we provide an overview of self-regulated learning theories. This is followed by an exploration of balancing feedback loops (see Table 1), drawing on complex systems theory (Butner, 2017; Jacobson et al., 2019) and systems dynamics modeling (Bala et al., 2017; Meadows, 2008). Using a simplified version of the model of school achievement introduced by Schuetze (2024), we conduct a simulation showing the effects of interventions on students engaging in self-regulated learning with different starting parameters (learning rates, performance goals). We conclude by addressing challenges that may emerge when attempting to alter the learning behavior of self-regulated learners in the context of large-scale field experiments.

Theoretical Framework

Self-regulated learning refers to the type of learning that occurs when students are engaged in directing their own pursuit of knowledge with some level of independence to choose the things they attend to, the learning strategies they use, and the goals they pursue. Models of self-regulated learning are plentiful within the domain of education research (Kim et al., 2023; Panadero, 2017). Despite the substantial number of models of self-regulated learning—such as those of Boekaerts (1997), Efklides (2011), Winne and Hadwin (1998), and Zimmerman (1990, 2002)—Puustinen and Pulkkinen (2001) argue most models of self-regulated learning are broadly similar in content.

The Plan-Do-Check-Act Cycle: The Fundamental Balancing Feedback Loop of Self-Regulation

Indeed, it appears this is an area of research defined by high theoretical alignment from model to model (Pintrich, 2004). Puustinen and Pulkkinen (2001) note that most self-regulated learning frameworks generally hypothesize three major steps: preparation, performance, and appraisal. These stages also resemble what Miller et al. (2017) called "test-operate-test-exit" (TOTE). Pintrich (2004) uses a similar framework with

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Loop Type	Other Name(s)	Description	Educational Examples	Non-Educational Examples
Balancing Loop	Negative Feedback	These loops seek stability, and often dampen the effects of interventions over time	Goal Pursuit, Self-Regulation	Homeostasis, Thermostats, Cruise Control
Reinforcing Loop	Positive Feedback, Reciprocal/Recursive Processes, Vicious or Virtuous Cycles	These loops intensify processes. Initial differences are exacerbated over time.	The Matthew Effect, Pygmalion Effect, Self-Fulfilling Prophecies	Network Effects, Feedback in Speakers and Microphones

Table 1: Comparison of Feedback Loops. Note: In this paper, we employ the term "balancing feedback" rather than the synonymous term "negative feedback." This choice of terminology has been made because the term negative feedback has a distinct meaning in the education literature, referring to the practice of providing a student with information about their performance.

four steps: forethought, monitoring, control, and reflection. More succinctly, in the words of Deming's cycle: plan, do, check, act (Moen & Norman, 2009).

This plan-do-check cycle is fundamentally the same as that of a thermostat, and thus represents a balancing feedback loop (Abdulwahed & Balid, 2013; Ballard et al., 2021). This relationship between feedback loops and self-regulated learning goes back to some of its earliest and most prominent theorists (Carver & Scheier, 1982, 1990; Miller et al., 2017; Zimmerman, 1989). For example, Zimmerman (1990) wrote that a "feature of most definitions of self-regulated learning is a 'self-oriented feedback' loop" (p. 5). In other words, the self-regulation loop (shown in Figure 1) is inherent in many theories of study time allocation and self-regulated learning (Zimmerman, 2000, 2002).

Over the last 25 years, several groups of researchers have noted the connection between theories of self-regulated learning and system dynamics/cybernetic theories. This connection has been most clearly made by Zimmerman (1990, 2000, 2002), Pintrich (2000), Wiliam (2012), Abdulwahed and Balid (2013), and Hilpert and Marchand (2018), with other researchers also pointing to the overlap between control theory and education research (Keith et al., 2024; Peña-Ayala & Cárdenas-Robledo, 2019; Roos & Hamilton, 2005; Westera, 2015). Apart from Hilpert and Marchand (2018) and Keith et al. (2024), these papers have not linked the issue of system dynamics to the interpretability of common statistical analyses in education research. Nor have they illustrated the potential connection between this feedback loop and low efficacy of educational interventions as measured using common approaches.

The existence of the feedback loop described by Zimmerman (1990) can be illustrated by drawing out the plan, do, check, act cycle as a causal loop diagram (see Figure 1 and Table 1). Causal loop diagrams are means of diagnosing the qualitative trends of a system governed by feedback (Crielaard et al., 2022; Haraldsson, 2004). Note that our use of feedback is distinct from the concept of feedback that a student receives from a teacher on an assignment. Rather, it refers to the general phenomenon where the outputs of the system feed back into the system as inputs. Feedback processes are implicated when a model shows a loop or a cycle. When feedback is implicated, the behavior of systems often develops in counterintuitive and unpredictable ways over time. As such, complex systems are usually not captured well by the cross-sectional research designs and linear models commonly used in social scientific research (Butner, 2017; Jacobson et al., 2019).

Relationship to the Discrepancy Reduction Model

More specifically, the self-regulated learning cycle depicted in the middle of Figure 1 is modeled from Thiede and Dunlosky's (1999) Discrepancy Reduction Model (DRM). Discrepancy reduction is the inherent process of goal pursuit, where a student strives to reduce the distance between their current state and their end goal state (Locke & Latham, 2002). The DRM attempts to answer the question "How do students allocate their limited amount of time when they need to learn material?" It posits that students have individual "norms of study" or performance criteria. This is a common element to many self-regulated learning theories, which Pintrich (2004) calls the "goal, criterion, or standard assumption" (p. 387). The DRM has often been applied to the study of individual word pairs in laboratory contexts. In these contexts, it is assumed that students will study the word pairs that are the furthest away from their norm of study (i.e., the least well learned). This maps onto the "do stage" of the plan, do, check, act cycle.

Under the DRM, students are assumed to study the items furthest away from their performance criteria. To determine which items are furthest away from the norm of study, students are assumed to be making metacognitive judgments (often elicited as judgments of learning in experimental settings). Pintrich (2004) calls this the "potential for control assumption" (p. 387). This process maps onto the "check stage" of the plan, do, check, act cycle. To minimize the distance between their current knowledge state and their desired state (norm of study), the student continuously adjusts their approach to studying. Although the DRM (upper case) has been tested primarily at the item-level, we can easily translate

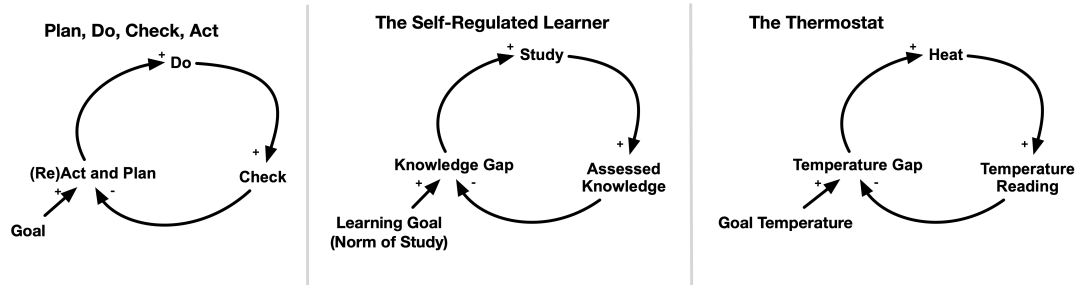

Figure 1: Three Feedback Processes. Note: The plus and minus signs indicate the qualitative (up or down) relationship between the previous step and the next step. Positive signs indicate that two factors move in the same direction, while negative signs indicate that the two factors move in opposite directions. For example, studying increases the assessed knowledge, which in turn decreases the gap between the learning goal and the assessed knowledge.

discrepancy reduction (lower case) to the concept of studying for a test – or the sustained pursuit of any goal (Locke & Latham, 2002). Students continue studying until they believe that they have reached their criterion knowledge level for the test as a whole. This is the model, which we formalize and simulate in the next section.

Simulation Methods

We simulate a discrepancy-reducing student engaging in self-regulated studying prior to an examination. Our student is represented as a self-regulated learner with three independent variables determining the system's behavior over time: time, norm of study, intercept, learning rate. Time represents the maximum number of hours a student is willing or able to study. Norm of study represents a performance goal and is measured as a students' forecasted test grade (% correct). The intercept represents where the learners start (i.e., their prior knowledge). Learning rate describes how fast the learner acquires knowledge per unit of study time. Faster rates mean that the student achieves their learning goals more quickly, while slower rates indicate a longer required time to meet goals. The student follows the discrepancy reduction principle, seeking to bolster their knowledge through studying, until either (a) the norm of study has been reached (or at least they think they have reached it) or (b) they run out of time. This is a simplified model compared to the full-fledged model described in Schuetze (2024), but captures many of the same critical dynamics of educational interventions on self-regulated learners (see Equation 1).

The simulated student can be described by the following set of finite difference equations:

$$\begin{aligned} Learned(t) &= Learned(t-dt) + (Studying) * dt \\ NotLearned(t) &= NotLearned(t-dt) + (-Studying) * dt \end{aligned} \tag{1}$$

Where the following variables are initialized as such: $Learned(0) = Intercept$ and $NotLearned(0) = 100 - Learned(0)$. $Studying$ is equal to $LearningRate$ if $Learned < NormOfStudy$, else $Studying = 0$.

$LearningRate$ can be any positive number, but for the purposes of the present simulation we consider 5, 10 and 15% per hour. $NormOfStudy$ can range between 0 and 100. In the present simulation, we consider study norms of 70, 85, and 100 (C-, B, and A+, respectively). The unit of time (t in Equation 1) is assumed to be equal to hours of studying. For simplicity, the total quantity of information in the model is set to 100 and is always split between two states: learned and unlearned information. Learning transforms the unlearned information into learned information.

As summarized in Table 2, we simulate three possible interventions to these nine self-regulated students. In the first intervention, we simulate shifting their learning rate up by 5 percent per hour. This could be thought of as being equivalent to helping the student adopt better learning strategies, for example retrieval practice or spaced practice (Carpenter et al., 2022). The second intervention on the system involves shifting students' intercept by 15 percent. One might conceptualize an intercept shift as modeling the impact of a better teacher helping the student learn more information before they engage in studying (thus beginning studying with higher prior knowledge). The third intervention simulates raising the students' norms of study by 15 percent, in essence motivating them to continue studying until they have achieved a higher anticipated mastery of the learning material at hand.

Results

Here, we summarize the effects of three potential interventions to a perfectly self-regulated learner. Each graph depicts learning (y-axis) as a function of time spent studying (x-axis). We highlight the areas of "no effect" with red horizontal intervals in the graphs below. These intervals signify situations where even an effective intervention would be predicted to show no treatment effect using traditional cross-sectional experimental methods; that is, evaluating the difference in group-means between two conditions at a specific amount of willingness to study, even with an infinite sample size.

Input	Effect on Simulated Learners	Potential Psychological Interpretation
Time (Hours Studying)	Changes the maximum number of hours a student is willing or able to study	The effect of raising or lowering the amount of time the student will allow themselves to study (or has available to study).
Norm of Study	Changes the goal-state at which students stop studying	The effect of having a more motivating educational environment or increased value of learning.
Learning rate	Changes the slope of the learning curve	The effect of changing the learning strategies that the student engages in.
Prior Knowledge	Changes the intercept of the learning curve	The effect of the student having more prior experience with a subject or better previous instruction.

Table 2: Summary of Intervention Types

Effects of Learning Rate Interventions

As described above, an intervention to each student's learning rate was applied to see how predicted effects would vary as a function of the students' initial learning rate, norm of study, and time spent studying. The results of this simulation are depicted in Figure 2.

As can be seen from Figure 2, the learning rate intervention improves student performance initially. Looking at the length of the "no effect zone" denoted by the red lines indicates that the intervention will be effective for the longest when the initial rate of learning is low and the students' norm of study is high. When the initial rate of learning is high and the students' norm of study is easily achievable, there is hardly any room for the learning rate intervention to benefit the student. Learners only investing a minimum number of hours studying may benefit theoretically from learning rate interventions. But, practically the benefit will be small, because the effects of a rate intervention are cumulative over time.

On the other hand, researchers should not assume that highly-motivated students' *grades* will benefit from interventions targeting learning rate either. In our simulation, learners with high performance goals (i.e., motivated students) benefit from the learning rate intervention by being able to meet their goals and discontinue studying earlier. This is a beneficial outcome, but not necessarily one that would be reflected in achievement-focused assessments of intervention effectiveness.

Effects of Intercept Interventions

As described above, an intervention to each student's learning intercept was applied to see how predicted effects would vary as a function of the students' initial learning rate, norm of study, and time spent studying. As shown in Figure 3, all simulated intervention conditions converge regardless of simulated starting point. In essence, the effect of the intercept intervention washes out to zero over time.

Effects of Norm Interventions

In the third intervention type, we simulated the effect of changing the students' norms of study. In essence, we tested a learning goals intervention, where students hold themselves to meeting a higher standard before they will disengage in studying (see Figure 4). Interestingly, we see the opposite patterns in terms of achievement compared to the previous two interventions shown in Figures 2 and 3. Raising the norm does not affect students' trajectories early on in their studying. In fact, if we limit our analysis to only the first four hours of study, none of the simulated learners show any effects of the norm of study intervention. Rather, the effects of the intervention only appear once the norm of study has been met in the control condition. This point of divergence is earlier in low-norm-of-study simulations (i.e., norm of study = 70%). When the norm of study is 100 percent (perfect performance), the two conditions never diverge, because there is no more room for the norm of study to be raised.

Discussion

Drawing on theoretical assumptions common to most models of self-regulated learning (Pintrich, 2004; Puustinen & Pulkkinen, 2001), we simulated students as perfectly self-regulated learners. Concretely, this simulation instantiated the fundamental loop of self-regulated learning (Figure 1) using finite difference equations built on system dynamics theory.

A Self-Regulated Learner is Hard to Change

The results of the present simulation suggest that if we truly succeed in fostering the development of self-regulated learners, we might find that any further interventions are ineffective. For example, retrieval practice is a tried-and-true lab intervention showing the beneficial effects of self-testing on memory (see Rowland, 2014). Yet, classroom efforts to boost performance using retrieval practice interventions often fail when they rely on students engaging in retrieval practice on their own time (as opposed to during class time or as scheduled by an app, see (Kang et al., 2023; Sana & Yan, 2022). For example, Rowell et al. (2023) failed to find a beneficial effect of teaching students about retrieval practice in an introductory psychology course, even though the students in the treated condition engaged more frequently in effective study strategies. Results like these may not be indicative of an (entirely) ineffective intervention. Instead, they could reflect situations akin to those described in the current simulation. Traditional cross-sectional designs simply may not be able to

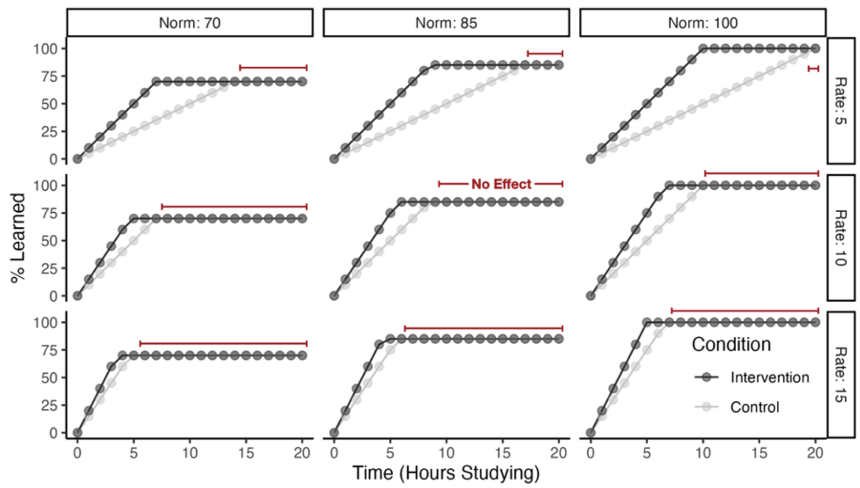

Figure 2: Learning Rate Interventions: Note: The x-axis maxes out at 20 hours for visualization purposes. The red horizontal intervals show the situations where the control and intervention conditions converge, indicating no effect of the intervention.

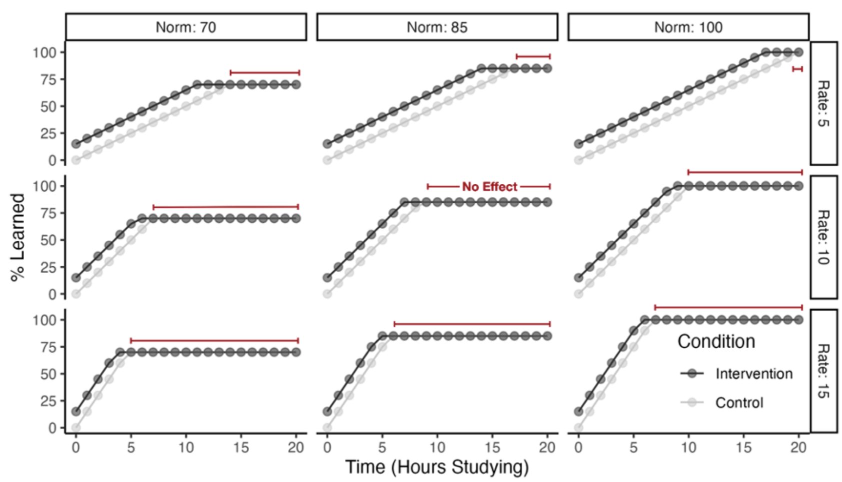

Figure 3: Intercept Interventions.

capture the effects of effective interventions after being mediated through self-regulated learning processes. Disconcertingly, the more effectively self-regulated students are, the less likely we may be able to find effects when trying to help them.

The present results might also help explain why educational interventions tend to be more effective for younger learners (Yeager et al., 2018). If one assumes that younger learners are less well-regulated, their outcomes should be more malleable. Of course, this conjecture ought to be studied further and other developmental mechanisms are likely to be involved. Furthermore, learners may be perfectly self-regulated in ways that educational psychologists might find counterintuitive. For example, it is possible that a self-regulated learner is failing their courses due to self-regulating to a much different goal than dominant educational paradigms assume (i.e., high achievement).

The present study also sheds light on the "glass half empty" problem first described by Schwartz et al. (2016), where seemingly all interventions seem to benefit at-risk students, but very few if any seemed to benefit non-at-risk or high-achieving students. This glass half-empty problem is fascinating because it seems to occur across various interventions that purport to leverage psychologically different mechanisms of behavior change. The self-regulated nature of students may explain why these psychologically distinct interventions have similar patterns of results. In our simulations, both the learning rate and intercept interventions benefited time-limited students. Norm of study was the only simulated intervention that benefited students with high time (t) investments' achievement, and only if their norm of study was below 100%. That said, rate and intercept interventions can help students with high norms of study, by increasing their learning efficiency.

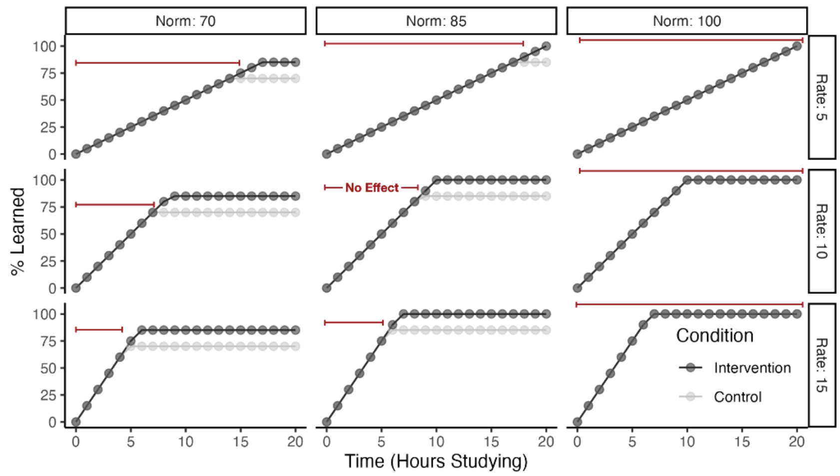

Figure 4: Norm of Study Interventions

How Can We Design Better Intervention Studies?

The implications of the present simulation may be discouraging. However, one potential path forward is through the adoption of research designs that measure and model fine-grained dynamics of student behavior over time (Hilpert & Marchand, 2018). For example, we could better understand the effects of our interventions longitudinally through ecological momentary assessment of study behaviors and learning.

Using this intensive longitudinal data, we could capture trajectories like those shown in Figures 2–4. This type of data would allow for the finer-grained analysis of student behavior over time and under different intervention conditions. In other words, analysis of educational interventions should focus not only on the end-product (i.e., GPA or standardized test scores) but also improvements to the process of self-regulated learning. Concretely, intervention studies may find it beneficial to measure learning efficiency in addition to learning outcomes.

Limitations

The primary limitation of the present simulation study is that it assumes perfect self-regulation and perfect metacognitive monitoring. Perfect monitoring accuracy was assumed for the sake of parsimony and to highlight a potential worst case scenario related to the paradox of self-regulated learning. In true educational contexts, students' ability to gauge their relationship to their norm of study is surely noisy and heuristic driven, as shown extensively in the literature on metacognitive calibration (e.g., Ackerman, 2019; Talsma et al., 2019).

Furthermore, the present model is a toy model; it simplifies the dynamics of self-regulated learning systems. Undoubtedly, there exist further feedback loops driving student behavior and educational outcomes in actual educational settings (Keith et al., 2024; Yeager & Walton, 2011). That said, by formalizing the process of self-regulated learning, this model enables us to refine our intuitions and deepen our understanding of how learning processes unfold (and how they should be measured). Furthermore, the present model follows closely self-regulated learning theory as it currently exists, instantiated in various models from Dunlosky and colleagues (Thiede & Dunlosky, 1999), Zimmerman (2002), and others (Puustinen & Pulkkinen, 2001). Accordingly, we must consider the implications of the consensus theory of self-regulated learning embodied in these models and illustrate potential issues with current analyses of educational field trials in light of these common assumptions. To contest the assumptions of the present simulation, would imply the need to reconsider theories of self-regulated learning.

Conclusion

The present findings suggest that well-motivated and self-regulated learners tend to resist external interventions in the long run, particularly those that target learning strategies or prior knowledge. However, the effectiveness of interventions becomes more pronounced in situations where students face time constraints and struggle to achieve their desired study norms. This is the paradox of self-regulated learning: Students cannot be simultaneously (entirely) self-regulated and (wholly) malleable. Generally, the less self-regulated our students are, the more effective our interventions will be. And conversely, the more self-regulated students are, the less effective our interventions will be. While the present model is by no means exhaustive, it presents a foundation for future research to develop more realistic representations of self-regulated learning and explore a wider array of interventions for a comprehensive understanding of optimal intervention design in the context of complex educational dynamics.

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