Stretching the Zone of Proximal Development:
Accelerating Learning Through ZPD Elasticity

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Abstract
Vygotsky's (1986) theory of the Zone of Proximal Development (ZPD) is often cited in pedagogical approaches that position the learning just above the learner's independent problem-solving level, but which the learner can do with the help of a More Knowledgeable Other (MKO). However, these approaches reflect only a partial understanding of Vygotsky's work, which describes learners of the same ability level as having ZPDs with vastly different potential for "stretching" to more complex content (Zaretskii, 2009). Learning situated at the outer limits of one's ZPD has the potential to increase the efficiency and quantity of learning over traditional methods of instruction. The present Randomized Control Trial placed Pre-K to 2nd grade learners (N = 1407) into a business-as-usual control group, or a treatment condition designed to explore the elasticity of their ZPDs and its leveraging effects on their learning. Key findings showed that when compared to the control group, learners in the treatment group were able to significantly increase their learning pace and the amount of content learned, while continuing to demonstrate mastery of the content. Implications from this work suggest that better understanding and leveraging the ways in which learners' ZPDs demonstrate varying elasticity (ability to stretch) may provide opportunities to accelerate learning and mastery of content, especially for learners who are most at risk for not meeting grade level expectations.

Keywords: Learning Sciences, Early Childhood Education, Literacy, Zone of Proximal Development, Learning Acceleration, Personalized Learning, Adaptivity, Smart Learning Systems, AI, Machine Learning, Big Data, Vygotsky, Bloom, Achievement Gap

Introduction

The performance of K-12 students in the United States has long faced significant challenges in mathematics and reading. National measures of achievement have consistently shown more than two-thirds of 4th and 8th graders performing below proficiency expectations (deBrey, et al., 2019; NAEP, 2022), with measures of international achievement well behind their peers in other nations (NCES, 2022; OECD, 2022). The recent Covid-19 pandemic intensified this challenge, with many learners as much as two years behind their grade level expectations (Dorn et al., 2021; Patrinos, Vegas, & Carter-Rau, 2022). Additionally, related research shows that students who leave kindergarten without critical math and literacy competencies are likely to fall further behind as they move from grade to grade (Duncan et al., 2007). Contributing to these challenges is dramatic learner variability present before learners even begin formal schooling (Thai, Betts, & Gunderia, 2022; Pape, 2018). Learners often begin kindergarten with vast differences in their prior knowledge and readiness-to-learn in school settings (Betts, Thai, Jacobs, & Li, 2020; McWayne et al., 2012). These differences are often exacerbated rather than addressed by traditional methods of instruction that target the collective learning needs of both whole and small groups of learners rather than the unique needs of individual learners. Unlike one-to-one tutors, most classroom teachers simply do not have the time to assess and address every individual need of each learner (Bloom, 1984).

The Problem

Addressing lost learning opportunities requires understanding and mitigating the factors that contribute to disparities in learning outcomes. It requires acknowledging that curricula and instructional approaches that adhere rigidly to grade-level standards without considering students' readiness-to-learn can cause gaps to form in the learner’s architecture of understanding. To bridge these gaps, a two-pronged solution is essential. Firstly, there must be mechanisms to swiftly identify and address gaps or misunderstandings in foundational or prerequisite content. Secondly, adaptive learning pathways that utilize individual learners' existing competencies to efficiently facilitate new learning must be developed. Solving for this in traditional classrooms is extremely difficult due to time and resource constraints. However, through combining various principles of the learning sciences and the affordances of “Smart Learning” systems that incorporate Artificial Intelligence and machine learning, it is now possible to develop solutions that can address these challenges at scale (Betts et al., 2020; Betts, Thai, & Gunderia, 2021).

Theoretical Framework

Various theories explain why some children seem to learn easily while others do not. Bloom's (1984) theory of Mastery Learning challenged traditional educational models by suggesting a move from ‘one-size-fits-all’ teaching modes to more personalized approaches. Bloom explained that the typical classroom setting, where all students receive the same instruction at the same pace culminating in a standardized assessment, benefitted some students while disadvantaging others (Guskey, 1997). For example, in traditional settings the test often marks the *end* of learning a concept, affording students only one chance to demonstrate their understanding. Moreover, learners are frequently required to move on to subsequent content whether or not they have mastered prerequisite content (Au, 2007). Consequently, this approach can create a cumulative disadvantage for those who do not grasp concepts as quickly, leading to a widening gap in understanding as the curriculum progresses (Bloom, 1968, 1984; Guskey, 1997).

In contrast, Bloom's observations of one-on-one tutoring revealed a strikingly different outcome. Tutors provided highly individualized feedback, allowing students to proceed only after they had shown proficiency in the current topic (Bloom, 1984; Guskey, 1997). This required the tutor's deep knowledge of the content, including understanding of granular learning objectives and optimal learning trajectories (Guskey, 1997). This led Bloom to posit that if classroom instruction could emulate the individualized approach of tutors, including elements like detailed knowledge maps, pre-assessments, targeted feedback, corrective measures, and enrichment activities, all students could achieve a higher level of understanding (see Figure 1; Bloom, 1968, 1984). Bloom's Mastery Learning theory held that all students could achieve with the right pace, high-quality materials, and pedagogy.

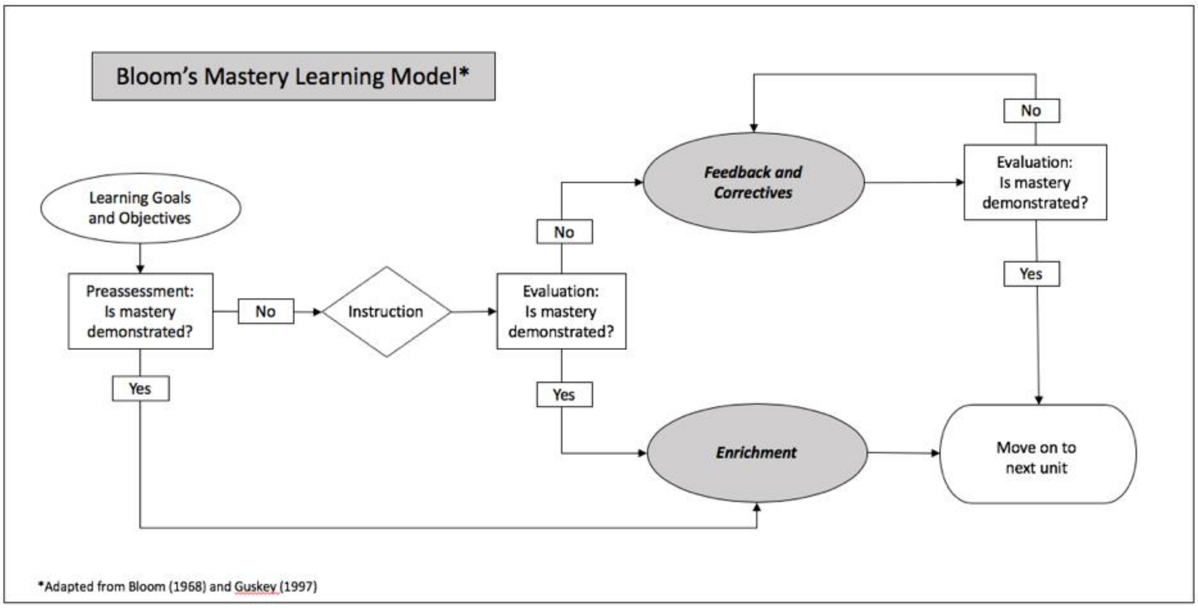

Figure 1: Bloom's Mastering Learning Model. Adapted from Bloom (1968) and Guskey (1997), sourced from Betts (2019)

Long before Bloom, Vygotsky (1986; Vygotsky & Cole, 1978) described the optimal conditions for learning—primarily the importance of learning that was guided by a More Knowledgeable Other (MKO) through Zones of Development (ZoD). Today, the application of Vygotsky's theories in K-12 education often lacks depth (John-Steiner & Mahn, 1996). Typically, the role of the MKO is narrowly ascribed to the teacher, overlooking the diverse array of individuals and resources that can facilitate learning (Rogoff, 1990), including "Smart Learning" digital resources that deploy "intelligent tutors" (Betts, Thai, & Gunderia, 2021). Moreover, common understanding of Vygotsky's ZoDs has frequently been reduced to a narrow focus on only the Zone of Proximal Development (ZPD)—without a clear understanding of how that ZPD fits within the overall learning theory. Furthermore, the ZPD is frequently misunderstood as a fixed range or level that can be addressed through uniform strategies (i.e., the very next thing to be learned), rather than as a fluid and elastic space of potential development unique to each learner (Zaretskii, 2009; Vygotsky, 1986).

Vygotsky's framework for understanding learning and development encompasses several zones that are critical to optimizing learning (see Figure 2; Zaretskii, 2009). The Zone of Actual Development (ZAD) represents what a learner can accomplish independently and serves as a baseline for assessing potential growth (Vygotsky, 1986). The Zone of Proximal Development (ZPD) is the area where learners can perform a task with guidance and support of an MKO; this is where learning is most effective (Chaiklin, 2003; Vygotsky, 1986). Beyond the ZPD lies the Zone of Insurmountable Difficulty (ZID), where the task becomes too challenging for the learner, even with assistance or help of an MKO (Daniels, 2008; Vygotsky, 1986). More importantly, at the boundary between the ZPD and the ZID lies the Point of Difficulty (PoD), which represents the point at which the potential for maximum learning with an MKO can occur (Vygotsky, 1986; Zaretskii, 2009). A comprehensive understanding of these zones enables educators to scaffold instruction effectively in the moment, ensuring that students are neither under-challenged within the ZAD nor pushed beyond their ZPD into frustration (Gallimore & Tharp, 1990).

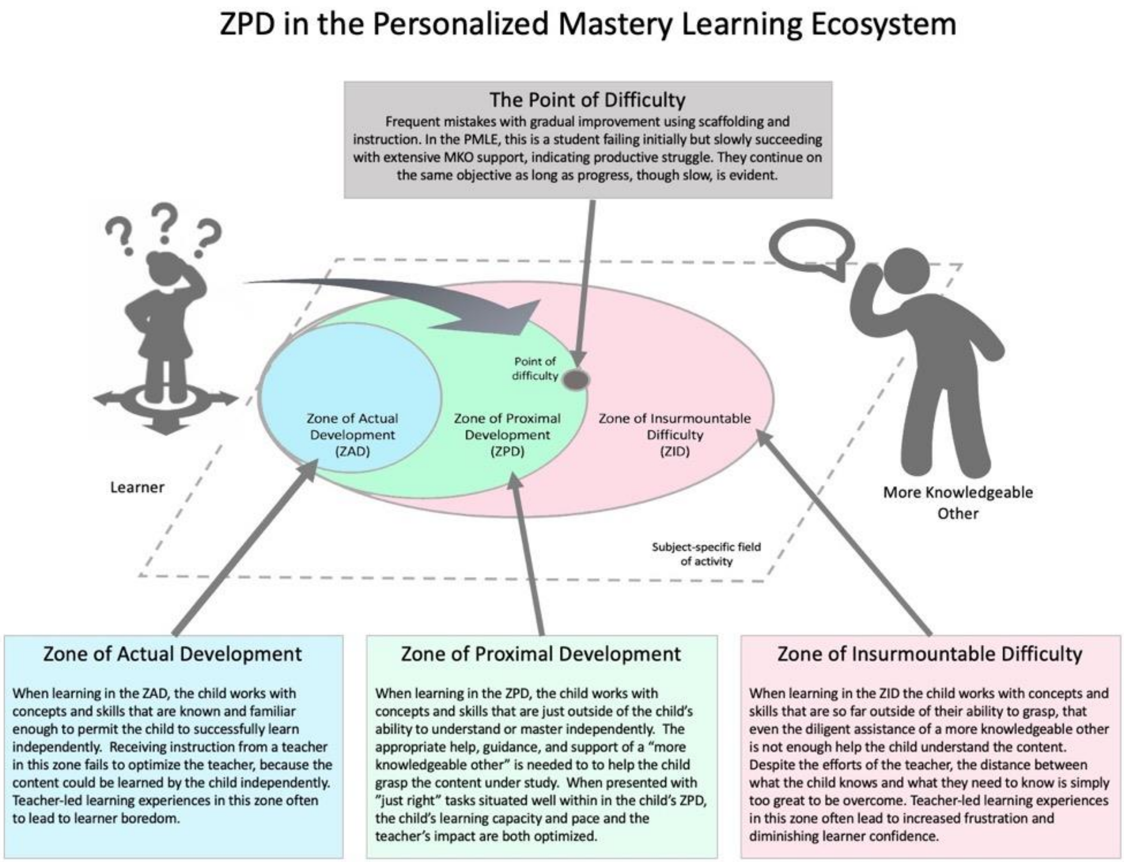

Figure 2: Vygotsky's Zones of Development (Betts, Thai, & Gunderia, 2021; Zaretskii, 2009)

Furthermore, it is vital to understand the ways in which each learner's ZPD varies. Citing Vygotsky's work, Zaretiskii (2009) explains that while two learners are similar in terms of their actual development, they may differ greatly in what they can learn with support:

> One child can solve problems at a nine-year-old level, while the other one performs at a twelve-year-old level. This begs the question: do the levels of development of these children differ? Obviously, yes, but not in terms of their actual level. Instead, they differ in terms of the breadth of their ZPD. One child, as Vygotsky wrote, has a ZPD that is four years ahead of his mental age, while the other is one year ahead. In terms of the state of maturing processes, one child has gone four times farther than the other, and this must be kept in mind both in assessing that child's development and in educating him (p. 75).

Understanding the elasticity of the ZPD is an important part of increasing learning efficiency. It may also inform the design of interventions, including those deployed in Smart Learning systems, that are sensitive to learners' individual capabilities and can quickly identify the optimal level of challenge required for learning, thereby fully leveraging the potential of the ZPD (Zaretskii, 2009).

Building "Smart Learning" Systems That Leverage Bloom and Vygotsky

Applying the learning theories of Bloom and Vygotsky, the learning engineering team at Age of Learning, an international EdTech company, has spent nearly a decade developing a smart learning system for identifying and teaching students within their ZPDs. This Personalized Mastery Learning Ecosystem (PMLE) uses formative assessment, direct instruction, and dynamic scaffolding features to locate a student's ZPD and act as a More Knowledgeable Other to facilitate optimal and efficient learning (Betts, Thai, & Gunderia, 2021; Owen & Hughes, 2019; Thai, Betts, & Gunderia, 2022). This system is the underlying framework upon which our personalized learning program—My Reading Academy—is built.

Components of the Personalized Mastery Learning Ecosystem (Adaptive System Only)

The complete Personalized Mastery Learning Ecosystem is comprised of many components. For the purposes of the present discussion, only the components of the digital adaptive personalized learning system used by the student are discussed. Other components of the PMLE (e.g., parent/caregiver portal, teacher portal, etc.) are beyond the scope of this study (e.g., see Betts, Thai, and Gunderia, 2021; Thai, Betts, and Gunderia, 2022).

Knowledge Map

To find a student's ZPD, it is important to have a comprehensive understanding of the possibility space for a learner's potential ZPD. In the PMLE, this possibility space is described in a data structure called a Knowledge Map (KM). Deeply aligned with Bloom's (1984) theory of Mastery Learning, a KM is a framework that uses discrete and granular learning objectives to map out all the relationships between concepts, principles, skills, and data in a knowledge space (e.g., foundational reading skills, etc.). A KM provides the basis for efficient identification of what students know, what they do not yet know, and what they are most ready to learn next (Figure 3). Each "node" on the KM represents a specific learning objective (LO). These LOs are connected by various relationships (e.g., pre-requisite, successor, parallel, etc.), forming numerous potential pathways through the KM for students to achieve mastery in a subject (Figure 4).

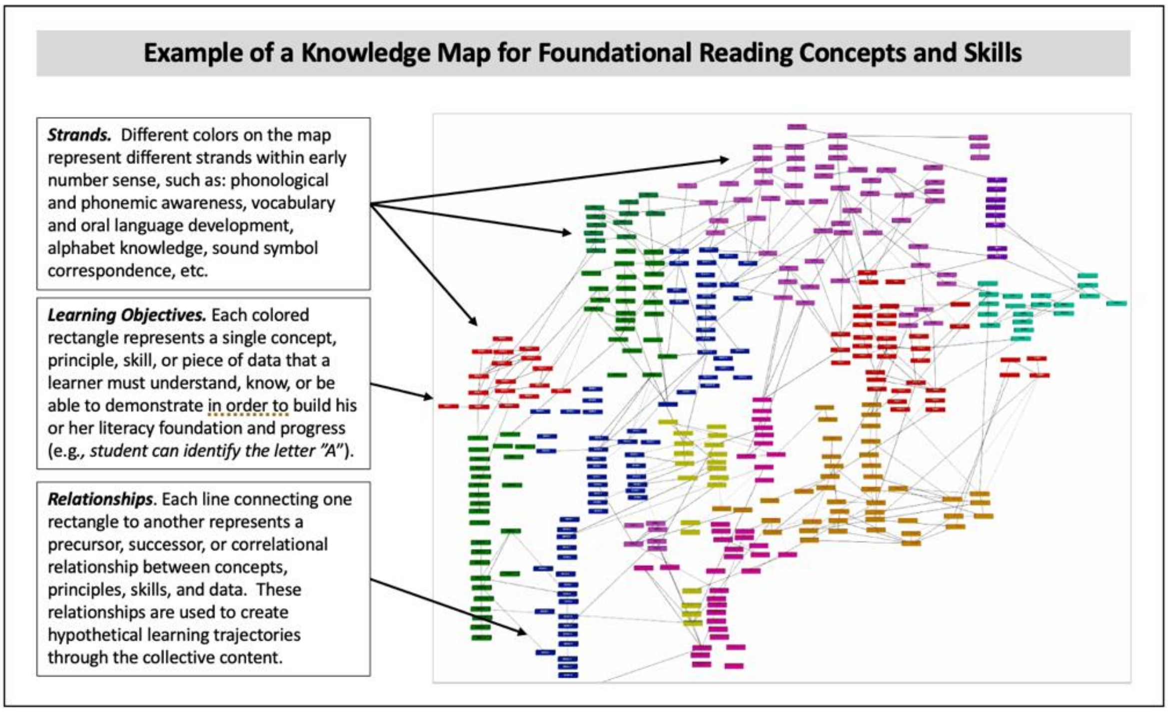

Figure 3: Example Knowledge Map

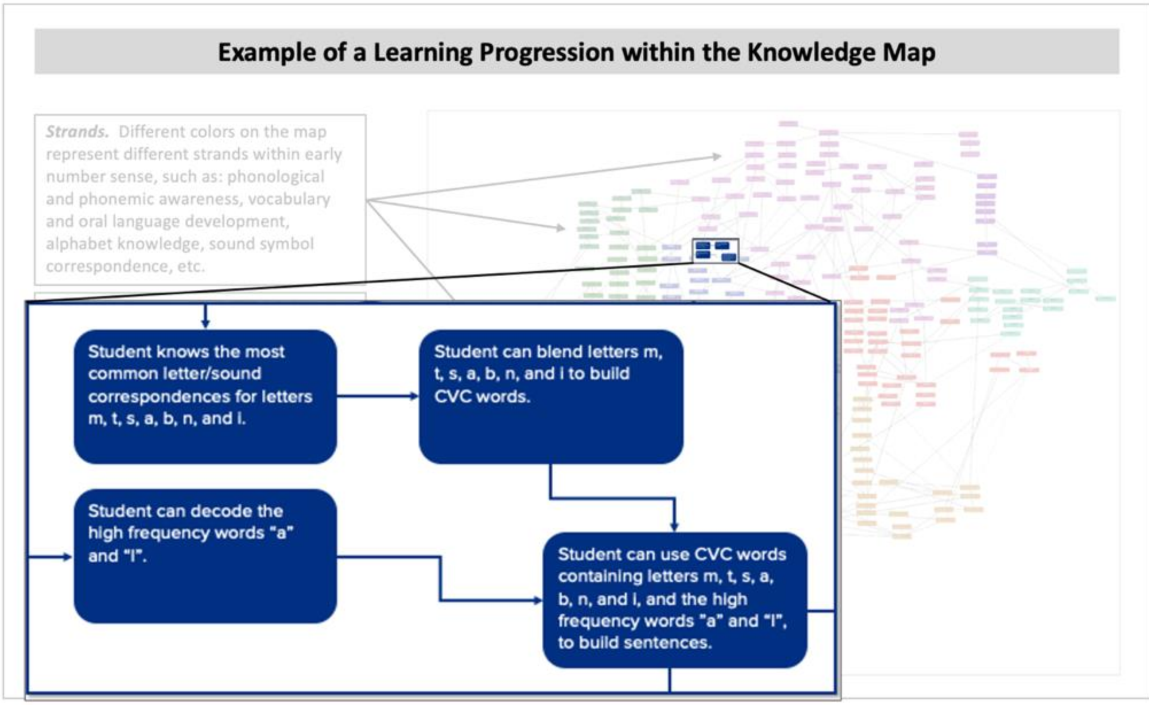

Figure 4: Example learning objectives in a learning progression

Learning Activities

Students advance through the system by demonstrating their mastery via digital interactions called Learning Activities (e.g., games, digital books, etc.). These activities are continuously assessed to determine the learner's level of understanding, and to identify where and when MKO features (e.g., wrong answer feedback, scaffolding, modeling, etc.) can be deployed to advance in-the-moment learning. Within the system, there are two main types of learning activities: *Direct Instruction* and *Scaffolded Assessment (*i.e., practice activities with formative assessments).

Direct Instruction

Digital games or videos used for explicit teaching of specific objectives are defined as Direct Instruction. For example, My Reading Academy uses videos featuring Miracle, a human host, and Nano, a virtual robot (Figure 5). Miracle is the digital embodiment of the MKO who both instructs and provides feedback and scaffolds to Nano, who proxies the student. Nano, by design, always learns in their ZPD, mirroring potential student questions and misunderstandings. In this way, the student benefits from the support of the MKO even when they are not able to directly interact with her.

Figure 5: Human host Miracle acts as the MKO for Nano, the robot proxy for the learner

Scaffolded Assessment

Scaffolded Assessment (SA) activities serve two purposes: to provide support to the student while practicing within their ZPD (should they need it) and to conduct formative assessment without supports to determine if the student is ready to advance. Each activity during Scaffolded Assessment provides students an opportunity to demonstrate mastery of a learning objective. The activity represented in Figure 6, for example, assesses a student's ability to match spoken words with their written form. When a student struggles, the system applies various levels of support, and offers direct instruction again as needed—just as an MKO would in a real-world learning context. Subsequent rounds are again presented without supports to reevaluate if the student's proficiency has improved or if the objective remains within their ZPD (i.e., the learner needs the help of an MKO). This cycle of assessment and support, typically over 4-6 rounds, repeats throughout the activity. When the student demonstrates mastery by completing the task correctly without help, they are considered to have moved into their Zone of Actual Development (see Figure 2), and it is time to move onto a new LO and a more challenging activity.

Figure 6: My Reading Academy task to demonstrate mastery of matching written words to auditory prompts

Scoring and Knowledge (Node) Map Traversal

Data from Scaffolded Assessment activities are used to evaluate student proficiency on a learning objective, resulting in a *Pass, Stay,* or *Fail* condition (Figure 7). This designation depends on the student's incorrect attempts and the amount of scaffolding needed. A *Pass* progresses the student to Direct Instruction on the next topic. A *Stay* keeps them in the same activity with new tasks and opportunities to receive scaffolds and feedback again as needed. A *Fail* sends them back to Direct Instruction for material review before reattempting the assessment.

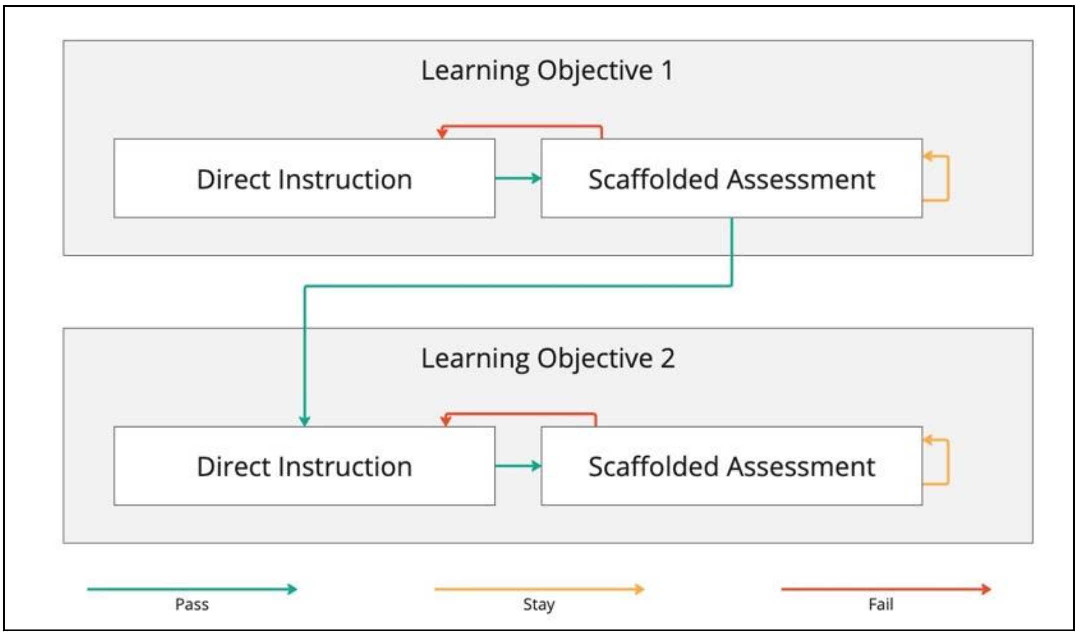

Figure 7: Node Traversal

Opportunities for Iteration and Tuning

Data gathered from learning activities provides opportunities for dynamically determining in which ZoD a learner is operating at any given moment. Learners requiring little to no help to successfully complete activities are likely working in their ZAD. Learners who are unable to pass activities across multiple attempts, even when provided with all feedback, supports, and scaffold features, are likely working in their ZID. Learners who require the support of many or all the support features but are making consistent progress toward mastery across attempts are likely working in their ZPD (see Figure 8).

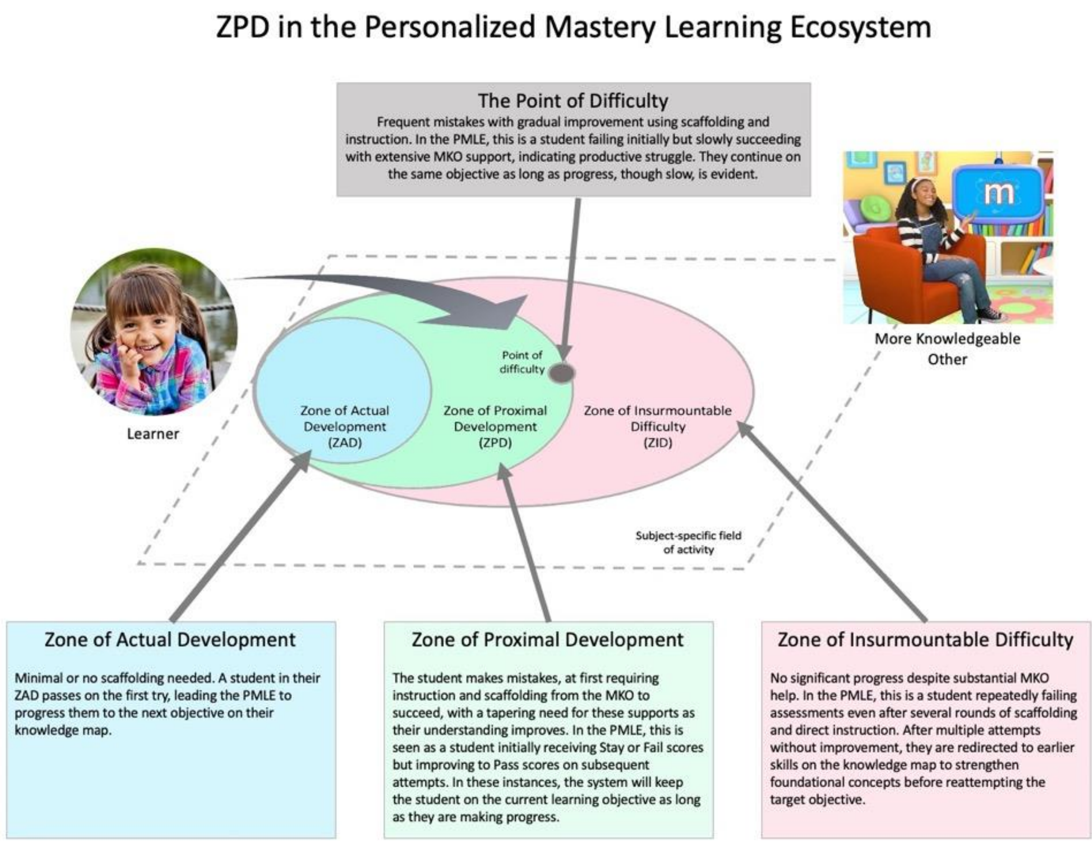

Figure 8: Zones of Development in the Personalized Mastery Learning Ecosystem

The system provides various adjustable levers to tailor its functionality and optimize for different goals. For instance, increasing initial scaffolding can benefit students at their Point of Difficulty when learning a new objective.

Tunable aspects of the system include:

- Movement extent on passing or failing (default is sequential completion without skipping)
- Activity sequence for each objective (default is Direct Instruction followed by Scaffolded Assessment)
- Scaffold level and escalation pace (default is starting without scaffolds, increasing gradually with each wrong answer)
- Duration of assessment activities (default is 4-6 rounds per activity)

These tunable aspects allow for a wealth of exploration and research opportunities to investigate how the learning theories of Bloom and Vygotsky can be embodied in a digital learning context.

Methods

In the present study, we used a Randomized Control Trial (RCT) to investigate how a digital, adaptive, Smart Learning system can effectively identify and engage each learner's ZPD, dynamically adjust their learning path accordingly, and assess learning outcomes, all while maintaining learning efficacy. The specific research questions that guided this study were:

(1) Can we use adaptivity levers in the system to increase learning efficiency while maintaining learning efficacy?
(2) Can we use student performance in the system to identify evidence-based boundaries between a learner's ZAD and ZPD?
(3) Can the system identify learners operating within their ZADs who could increase their learning if advanced to later content with the support of MKO features?

The significance of this research is threefold: theoretically, it contributes to the broader knowledge base of the learning sciences by testing foundational learning theories in a digital age. Practically, these findings can inform the design and development of adaptive learning products that produce more student learning more efficiently at scale. And lastly, findings may inform curriculum development and pedagogical strategies to better accommodate individual learner needs and increase learning efficiency within the classroom setting.

Treatment

For the purposes of this study, a new "Accelerate Mode" (AM) feature was developed as an intervention to implement with a test group of students. The AM is designed to leverage the relationships between learning objectives in our knowledge map, as well as scaffolding within activities, to digitally simulate the ways an MKO would dynamically respond to the teaching needs of an individual learner. By strategically adjusting the activity sequence for an LO, it is possible to determine whether the learner is operating within their ZAD or their ZPD.

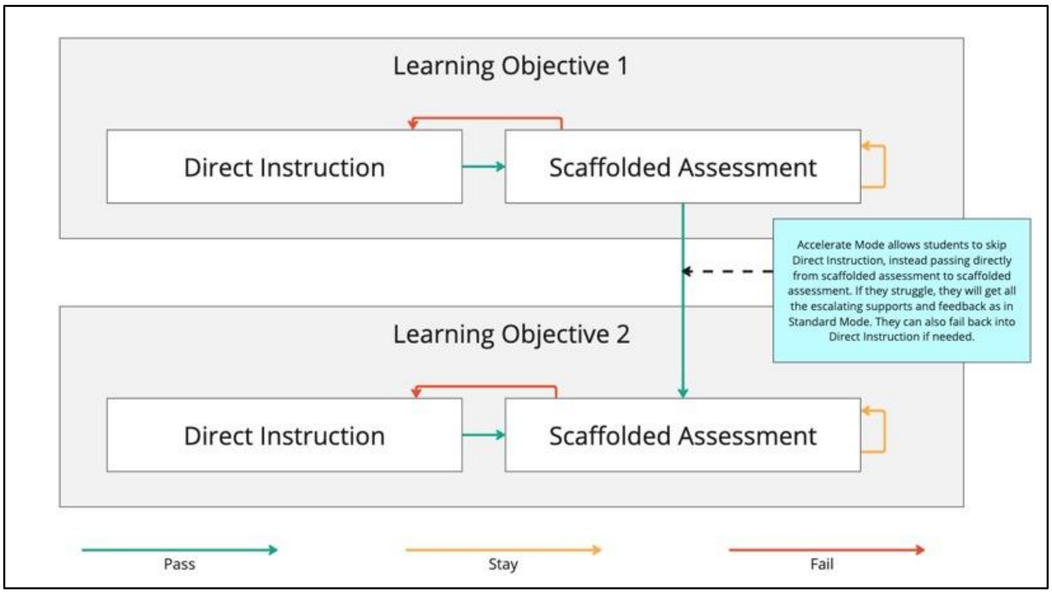

Figure 9: Node traversal in Accelerate Mode

Accelerate Mode permits students to move directly to the terminal Scaffolded Assessment activity for a successor LO (or node), bypassing direct instruction and practice activities (Figure 9). If, when accelerated to the new node, the learner requires many or all of the MKO features (i.e., scaffolded supports and feedback) but still shows progress, the learner is deemed to be in their ZPD. In this case, AM is turned off for this student, allowing them to proceed through the new node and its successors with the default activity sequence and supports. Conversely, if the learner is able to successfully complete the successor node using few or none of the MKO supports, they are deemed to be in their ZAD, and are then accelerated to the next successor LO, where the process is repeated.

Metrics & Hypotheses

Successful placement of a learner in their ZPD was measured using four different metrics, including (1) *Activity attempts per node* (i.e., how many activities did learners play to "Pass" a node?), (2) *Time spent per node* (i.e., how long did it take for a learner to "Pass" a node?), (3) *Node reach count* (i.e., how many unique nodes did learners "Start"?), and (4) *Performance on subsequent nodes* (i.e., what was the pass rate on the first attempt of the "Terminal" activity of each subsequent node after beginning the experiment?). Related to these metrics, we developed three separate hypotheses as follows:

I. The test group in Accelerate Mode should have lower activity attempts per node compared to the control group in default mode (i.e., learners are able to "Pass" the node in fewer play-throughs of each activity)
II. The test group should have a lower quantity of time spent learning per node compared to the control group
III. There should be no significant difference in performance on subsequent nodes between test and control groups (i.e., future learning remains robust even though only the terminal activity is played while in AM)

Study Sample

Dual performance-based criteria were used to determine student eligibility for the Accelerate Mode intervention. This dual-criteria approach was instrumental in capturing a broad spectrum of learner profiles, essential for delineating the boundaries between ZAD and ZPD accurately. Multiple eligibility criteria also allowed for investigation of learner variability and its impact on students' respective ZPDs. The criteria for inclusion were:

1) A streak of consecutive passed terminal assessment activities on the first attempt, referred to as "Boss Streak"
2) An average of 90% pass rate on all activities played with at least 7 nodes completed, referred to as "High Pass Rate"

These criteria were applied to a population of approximately 13,400 children enrolled (at the time) in the My Reading Academy program, resulting in the identification of about 1,400 Pre-K to 2nd Grade students for inclusion in the sample. The split between Boss Streak and High Pass Rate learners was 80% versus 20% in both test and control.

Data & Results

The RCT was deployed for 3 weeks in which random sampling of eligible students generated about N = 700 observations per arm of the test. To control for Type I and Type II errors in our test results, we set the statistical thresholds of $\alpha = .05$ and $\beta = .2$ respectively. After 3 weeks we were able to call the test with the following results (Table 1).

	N		Mean		
	Control	Test	Control	Test	*p*-value
Nodes Reached	706	701	6.52	9.16	.00
Activity Attempts per Node	706	701	4.34	3.43	.00
Avg Time Spent per Node (Mins)	706	701	14.48	11.88	.01
Subsequent Node Pass Rate	706	701	.35	.42	.02

Table 1: Summary Data for Accelerate Mode 1st Test

Results demonstrated a remarkable set of outcomes for the test group over the control, including:

- Improved learning speed—fewer attempts, less time to complete nodes
- Increased node progress—more nodes reached
- No appreciable negative impact on performance—higher pass rate

When we looked at the results by the eligibility criteria segments, we observed an informative divergence that served as important investigative milestones into the questions of learner variability and students' respective ZPDs (Tables 2 and 3). We observed that:

- Both criteria increased node progress—more nodes reached for both Boss Streak & High Pass Rate cohorts
- High Pass Rate cohort increased total learning efficiency—more nodes, in fewer attempts, in less time
- Boss Streak cohort improved performance—pass rate on subsequent nodes was higher than control with mixed efficiency results (i.e., similar number of attempts in a similar amount of time)

	N		Mean		
	Control	Test	Control	Test	*p*-value
Nodes Reached	565	561	6.38	8.33	.00
Activity Attempts per Node	565	561	4.59	3.90	.40
Avg Time Spent per Node (Mins)	565	561	15.54	13.58	.10
Subsequent Node Pass Rate	565	561	.33	.39	.01

Table 2: Summary Data for Accelerate Mode 1st Test: Boss Streak Cohort

	N		Mean		
	Control	Test	Control	Test	*p*-value
Nodes Reached	141	140	6.98	11.88	.00
Activity Attempts per Node	141	140	3.49	1.86	.00
Avg Time Spent per Node (Mins)	141	140	11.33	6.18	.00
Subsequent Node Pass Rate	141	140	.45	.53	.14

Table 3: Summary Data for Accelerate Mode 1st Test: High Pass Rate Cohort

Extended Research and Results

To further our investigation and understanding of how Accelerate Mode impacted learner variability and stretching the ZPD, we chose to run a second RCT test with all students regardless of past performance. Students who were part of the first RCT test were excluded from our second test, resulting in roughly 12,000 students in our second test, with about N = 6000 per arm. Similar in design to our first test, this test ran for 3 weeks, after which time we saw no significant difference in any of our impact metrics between the test and control groups (Table 4). That is, students in the test group did not show improved learning speed from the Accelerate Mode treatment. As a result, we called the test for the control.

	N		Mean		
	Control	Test	Control	Test	*p*-value
Nodes Reached	6,044	6,019	9.54	9.44	.21
Activity Attempts per Node	6,044	6,019	4.93	4.98	.32
Avg Time Spent per Node (Mins)	6,044	6,019	14.72	14.83	.38
Subsequent Node Pass Rate	6,044	6,019	.28	.28	.40

Table 4: Test Summary for Accelerate Mode 2nd Test

Discussion

In our initial RCT, we identified 2 groups of students who we hypothesized were not working in their ZPDs, or at least not at their PoDs. In other words, we believed that in their current placement they could learn the requisite LO without the support of an MKO (i.e., they were in their ZADs). Our test results strongly supported this hypothesis. Students in the test group were able to progress faster and farther through our Knowledge Map without weakened performance. Of the test group students who completed at least 1 final assessment activity while in the test, 78% passed on their first completed attempt, without Direct Instruction or other MKO support. Moreover, 48% of test group students who completed 5 final assessment activities passed all 5 on their first completed attempt and another 32% passed 4 out of 5 on their first completed attempt. And, while only 22% of test group students completed 20 final assessment activities, over 90% of those students passed 16 or more of the activities on their first completed attempt. Such strong performance without MKO assistance confirmed that these students were working in their ZADs rather than their ZPDs. In addition, as many as half of the test group students who did not pass the final assessment activities on the first attempt succeeded on their second attempt after receiving direct instruction and varying degrees of MKO support. This provided evidence that these students were working at least partially in their ZPDs.

Dynamically identifying which Zone of Development a given student is working in at any given moment illustrates one of the challenges of a Smart Learning system. That is, the system does not know what other instruction a student is receiving outside the system, including in a traditional classroom, on other digital tools or products, with a tutor, or otherwise. Thus, it is an ongoing effort to identify whether the student is being presented with LOs currently in their ZPD versus LOs that were in their ZPD at the time of the initial placement assessment but are no longer stretching the learning of the student. Our program uses successful completion of an LO's activities and its prerequisites to determine whether a student has reached their ZAD on a given LO. We assume that this status means they are not likely to be in their ZID for the next LO. But given the elasticity of individual learners' ZPDs, performance on prerequisites does not indicate whether a student will be in their ZPD or still in their ZAD on the next LO. Understanding in which zone the student is operating on any given LO provides an opportunity to improve their learning experience with the right level of support.

Our analysis of the test group students in our RCT revealed that most students were working in their ZADs when the test started and continued to do so through a number of subsequent nodes (i.e., they passed final assessment activities without help). While we achieved our goal of improving learning efficiency while maintaining efficacy for these students, another goal – enabling students who were not learning in their ZPD (i.e., content was too easy) to reach their ZPDs – remained. To determine whether we met this goal, we monitored students in both the control group and the test group for 6 weeks post-test to assess whether the test group reached their ZPDs. We tracked the same metrics used in our original RCT to evaluate the hypothesis that test group students would need more time and more attempts to pass the final assessment activity on each LO and that pass rates would drop as these students entered their ZPDs and approached their PoDs.

Our analysis found that as the test group students progressed through more advanced content, they began to make more use of MKO features, indicating that after the initial acceleration, they reached and then continued to learn in their ZPDs. Specifically, for the test group students, learning speed decreased, more MKO features and attempts were needed, and pass rates declined over time, suggesting that students were approaching their PoD and engaging in more in-the-moment learning. The ability to identify students not working in their ZPDs and, even more importantly, to move them there as quickly as possible, is a valuable finding for our program and the broader education community, especially for those developing adaptive learning products and models.

Limitations

Our initial RCT included two groups of students, identified with rather specific criteria described above. After this test's success, we hypothesized that there could be other students not working in their ZPDs who did not meet either of our eligibility criteria. Since developing a comprehensive set of criteria to identify these other students could be challenging, we applied the Accelerate Mode treatment to all students to determine whether students already working in their ZPDs would not be harmed by the treatment or even could benefit from it.

This second RCT was not a success (Table 4). While the learning pace and performance of the test group students did not meaningfully differ from the control group students, this result does not imply that no harm was done to students already working in their ZPDs. Our first RCT showed that the eligible students (high performers in our system) moved faster under the intervention. Thus, to see no difference between the test and control groups in test 2, non-high-performing students in the test group would have to move more slowly, thereby balancing out faster progress by the high performers in the test group. As a result, it is unclear that more students reached their ZPDs by starting all students on the final assessment activity for each new LO and we rejected this option for finding additional students outside of their ZPDs. Exploring further methods to recognize other groups not working in their ZPDs remains an important area for future research.

Conclusion

In sum, our Accelerate Mode treatment succeeded in moving test students into their ZPDs. However, assigning final assessment activities at the beginning of an LO, even for students identified as likely to benefit from this intervention, is somewhat of a blunt instrument. To achieve even more efficient student learning, it is necessary to better understand the conditions in place when a student enters their ZPD and as they approach their PoD. The more we understand about the transition to the ZPD and the approach to the PoD, the more we can do to get students there and ultimately increase the pace of their learning.

As described earlier, a critical problem to solve remains devising ways to help students become proficient in their grade level expectations as quickly as possible. For the two-thirds of students who are a year or more behind, the need to find better ways to foster more learning at a faster pace is critical. A major insight that emerged from this study centers on how typical pedagogical approaches may or may not support maximum learning efficiency. In line with Bloom's theory of Mastery Learning, many instructional approaches, including those deployed in many digital adaptive learning systems, require the learner to successfully "pass" an activity without help (i.e., prove mastery) before moving on. However, keeping a learner in an activity until they can complete it without help means that at least for some portion of the time the learner is working in their ZAD (i.e., learning is not maximized). Vygotskyan theory would suggest providing the learner with more ongoing opportunities to work at their Point of Difficulty where the most learning can occur. A question to consider is whether or not different adaptivity schemes based on stretching each learner's ZPD to their Point of Difficulty may potentially produce more learning gains than strategies that require full mastery of every learning objective before moving on. A related exploration would include determining the optimal moment to move the learner on to more advanced material (i.e., their next Point of Difficulty). While our study helped to shed light on these questions and others, it is only a beginning. More research in this area is needed.

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