Learning to Choose Challenge

Growth mindset coaching: the next frontier of personalized learning

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We all know of promising students who develop the crippling misconception that they’re “just not good at math.” Technology can help us visualize the consequences of this belief as it forms. One example shows up in this player history graph of an addition math game, from a student we’ll call “Russell.” Russell decides to play addition levels 1, 2, 3, 4, 5, and 6. With each win he chooses to move up to more difficult math content. Then Russell loses on level 7, and this single loss seems to destroy his appetite for challenge. He previously beat level 6, now he doesn’t choose to venture past level 3.

Following his single loss, Russell isn’t advancing his math skills because he’s sticking to easier content. If this behavior persists, it may feed into a crushing cycle of avoiding challenge that would limit Russell’s future academic and life choices. Ideally, an alert teacher would witness Russell’s struggle, and coach him on his misguided belief about losing. But in a classroom full of students it’s impossible for a teacher to be ubiquitous. What if we could reach out with digital technology to help Russell in this moment?
A typical adaptive software program would automatically place Russell back to the appropriate challenge of level 7, or provide him with a tutorial. This might be beneficial in the short-term to help him learn the content, but there are two problems with this approach. Reducing choice, forcing Russell to solve a conveyor belt of problems he can’t control, would probably decrease his motivation. Also, at some point, Russell will be expected to shape his own learning trajectory, whether choosing a project in elementary school, a high school elective, or a college major. We don’t want to merely challenge him; we want to help him learn to choose challenge. The normal edtech personalization techniques – which vary the pace, difficulty, or style of the content – won’t suffice; we need to impact Russell’s psychology as a life-long learner so he can navigate any kind of content. To truly help Russell, we need a deeper form of personalized learning.

Growth mindset to the rescue

Why did Russell not persevere through challenge? A powerful explanation comes from the theory of growth mindset. Numerous psychological studies have shown that our belief about the malleability of own intelligence impacts motivation, how we react to success and failure, and how we perform on measures of academic success. Broadly put, learners with a growth mindset believe that their intelligence can expand through effort, challenge, guidance, and persistence. In contrast, learners with a fixed mindset believe their intelligence cannot be changed, and if they make mistakes, or exert a lot of effort, then they must have low ability. Math education, in particular, is rife with fixed mindsets, all the way through college; a recent study found that “of all the STEM fields (science, technology, engineering, and math), math scholars were the most extreme in emphasizing fixed, innate abilities.” Fortunately, a growing body of evidence has shown that mindset can be improved with training interventions.

Could we embed mindset interventions in the math game experience, coach Russell, and improve his approach to challenge? To explore this question, we built a mindset coaching platform and performed an experiment, framing struggle through challenge as the best way to grow one’s brain. The exciting results point to several opportunities to extend mindset coaching and make personalized learning more powerful for all.
Embedding growth mindset – an experiment

Because our experiment aimed to improve the quality of students’ choices, we chose to apply mindset coaching to Hungry Fish, a game in Motion Math’s suite which gives the player total freedom to choose any of the 18 levels of difficulty. In Hungry Fish, players merge integer bubbles together to feed a target sum to a fish; for example, 10 in the example shown below. In contrast to most addition practice, which asks students, “what is the one correct answer of 3 + 7?”, this game challenges students to find all the possible ways to create a 10, using two or more addends. More difficult levels feature larger sums. The game aims to help students improve their number sense and develop a flexible approach to addition.

To see if we could measurably help students like Russell, who avoid challenge, we randomly assigned classrooms of students to two different experimental conditions of Hungry Fish. One group of students (the Control) played the normal Hungry Fish; the second group experienced Mindset Coaching. (A third group of students was placed into a Rewards condition. The details of the entire experiment, which built on previous exploration with the fractions game Refraction, are presented in the Appendix.) More than 5,000 students in grades 2-6 participated in the experiment over a period of three months.
Students in the Mindset Coaching group experienced three differences in their version of the game. First, they saw a brief introductory slideshow, which coached them about the principles of growth mindset using the metaphor of a brain which grows by lifting heavy weights.

Second, right at the highly relevant moment of victory and defeat, results were presented in terms of growth mindset and brain growth, rather than traditional success or failure. Students who won a level that was too easy (based on their previous record of wins and losses) were encouraged to try something more challenging, while students who lost an appropriately challenging level were encouraged with the message, “Great brain workout!”
Finally, while students in the Control group chose any level between 1 to 18 using a slider, Mindset Coaching students had their choices reduced and framed in the language of growth mindset. These students chose between four levels: one below their appropriate challenge (symbolized by a sleeping brain), two within (a brain successfully lifting weights), and one above (a brain unable to lift the heavy weight).
Mindset coaching for the win

Would students in the Mindset Coaching group choose challenge more often? We analyzed not only this central question, but also how students would perform throughout the learning process: from content engagement, to challenge selection, to persistence through challenge, to content mastery. Compared to the Control group, students in the Mindset Coaching condition scored higher in all four stages:

- **Engagement**: the percentage of time each student chose to play Hungry Fish within the nine-game suite
- **Challenge**: the percentage of levels a student chose to play that were challenging
- **Persistence**: the percentage of challenging levels a student completed without quitting
- **Mastery**: the highest level a student consistently won (expressed as a percent of the total levels)
Importantly, the positive impact of mindset coaching on challenge, persistence and mastery did not come at the cost of engagement; we initially feared that coaching might dampen the player experience by appearing pedantic or disrupting game flow. That coaching seems to have increased engagement is a particularly exciting outcome because engagement is the gateway to learning and one of the core promises of digital learning. We were also happy to find that the effects were consistent across genders. This initial investigation combined several features into each treatment condition to explore multiple questions; future experiments will tease apart the individual impact of mindset messaging, choice constraints, choice framing, and results framing. For now, the experiment demonstrates that embedded coaching can help students improve the effectiveness of digital learning, and inspires us to think big.

Our vision: personalized learning for the whole learner

Beyond this initial experiment, what would personalized mindset coaching look like, when fully realized? Let’s imagine a day of Russell’s life as a learner. In math class, Russell interacts with research-backed coaching that’s integrated throughout his math games, practice problem sets, and constructivist digital projects. This coaching frames critical moments of frustration and success, guides his decisions, and helps build a growth mindset in math. In Language Arts, Russell already believes he can become a strong writer, and exhibits a growth mindset. However, he sometimes struggles to concentrate while writing, so personalized coaching focuses on self-regulation, guiding him to visualize his future self and how he’ll avoid distraction along the journey. At home, Russell struggles to find the motivation to complete science simulation assignments, so coaching taps into Russell’s altruism: he learns by giving feedback to struggling students. From all these experiences, Russell gets feedback on how he’s growing as a learner and his teachers get feedback as well: not just about Russell’s academic performance or his time-on-task, but his behavior, his choices, as a digital learner. His teachers can use this information to steer how they motivate and reach Russell in class, and even influence the digital coaching content.

How might we realize this vision of truly personalized learning, beyond games, beyond math, and even beyond growth mindset? How might personalization not only adjust learning content, pace, modalities, and difficulty, but also improve each learner’s approach to learning? We see three major guiding principles for the future of personalized mindset coaching.
Respond to ongoing behavior

First, mindset coaching should be continuous and based on student actions. Too often, when educators try to move the needle on growth mindset, they merely put up posters on the wall, or show videos a few times a year. However, to coach students in a personalized way, we need ongoing insight into who is struggling with mindset, and in what contexts.

Typically, mindset is measured by giving students surveys and asking them to respond to statements such as “The harder you work at something, the better you will be at it.” These surveys are problematic as formative measures; not only do they consume valuable instructional time, but students learn to give answers that match the ideals of their teachers, as Carol Dweck, the discoverer of growth mindset, has herself lamented. In contrast, embedded measures of student behavior enable timely and personal feedback at critical moments, such as when Russell turns away from challenge, that would augment rather than interrupt learning.

In order to bring coaching to critical moments in diverse subjects, we need a way to represent learner behavior in a generalized way, not limited to Hungry Fish, or math, or even games. That’s why we built our coaching platform to operate on content-agnostic models. These models describe learning (each step, problem, and level a learner completes), personal challenge (the set of problems predicted to be challenging for each learner), and choice (how a learner quits, persists, and moves to and from challenge). Nearly any learning application could be represented with these abstractions and readily hooked into the platform to embed personalized mindset coaching into the digital learning experience.

Leverage diverse factors

Second, coaching should draw on research about the diverse psychological constructs that impact learner outcomes. While growth mindset is one of the most promising, it’s certainly not the only one. The remarkable range of factors was displayed in a recent issue of the Journal of Educational Psychology, dedicated to “a promising but underexplored approach
to improving students’ motivation and learning in schools: the design and implementation of psychologically informed instructional activities to change students’ attitudes and beliefs.” These interventions improved many factors of learning, including self-control, persistence, self-affirmation, and belonging. If these interventions can be thoughtfully integrated with ubiquitous digital learning experiences, we’ll more quickly figure out what kind of coaching works and ultimately provide more impact to a greater diversity of students.

We have already begun experimenting on how to impact these other factors of learning, with promising early results. For example, for students who seem to display low confidence, we encourage them by showing their past successes. For students who seem to have low self-regulation (e.g. they quit and jump around often), we encourage them to reflect and reconsider before they quit a level. For students who seem to lack a level progression plan, we provide an interactive brain visualization, which students grow by “feeding” it challenging levels. For students who seem to display low effort, we appeal to altruistic motivation; by changing language from “show what you can do; try your best” to “help us improve our software by trying your best,” we improved learner effort by 5% (p < .05, across 1120 assessments). It would be a waste of instructional time to show these targeted interventions to every student because, for example, for students who already exhibit great focus and self-regulation, telling them not to quit is unnecessary and potentially counter-productive. We’re eager to continue our experimentation to intervene at the right time, with the right students, with the right research-backed content, to help all students develop healthy learning habits.

Coaching for the long-term: a self-directed learner

Finally, we think it’s crucial that personalized digital coaching stays focused on the ambitious long-term goal of helping students become self-directed learners. This will partially be achieved by empowering teachers: there are tremendous opportunities to support teachers by surfacing the choices students make in digital learning environments. Within the classroom, teachers can readily observe visible signs of student confidence, challenge-seeking, persistence, and self-regulation. But these vital characteristics are more difficult to observe when students work digitally. Motion Math has just released a “factors of learning” dashboard to show teachers our internal behavioral measurements; we’re in the early stages of
understanding how teachers can best use this data to keep the digital pulse of their students. Initial testing indicates that with insights into students’ choices and responses to challenge, teachers can provide amplified and personalized support for those who need it most.

In addition to empowering teachers, personalized coaching should leverage the most underutilized resource in education: students themselves. “The most powerful learners are those who are reflective, who engage in metacognition – thinking about what they know – and who take control of their own learning”; indeed, leading researchers have posited that the ability to make good choices is the most important educational outcome. This necessarily requires exploration, missteps, dead ends, and failure. Giving a student meaningful choices is a long-term bet. It can look like wasted time, but it’s worthwhile if the student discovers that:

1. Choices abound in all my learning trajectories
2. I have agency over many of these choices
3. These choices will help or hinder my learning

Two generations into the era of digital learning, the promise of personalization – that we can support the distinct needs, interests, and goals of each student – remains captivating, is yet unrealized, and is worthy of an expanded approach. We’re confident that personalized coaching can be an important part of realizing the promise, and help students become self-directed learners.
Acknowledgements

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Notes

1. “Such subjective construals—and interventions or teacher practices that affect them—can affect behavior over time because they can become self-confirming. When students doubt their capacities in school—for example, when they see a failed math test as evidence that they are not a “math person”—they behave in ways that can make this true, for example, by studying less rather than more or by avoiding future math challenges they might learn from. By changing initial construals and behaviors, psychological interventions can set in motion recursive processes that alter students’ achievement into the future.” Yeager, David S., Carissa Romero, Dave Paunesku, Christopher S. Hulleman, Barbara Schneider, Cintia Hinojosa, Hae Yeon Lee et al. “Using design thinking to improve psychological interventions: The case of the growth mindset during the transition to high school.” Journal of Educational Psychology 108, no. 3 (2016): 374.


7. Note for example, a well-regarded definition of personalized learning, which references learner motivations and goals, but not psychological factors such as mindset: http://www.edweek.org/ew/collections/personalized-learning-special-report-2014/a-working-definition.html
19. The decision to group by classroom was made to ensure a common user experience for co-located students. Unlike typical A|B experiments that test small or invisible features, the significant visual differences in our treatment conditions threatened to contaminate the user experience by opening the possibility of students comparing, contrasting, and discussing their alternative conditions. As such, we chose to group experiences by classrooms but analyze the results at the level of the student, because gameplay behaviors and performance are still largely individualized. This decision amounts to a tradeoff between independence in selection and treatment contamination. We sided with avoiding the latter and performed a secondary analysis to see if this selection method resulted in unbalanced groups in terms of our experimental metrics. We found that students who played Hungry Fish prior to the experiment were statistically similar in terms of playing in and above ZPC, as well as their level of mastery in the app. Furthermore, students who were selected for the Control condition scored higher in engagement and persistence in pre-experiment play than students who were selected for the Mindset and Rewards conditions, trends which reversed after treatment. This analysis provides us with a degree of confidence in the experiment results.
Appendix: Experiment Details

Our experiment began with the following questions, aimed at understanding how best to improve student orientation toward challenge:

- Can we improve student’s relationship to challenge by explicitly rewarding effort in challenging levels?
- Is it more effective to coach students about why it is important to challenge themselves, in addition to rewarding them?

Experimental Platform

To answer these questions, we built an experimental platform that measures the impact of real-time content interventions in response to gameplay. The experimental capabilities of the platform include:

1. Real-time modeling of a student’s Zone of Proximal Challenge (ZPC) – the range of levels that provide a reasonable to extensive challenge for the student (roughly, 25% to 75% chance of success).

2. Real-time tracking of student choices and behaviors with respect to ZPC, including whether or not a selected level is below, in, or above ZPC, and if the student wins, loses, or quits.

3. The ability to create personalized coaching around a pre-existing game by displaying content at critical moments of gameplay (application start, level difficulty selection, level result, and achievement/rewards views). Importantly, this content can be customized with respect to student choices as they occur in real-time.

4. The ability to conduct A/B tests to measure the impact of coaching interventions on metrics of interest: engagement, mindset, mastery, etc.

Personalized Coaching Conditions

Using this platform, we built three independent versions of personalized coaching around Hungry Fish, a popular addition game in the Motion Math suite. In the (1) Mindset condition, students were presented with an introductory slideshow explaining one important component of growth mindset: the idea that challenging yourself is necessary for growing your brain. This messaging was also used to frame challenge selection and level results. The (2) Rewards condition also framed level selection and results, but in terms of rewards rather than mindset and effort. Lastly, the (3) Control condition consisted of the existing Hungry Fish game that rewarded achievement regardless of personal challenge.

For the Mindset and Rewards conditions, content was customized based on student choices and achievements relative to their personal ZPC. The content of each condition is outlined below.
Mindset Condition

Intro Slideshow
Students in the Mindset condition were treated to a one-time introductory slideshow that included avatar selection (with a choice of gender) and messages conveying the benefits of struggling through challenge.

Level Selection View
Level selection was framed as a choice between three degrees of challenge: too easy, appropriately challenging, and too hard, each with images from the slideshow indicating the degree of brain workout. Appropriately challenging levels also indicated the potential for rewards.
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**Level Result Views**

Level results were framed in terms of degree of challenge. Importantly, if students lost in an appropriately challenging level, they were reminded of the benefit of that struggle. On the other hand, if they excelled at an easy level, they were reminded of the vacuousness of success absent challenge.

“Too Easy” Loss  
“Challenging” Loss  
“Too Hard” Loss

“Too Easy” Win  
“Challenging” Win  
“Too Hard” Win

**Achievement Views**

Finally, when students earned rewards in the Mindset condition, they were further reminded of the positive impact of challenge on their learning.

"Sophia’s Challenges"
Rewards Condition

Students in the Rewards condition were not presented with an introductory slideshow or mindset-related messaging. Rather, level selection and feedback were framed in terms of rewards for achievement in appropriately challenging levels.

Level Selection View

The range of levels where rewards are available were personalized for each student based on ZPC, and highlighted during level selection.

Level Result Views

Level results reinforced the concept that rewards were only provided for wins on challenging levels.
Achievement Views
Finally, the achievement view reinforced the mechanism that rewards were administered for success in challenging levels.

Control Condition
The Control condition integrated level result, rewards, and level selection, into one screen. With the completion of each level, students were given feedback and rewards based on winning or losing, regardless of level of personal challenge, and selected difficulty using a slider bar.

Integrated Level Selection, Level Result, and Achievement Views

Level Loss
Level Win
Hypotheses

Our hypotheses regarding the effect of these conditions on student play were as follows:

1. Students in the Mindset condition would seek out appropriate challenge and persist through challenge at greater rates than students in the Control and the Rewards condition.

2. Students in the Mindset condition would achieve higher levels of mastery than students in the Control and the Rewards condition.

3. Students in the Mindset condition might be less engaged with Hungry Fish relative to students in the Control or Rewards conditions.

Methodology

We performed a split treatment (A|B|C) experiment by randomly assigning a subset of Motion Math students, grouped by classroom, to each of the three experimental conditions. Data from naturally occurring gameplay within the classrooms was collected during February, March, and April, 2016. Students who played Hungry Fish at least once were included in analysis (Control=721, Rewards=2590, Mindset=2419).

We then performed an Analysis of Variance (ANOVA) to determine if there were significant differences in the effect of each condition on four metrics of interest:

<table>
<thead>
<tr>
<th>Category</th>
<th>Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engagement</td>
<td>Hungry Fish Share: the percentage of Hungry Fish play time versus the rest of the game suite (i.e. how much each student engages with the game).</td>
</tr>
<tr>
<td>Mindset</td>
<td>Challenge Seeking: the percentage of levels completed by the student within and above ZPC. This metric excludes quits as they tend to be associated with exploration or lack of self-regulation at high difficulty, rather than challenge-seeking. (Lack of) Persistence: the percentage of levels started in ZPC in which the student quits. Quits at the end of sessions are excluded, as these tend to result from teacher-imposed classroom transitions.</td>
</tr>
<tr>
<td>Mastery</td>
<td>Zone of Proximal Challenge (ZPC): the range of Hungry Fish levels our model deems challenging but achievable for the student, based on their historical play. The midline of this range is used as the measure of the student’s level of mastery of the app content.</td>
</tr>
</tbody>
</table>
Results

The results indicate that the Mindset condition was most effective in lowering quit rates, increasing the amount of time students play challenging levels, and, importantly, attaining higher levels of mastery within the game. Students in the Rewards condition enjoyed similar benefits, although the impact on mastery was not as pronounced.

Engagement

Students in the Mindset (16.6%, Z=.456) and the Rewards (15.9%, Z=.433) conditions played Hungry Fish at a higher rate than students in the Control (5.7%) condition (p < 3.2x10-46). This suggests that personalized coaching with mindset messaging is as appealing as coaching with rewards messaging, and that more explicit coaching is generally more appealing than unguided challenge selection.

Mindset

Challenge-Seeking

Students in the Rewards and Mindset conditions completed levels above ZPC more than students in the Control group, and below ZPC less, suggesting greater challenge seeking. Between Rewards and Mindset, students in the mindset group played below challenge slightly more, suggesting that the Rewards group may have “chased rewards” even outside the suggested range, whereas students in the Mindset group were selecting challenge more judiciously and reinforcing their mastery of sub-challenging levels. Specifically:

- Students in the Control (10.1%) condition completed levels below ZPC more often than students in the Mindset (8.8%, Z=.076) and Rewards (7.0%, Z=.177) conditions (p = 0.007).
- Students in the Rewards (42.6%) condition completed levels above ZPC at a higher rate than students in the Control (31.6%, Z=.322) and Mindset (40.9%, Z=.048) conditions (p = p < 2.0x10^-5).
- Students in the Control (20.9%) condition completed levels in ZPC at comparable rates to students in the Mindset (21.1%, Z=.005) and Rewards (21.2%, Z=.008) conditions (p = .993).
- Students in the Control (37.2%) condition quit levels at a higher rate than students in the Mindset (29.1%, Z=-.265) and Rewards (29.2%, Z=-.261) conditions (p = 2.8x10^-4).
Persistence

Students in the Control (15.4%) condition quit in challenging levels more frequently than students in either the Mindset (8.2%, Z=-.375) or the Rewards (8.0%, Z=-.383) conditions (p = 9.1x10^-9). Note that a negative effect size indicates a lower quit rate vis-à-vis the Control condition. This suggests that selecting levels with a clear outcome in mind has a significant impact on whether the student will persist through to the end of the level, regardless of outcome.
Mastery

Students in the Mindset (11.27) condition achieve overall higher levels of mastery (ZPC Midline) within Hungry Fish than students in the Rewards (10.72, Z=.159) and Control (10.49, Z=.233) conditions (p = 2.3x10^-4). These results confirm the benefits of playing and persisting through challenge. More specifically, they suggest that occasionally playing sub-challenging levels contributes to overall mastery more so than occasionally playing super-challenging levels (the main distinction between the Rewards and Mindset condition effects).

Gender Analysis

Given that there is a documented gender discrepancy in mindset, with girls more likely to be damaged by fixed ability beliefs, we performed a breakdown of the results by gender to see if there were any differences in the impact of the treatment conditions. To do this, we performed post-hoc tagging of gender for all students in the experiment based on student name (categorizing them into male, female, and undetermined). We then ran a consistency check against a set of teacher surveys that included gender, as well as with the gender of the avatars the students selected. The consistency check indicated that our gender tagging was sufficiently reliable for this analysis, matching survey responses with 95.5% accuracy (n=111) and with avatar selection with 92.5% accuracy (n=1460). As a cross-check, we confirmed that survey response matched avatar selection 100% of the time (n=29).

In general, the gender subgroup results matched those of the overall experiment, with two minor exceptions. First, girls in the Mindset condition played below ZPC at a higher rate than girls in the Rewards condition (Z=.135, p=0.21), while Boys in the Mindset and Rewards condition played below ZPC at comparable rates (Z = .04, p=.63). Second, girls in the Mindset condition quit in challenging levels at a higher rate than girls in the Rewards condition (Z=.086, p< .01), whereas boys in the Rewards condition quit in challenging levels at a higher rate than boys in the Mindset Condition (Z=.039, p< .01). Overall, these results indicate that the effects of the Mindset and Rewards interventions were consistent across gender lines, with the exception of these relatively small differences in the areas of challenge selection and persistence.
Discussion

The results of the experiment are promising, particularly the finding that framing challenge selection and achievements in terms of growth mindset is as engaging and effective as rewards alone. This should be explored further in the larger context of learning technologies, as rewards are often leveraged as a critical component of retention and engagement; that mindset coaching may yield equal engagement and greater learning gains is a prospect worth pursuing. The finding that more conscious challenge selection may positively impact persistence is also exciting, and illustrates the power of attention, reflection, and metacognitive awareness throughout the learning process.

The experiment also merits several follow-up investigations to understand the individual effects of mindset messaging, choice constraints, choice framing, results framing, and rewards. It’s important to note that this experiment contrasted the effects of full feature sets rather than isolated variations within the same feature set. Thus, although the combined effect of each intervention is known, the individual contributions of subcomponents (e.g. mindset messaging versus constrained choice for the Mindset condition) are not. This was a conscious practical approach, intended to yield insight into which coherent combinations are most promising, which should be readily discarded, and which should be built upon and studied further. For example, we might wish to understand the exact impact of mindset messaging versus constraint of choice on challenge selection. To do this we might compare the current Mindset variant of four level options with another that provides an open level slider. With our platform, future experiments can be instrumented and evaluated quite readily, dependent only on custom content creation for each treatment variant.

Finally, the experiment reveals a tremendous opportunity for more targeted student interventions, particularly for subjects who did not respond to the current set of treatments. The metrics we used to evaluate the treatment conditions reveal subgroups who do not respond to initial interventions, suggesting an evolutionary process whereby the outcome measures are used as inputs to identify specific groups for more nuanced intervention. This is a promising cycle that we seek to implement in further iterations of research.