The Usage and Impact of Differentiation: Evidence from an Online EdTech Platform*

Zekun Liu† New York University

Tülin Erdem‡ New York University

Masakazu Ishihara§ New York University

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Abstract

We study the impact of a digital differentiation tool on student learning outcomes across socioeconomic segments, taking into account teachers' usage and implementation of differentiation. Using a structural model incorporating a hidden Markov model and a two-stage process for teachers' differentiation decisions, we assess the tool's effectiveness in improving student performance and addressing educational disparities. Our findings suggest that while the differentiation tool has the potential to improve student learning outcomes, its actual effectiveness is hindered by limited usage among teachers, regardless of socioeconomic background. Furthermore, our analysis reveals that teachers from different socioeconomic segments exhibit varying preferences when implementing differentiation, with low-poverty school teachers prioritizing medium-achieving students to a greater extent. To enhance student learning outcomes and address educational disparities, we explore possible interventions in our counterfactual analyses. We find that while cost reduction encourages greater tool usage and benefits students, the effect is more pronounced in low-poverty schools, potentially exacerbating the existing gap between socioeconomic segments. We further identify targeted professional training that enhances the valuation of the differentiation tool in high-poverty schools as a potential strategy to mitigate the negative impact of cost reduction on education disparity and bridge the usage divide between socioeconomic segments. Our findings emphasize the need to consider not only product design but also the usage divide to maximize the effectiveness of differentiation tools and promote equitable education.

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†PhD Candidate of Marketing at Leonard N. Stern School of Business; email: zl3126@stern.nyu.edu; 40 W 4th Street, New York, NY 10012

‡Leonard N. Stern School Professor of Business and Professor of Marketing at Leonard N. Stern School of Business; email: te17@stern.nyu.edu; 40 W 4th Street, New York, NY 10012

§Associate Professor of Marketing at Leonard N. Stern School of Business; email: mi25@stern.nyu.edu; 40 W 4th Street, New York, NY 10012

1 Introduction

With the advancement of digital technology, the proliferation of emerging education technology (edtech) products has reached a broader student population,[1] offering access to high-quality resources and materials while streamlining technical aspects to better meet students' needs. Within this context, the facilitation of differentiation in education stands out as a critical area where edtech plays a pivotal role (Ganimian et al., 2020). Differentiation, as a pedagogical approach, aims to personalize instruction to cater to the unique abilities, interests, and learning styles of individual students, ultimately fostering a more inclusive and effective learning environment. The integration of edtech into differentiation strategies has provided educators with a wealth of resources, including adaptive learning platforms, customizable content, and personalized assessment tools. These technologies offer the potential to enhance the implementation of differentiation by providing tailored learning experiences, immediate feedback, and adaptive interventions. Consequently, students can engage with educational content that fits with their readiness level, and receive targeted support to address their specific learning needs.

While the potential benefits of differentiation and edtech integration are widely acknowledged,[2] it is crucial to consider the complexities involved in its implementation. The effectiveness of differentiation strategies relies not only on the availability and design of technology but also on teachers' utilization of edtech tools (Suprayogi et al., 2017). Therefore, it is not enough to solely focus on the availability and design of edtech products; the actual effectiveness of these technologies in improving student outcomes must be thoroughly examined. Moreover, understanding and addressing teacher usage behavior is crucial in optimizing the design and effectiveness of edtech products for differentiation.

The goal of the paper is to examine the effectiveness of a digital differentiation tool on student learning outcomes while accounting for teacher usage. Specifically, we focus on a digital differentiation tool provided to help teachers and students in the K-12 segment. As of 2022, the K-12 segment accounted for over 50% of the overall market share 2022 and is expected to observe significant growth from 2022 to 2026.[3] The K-12 segment is characterized by its rich diversity, with students varying in their cognitive abilities, interests, and learning preferences. Traditional "one-size-fits-all" approaches may not effectively address these unique differences, leading to potential

[1] https://www.edweek.org/technology/the-number-of-ed-tech-tools-school-districts-use-has-almost-tripled-thats-a-problem/2022/08

[2] https://www.edweek.org/teaching-learning/opinion-differentiation-does-in-fact-work/2015/01

[3] https://www.globaldata.com/store/report/edtech-market-analysis/

gaps in student learning and limited opportunities for growth.

We delve into the exploration of ReadWorks, which is a renowned online platform specifically designed to support teachers and students in the K-12 segment in developing strong reading comprehension skills. The platform provides educators with access to a wide range of grade-level appropriate reading materials along with corresponding comprehension questions, covering various genres and subjects. One notable feature of ReadWorks is its emphasis on differentiation. The platform offers leveled readings, allowing teachers to assign texts that match individual students' reading abilities. This approach ensures that students are appropriately challenged and supported, promoting their growth and progress in reading comprehension. Additionally, ReadWorks provides tools and resources for educators to customize instruction, monitor student progress, and provide targeted interventions based on individual needs.

Our first research question centers on examining the effects of the digital differentiation tool offered by ReadWorks on student learning outcomes. While recognizing the potential of this tool to improve student performance, it remains unclear whether teachers and students can truly benefit from its implementation. Intuitively, the digital differentiation tool has the capacity to enhance student learning outcomes by fostering greater engagement. One possible explanation could be when students perceive that they receive individualized attention from their teachers, they experience a sense of inclusiveness, leading to increased participation and effort in their assignments (Cents-Boonstra et al., 2021). Furthermore, differentiated assignments can better align with each student's unique reading abilities. For students who may struggle to keep up with the class, differentiated assignments provide tailored support, preventing them from falling further behind. Conversely, for high-achieving students, teachers can ensure they are appropriately challenged through differentiation. Therefore, our investigation aims to evaluate the impact of the differentiation tool on different student segments, as each group may derive distinct benefits from its implementation. Moreover, we also investigate the impact of differentiation across classes from different socioeconomic segments. Given the persisting educational inequalities, classrooms in high-poverty schools tend to have a more diverse student body in terms of ability (Reardon et al., 2019). This suggests that the potential benefits of the differentiation tool may be particularly significant for high-poverty schools. Hence, the digital differentiation tool has the potential to address educational disparities by mitigating the gap between high-poverty and low-poverty classes.

Our second research question focuses on the crucial but often overlooked element of teachers' usage behavior when examining the effectiveness of the digital differentiation tool. As teachers play a pivotal role in implementing and enforcing differentiation strategies, their utilization of the digital tool directly impacts its effectiveness in enhancing student learning outcomes. Therefore, gaining insights into teachers' usage patterns holds practical implications for optimizing the design and effectiveness of digital tools in educational settings.

Several factors contribute to teacher usage of the differentiation tool. First, the expected impact of differentiation on student progress significantly affects teacher usage. When teachers expect improvements in student learning outcomes as a result of differentiation, they are more likely to embrace and utilize the tool. Second, the extent to which teachers assign importance to student progress resulting from differentiation influences their usage behavior. When teachers assign significant importance to the impact of differentiation on student progress, they are more likely to recognize the value of personalized instruction and its role in addressing individual students' unique needs. This recognition reinforces their commitment to utilizing the differentiation tool. Additionally, teachers' preferences (Mercer and DeRosier, 2008) and instructional priorities play a crucial role in their usage of the differentiation tool. Based on their preferences, some teachers may prioritize providing additional support to struggling students, while others may focus on challenging high-achieving students through differentiated assignments. These instructional priorities guide their usage patterns, as they strive to tailor assignments and meet the diverse needs of their students. Lastly, the ease of use of the differentiation tool, along with the availability of resources and support for teachers, plays a crucial role in its usage, as they directly influence the associated costs of using the tool.

In addition, we explore whether and why teachers' usage behavior varies across socioeconomic segments in relation to the differentiation tool. This investigation not only helps us evaluate the tool's effectiveness but also allows us to gain insights into teachers' differential valuation of different student segments. Obtaining reliable information on these preferences is challenging, as relying solely on surveys may yield unreliable results due to the sensitive nature of the topic or teachers' limited awareness of their own preferences. However, uncovering these unobserved incentives provides valuable insights, enabling a better understanding of teachers' behaviors and offering practical implications for addressing educational inequality.

The third research question focuses on identifying interventions that can enhance student learning outcomes and address educational inequity. Firstly, a potential intervention involves enhancing usability and reducing the cost associated with the digital differentiation tool. By making the tool more user-friendly and accessible, teachers are more likely to adopt it, leading to increased student growth. Secondly, based on an understanding of the importance that teachers attribute to student progress resulting from differentiation, targeted support and professional training can be provided to reinforce the recognition of differentiation's value. By highlighting the benefits of differentiation, teachers are more inclined to perceive its significance and incorporate the differentiation tool into their instructional practices. Moreover, the combination of these two interventions can yield practical implications for maximizing the effectiveness of the differentiation tool. By simultaneously enhancing usability and providing tailored support to teachers, the platform can promote widespread usage of the tool and facilitate meaningful improvements in student learning outcomes.

In sum, we ask three research questions: 1) What is the impact of the digital differentiation tool on the learning outcomes of students? Does the impact differ for students from different socioeconomic segments? 2) What are teachers' preferences when implementing differentiation? Do the preferences differ for teachers from different socioeconomic segments? 3) What are the possible interventions regarding the differentiation tool to improve student learning outcomes and address education inequity?

Our sample contains 5,138 teachers who signed up on ReadWorks between 2017-09-01 to 2021-07-15 and 11,372 classes taught by them from 2017-09-01 to 2022-07-01. Among these teachers, 32% of them are from high-poverty schools. We have detailed information about the assignments given by these teachers, including assignment type (differentiated or non-differentiated), difficulty level, and the number of students who opened the assignment. Additionally, for students who opened the assignment, we have data on their performance.

We first present evidence on the effectiveness of the differentiation tool and teachers' differential preference for usage and implementation of differentiation through reduced-form analyses. First, we find that differentiated assignments are linked to improved student performance. Specifically, differentiated assignments are associated with better student performance, e.g., an 11% higher assignment open rate and a 1.3% higher correct rate for multiple choice questions. Moreover, past usage of differentiation by teachers is associated with higher student performance. Secondly, teachers' usage and implementation of differentiation differ across socioeconomic segments. Overall, teachers from high-poverty schools use differentiation less.While teachers in both poverty groups are more likely to use differentiation when the performance variance within the class is larger, teachers from different poverty groups demonstrate various preferences when implementing differentiation. Specifically, students with relatively poor performance in a class are more likely to receive differentiated assignments, and this is only significant for classes in low-poverty schools.

To comprehensively examine the impact of the digital differentiation tool on student learning, while considering teachers' usage and implementation of differentiation, we develop a comprehensive structural model. Our model incorporates a hidden-Markov framework (Netzer et al., 2008; Ma et al., 2015), which captures the student's underlying ability evolution over time, allowing for a more accurate evaluation of the tool's effectiveness. In our model, student ability is reflected in their intrinsic tendency to open assignments and their intrinsic baseline performance. By accounting for these factors, we can assess the impact of the differentiation tool beyond solely relying on observed student performance, which is subject to the assignment they receive. Meanwhile, we model teachers' differentiation decisions as a two-stage process. First, teachers determine whether to differentiate assignments at the class level. Subsequently, if differentiation is chosen, teachers decide how to implement it, deciding what assignments to give to individual students in the class. Our model considers various drivers for teachers' decisions, including their preference for students at different ability states, the expected progress of students in terms of transitioning to higher states, the operational cost associated with providing differentiated assignments, and the utility derived from alternative options available to teachers.

First, our parameter estimates indicate that differentiated assignments have a positive impact on student ability compared to non-differentiated assignments. This suggests that the digital differentiation tool has the potential to effectively enhance student learning outcomes. Specifically, students in all ability states, regardless of their socioeconomic background, are more likely to transition to a higher ability state or maintain the highest state when they are assigned differentiated assignments, as compared to non-differentiated assignments.

Secondly, our analysis reveals that teachers demonstrate differential preferences towards students of different ability states when implementing differentiation, and these preferences also vary between teachers from high-poverty and low-poverty schools. When teachers choose to implement differentiation at the class level, i.e., teachers opt for differentiation at the first stage, the likelihood of students receiving differentiated assignments varies depending on their ability states. On average, students in the lowest ability state have a lower probability of receiving differentiated assignments, irrespective of the socioeconomic background of their schools. Additionally, medium-achieving students from low-poverty schools have a higher likelihood of receiving differentiated assignments compared to their counterparts in high-poverty schools. This indicates that teachers in low-poverty schools may prioritize medium-achieving students to a greater extent than teachers in high-poverty schools when it comes to implementing differentiation strategies.

However, despite these preferences, we find the usage of differentiation is not prevalent among most teachers, regardless of the socioeconomic context. In fact, only approximately 22% of classes from low-poverty schools (23% for high-poverty schools) frequently choose to differentiate assignments for the class. This limited usage of differentiation may potentially hinder the overall effectiveness of the digital differentiation tool in supporting student learning outcomes. Using the parameter estimates, we simulate the student ability evolution in our first counterfactual analysis where all assignments are non-differentiated and indeed find that the actual effectiveness of the digital differentiation tool is very limited in enhancing student learning outcomes.

Lastly, in our efforts to enhance the effectiveness of the digital differentiation tool and reduce educational disparities between low- and high-poverty schools, we explore possible interventions. The first intervention aims to reduce the cost of differentiation on ReadWorks. This can be achieved by streamlining and simplifying the implementation of differentiation such as automating the differentiation assignment process. The second intervention focuses on enhancing teachers' recognition of the value of student progress from differentiation. This can be achieved through comprehensive professional development opportunities and training sessions that emphasize the benefits and positive impact of differentiation on student learning outcomes. While both interventions encourage increased usage of differentiation, it is important to note that solely focusing on cost reduction may inadvertently widen the gap between high-poverty and low-poverty student learning outcomes. This is because the increase in usage among low-poverty school teachers is much larger compared to high-poverty school teachers. To address this issue, we further investigate the impact of both reducing differentiation costs and providing targeted training specifically designed for high-poverty school teachers. Our findings suggest that providing targeted training has the potential to mitigate the negative impact of solely focusing on cost reduction on education disparity (despite the positive impact on student learning outcomes for both socioeconomic segments) and help narrow the gap between high-poverty and low-poverty student learning outcomes.

Our research findings shed light on the potential of a differentiation tool in enhancing student ability and addressing educational disparities. We find the differentiation tool has the potential to enhance student ability for students from both high-poverty and low-poverty schools. However, the overall usage of the tool is limited among teachers in both high- and low-poverty schools. This hampers the actual effectiveness of the tool and prevents students from fully benefiting from it. Second, we document that teachers from different socioeconomic segments have differential preferences when implementing differentiation. Specifically, low-poverty school teachers tend to prioritize medium-achieving students to a greater extent compared to their counterparts from high-poverty schools. Lastly, our research emphasizes that improving the effectiveness of the differentiation tool goes beyond product design alone. It requires addressing the usage divide and providing targeted training to teachers in high-poverty schools. By considering both cost reduction and enhancing teacher valuation, we can work towards bridging the educational gap and promoting equitable access to digital learning resources.

1.1 Literature

Our paper is closely related to the literature that studies the impact of digital technology on social inequality. Digital technology has the potential to reduce social inequality. Fu et al. (2022) study the impact of Zillow's Zestimate on housing market outcomes across different socioeconomic segments and find that Zestimate may reduce socioeconomic inequality as poor neighborhoods benefit the most in terms of increased total welfare. Tucker et al. (2021) focus on a mobile application that digitizes the consumer complaint process and find that it can partially eliminate the disparity between educated and uneducated people by providing a tool that substitutes the communication skills required for the resolution of complaints, and therefore, enhance the equality in the customer service domain. Despite digital technology's capacity to diminish social inequalities, it can also amplify them when there are existing digital divides such as access divide and usage divide. Zhang et al. (2021) show that while the Smart-Pricing tool has the potential to mitigate the hosts' revenue gap, its actual effectiveness is limited due to the low adoption rate among Black hosts. In fact, at the population level, the revenue gap is exacerbated after the introduction of the Smart-Pricing tool. Cao et al. (2022a) investigate the effect of providing free access to reading materials on K-12 children and find that children from more developed regions benefit more in the long run, which exacerbates the existing education inequality. Overall, the impact of digital technology on social inequality is intricate and diverse. Our paper adds to the literature by investigating the impact of the differentiation tool on the learning outcomes of students from different socioeconomic segments. Specifically, we closely examine the usage behaviors of teachers to understand the role of teacher usage preferences on the differentiation tool's effectiveness in addressing educational inequalities and propose possible interventions to mitigate education inequalities.

Our paper is also related to the literature on the usage of educational technology. Past literature has studied various factors that may impact learner engagement, such as content sharing strategies (Narang et al., 2022), the role of payment and certificate (Goli et al., 2022), the pairing of image and text (Cao et al., 2022b), and the calls to action interventions (Huang et al., 2021). Lu et al. (2022) model individual learners behaviors to capture different patterns related to theories of goal progress. Akchurina and Albuquerque (2019) develop a duel-agent model to investigate the misalignment of usage and purchase decisions of an online math platform. Kim et al. (2022) investigate an AI application of private in-home tutoring services by building a conceptual framework that combines tutors' utilization of AI assistance and the effect on student performance. They find that providing the AI application to tutors could be a double-edged sword due to tutors' different levels of utilization, which is affected by tutors' internal characteristics and external tutoring environments such as AI aversion and technology overload. In a similar spirit to Kim et al. (2022), we explicitly model teachers' usage behaviors while evaluating the effectiveness of the differentiation tool in improving student learning outcomes. Furthermore, by incorporating teachers' preferences into our analysis, we can uncover their differential implementation of the differentiation tool based on their socioeconomic segments. This valuable insight into teachers' preferences is challenging to obtain through traditional methods such as surveys, which may be hindered by the sensitive nature of the topic.

Lastly, our paper relates to the vast education literature that evaluates the effectiveness of differentiation in improving learning outcomes. While differentiation by definition should have a positive impact on student learning outcomes, there is some mixed evidence of its effectiveness. Early literature has focused on structural differentiation or ability tracking which involves grouping students by their perceived ability level. While some works claim it can contribute to education inequities (e.g., Hanushek and Wößmann, 2006; Argys et al., 1996) by benefiting high-achieving students and harming low-achieving students, other works argue that such findings may be subject to endogeneity issue of tracking decisions and found that tracking might be beneficial to lower-achieving students (e.g., Duflo et al., 2011). With the digitalization of the education industry, people are turning to flexible and responsive approaches to differentiation that focus on meeting individual student needs. However, despite the potential benefits of this approach, there is one significant challenge that remains: effective implementation. This challenge has resulted in mixed evidence on the effectiveness of differentiation. While Haelermans et al. (2015) and Muralidharan et al. (2019) find significant test score gains with digital differentiation/personalization, Van Klaveren et al. (2017) and Iterbeke et al. (2021) find no significant learning gains from adaptive instruction. Pane et al. (2017) find that personalized learning appears to be promising for improving student achievement on average, however, the effect has large variation across different schools. While some of these studies use randomized field experiments to evaluate the effectiveness of different tools and programs, it is difficult to determine why they are effective (or not) without closely examining their implementation. Our paper complements this literature by building a comprehensive model that accounts for teacher implementation when we evaluate its effectiveness in improving student learning outcomes.

2 Background and Data

ReadWorks provides K-12 teachers with high-quality articles and integrated reading instruction tools to improve teacher effectiveness and student reading achievement. Its content and tools are designed for immediate use within the practical realities of current U.S. classrooms. Over 1 million teachers and 17 million students across 50 states use ReadWorks each year.[4]

One of the most popular tools teachers use is the text-dependent question set assignment. Question sets include 5-10 multiple-choice questions that provide practice in multiple key reading strategies while scaffolding important information to encourage a thorough understanding of the text. They help readers engage with texts and dig deeper into what they are reading, strengthening their skills as strategic readers. Students' answers to multiple-choice questions are automatically graded, and teachers can keep track of the performance of all students in the class. Specifically, teachers observe students' responses to all questions, i.e., whether they try to answer the question and whether they gave the correct answer.

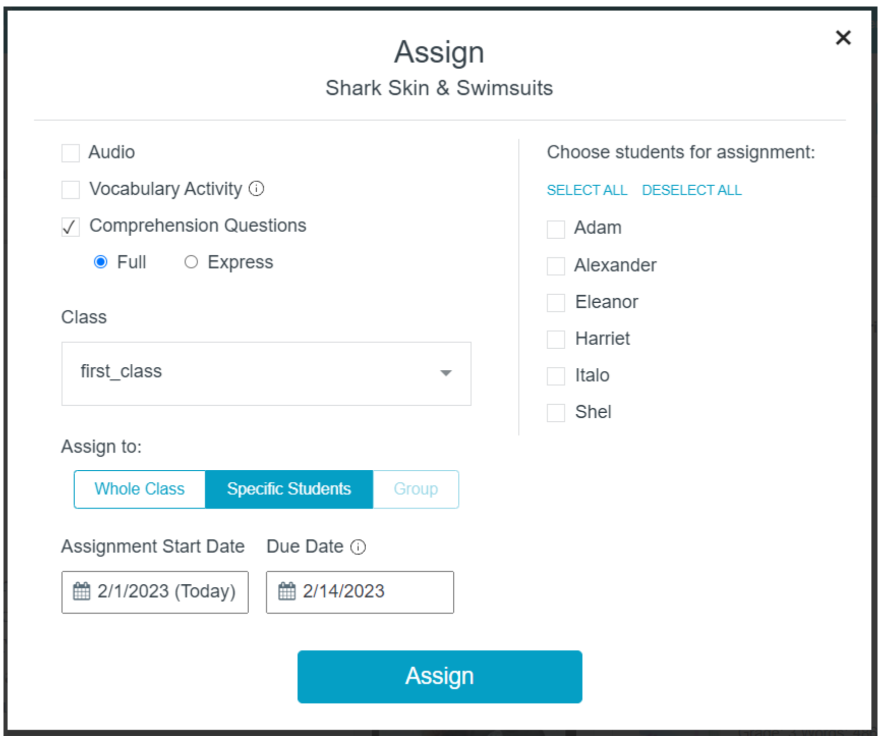
ReadWorks allows teachers to differentiate the assignments for students. Figure 1 shows the interface for teachers when deciding the assignment to give. Teachers can assign an assignment to the whole class or a specific group of students. It is up to the teachers to decide how to implement the assignment differentiation. When teachers choose to assign to specific students, they will need to specify the students by checking the boxes for all students they want to assign to. If they have pre-determined groups of students in the class, they can also achieve the same goal by using the assign-to-group feature. As the group feature was launched after 2019-03-25 and only a small portion of teachers ever used the group feature (less than 10%), we do not differentiate between these two types of differentiation in our main analysis.

When deciding the articles to assign, teachers can search for the content by Grade, Lexile, and topic. The grade and Lexile levels are informative on the reading level a student could fit into.

[4] https://www.readworks.org/

Teachers, therefore, can choose the articles/assignments of the right level for students by differentiating the assignments they receive, and students do not observe the Grade and Lexile levels of the article. In addition, teachers may also assign additional assignments to some students who they think need additional exercises but not to the rest of the class. We refer to the assignments assigned to the whole class as non-differentiated assignments and those assigned to a specific group of students as differentiated assignments. When implementing the differentiation, teachers can choose the give assignments to some of the students and vary the difficulty level of the articles/assignments received by students.

Figure 1: Assignment Differentiation on ReadWorks



With the systemic education inequality across socioeconomic groups, further exacerbated by the pandemic, the one-size-fits-all approach can be much less effective, especially for low-income areas, as they tend to have larger class sizes and fewer resources. Hence, the digital differentiation tool provided by ReadWorks can potentially lower the barrier to using differentiation in practice. Understanding how teachers from different socioeconomic groups use the tools and how effective the tool is extremely important so that we can advance educational equity by providing better instructions and tools. We use the poverty level of schools as a proxy for socioeconomic status. In the United States, the percentage of students eligible for free or reduced-price lunch (FRPL) under the National School Lunch Program provides a proxy measure for the concentration of low-income students within a school. Public schools are divided into categories by FRPL eligibility. High-poverty schools are defined as public schools where 75% or more of the students are eligible for FRPL.

Data Description

We randomly selected 20,000 users who created their ReadWorks accounts as educators between 2017-08-01 and 2021-07-15 and have used ReadWorks digitally. We only look at those who self-identified as teachers for grades 1-12 classes and have valid school information. This leaves us with 11,706 teachers and 32,690 classes. Further, we make sure we have enough observations for each teacher and student, we look at those classes that have 5-40 students, at least 5 observations of assignments, and span at least two months. Our final sample includes 5,138 teachers and 11,372 classes.

The teachers in our sample are affiliated with 4,188 schools spanning across 51 states. The vast majority, 99.8%, come from public schools, and approximately 33% of these teachers work in high-poverty schools. High-poverty schools are defined as those where more than 75% of students participate in the free/reduced-price lunch program. On average, each teacher in our sample teaches 2.2 classes, with a median of 1 class. Turning our attention to the classes themselves, approximately 80% of them are from grades 1 to 6. The average class size is 22 students, ranging from as small as 5 to as large as 50 students. The duration of the classes is, on average, 20 weeks, with nearly all classes (99%) lasting less than a year. Throughout the duration of the classes, students typically receive a varying number of assignments, ranging from 5 to 50 assignments. This translates to an average of 0.82 assignments per week. Notably, around 33.44% of classes include at least one differentiated assignment, indicating a degree of instructional diversity within the curriculum.

For each assignment, we use the assignment open rate to measure student involvement. Furthermore, we observe the number of multiple-choice questions a student has answered. In addition, as the multiple-choice questions are auto-graded, we also observe the number of multiple-choice questions a student got correct. Therefore, for each assignment with question sets, we can evaluate a student's involvement and performance using the following two measures: 1) assignment open rate and 2) multiple-choice questions correct rate. The assignment open rate is at the assignment level, and the multiple-choice questions correct rate is at the student-assignment level.Table 1 provides the summary statistics for assignment-level characteristics in panel A and student-assignment-level student performance in panel B.

Table 1: Summary statistics for assignment characteristics and student performance

Statistic	N	Mean	SD	Min	Max
Panel A: Assignment Level					
If Diff	203,228	0.223	0.416	0	1
Grade Level	203,228	4.271	1.907	0	11
Lexile Level	196,825	808.841	223.638	0.000	1,600
Open Rate	203,228	0.764	0.248	0.014	1.000
Panel B: Assignment-student Level					
MC Correct Rate	2,787,558	0.634	0.324	0.000	1.000

3 Descriptive Analysis

3.1 Evidence of Student Performance Gap

We begin by providing evidence of the student performance gap between high-poverty and low-poverty schools. We focus on class-level student performance, considering two key measures: the assignment open rate and the multiple-choice question correct rate. Specifically, our analysis is based on non-differentiated assignments, as these are uniformly assigned to all students within a class, ensuring a fair comparison of student performance within the same class. For each class, we calculate the assignment open rate, which measures the proportion of students who open the non-differentiated assignments. Additionally, we compute the average and standard deviation of the multiple-choice question correct rate, considering only those students who have opened the assignments. These measures provide insights into the average performance and the variation in performance within each class. By aggregating these measures across all non-differentiated assignments for each class, we obtain three class-level student performance indicators: the average assignment open rate, the average multiple-choice question correct rate, and the standard deviation of the multiple-choice question correct rate. These metrics allow us to compare the performance between classes in high-poverty schools and low-poverty schools. Specifically, we compare the class-level performance for classes in high-poverty schools and low-poverty schools by performing the following regression:

$$performance_c = class\_grade_c + \alpha_1 high\_poverty_c + \alpha_2 logged\_class\_size_c + \epsilon_c. \tag{1}$$

where $performance_c$ represents one of the three performance measures for class c. The variable $class\_grade_c$ captures the class grade fixed effect, while λ_g represents the class grade fixed effect. The dummy variable $high\_poverty_c$ takes the value 1 if class c is taught by a teacher in a high-poverty school. The logged class size of class c is denoted as $logged\_class\_size_c$. The error term is represented by ϵ_c. The coefficient α_1 is of particular interest as it indicates the performance difference between high-poverty classes and low-poverty classes.

Table 2 presents the findings regarding the performance gap between high-poverty and low-poverty schools. The results indicate that, on average, classes in high-poverty schools exhibit lower performance levels. Specifically, compared to classes in low-poverty schools, classes in high-poverty schools show a significant decrease in assignment open rates by 6.86%. The negative and statistically significant coefficient of *high_poverty* in column (2) reveals that classes in high-poverty schools have an average multiple-choice question correct rate that is lower by 8.36% compared to the class average in low-poverty schools. Additionally, classes in high-poverty schools demonstrate a greater variation in the correct rates of multiple-choice questions within the class. Column (3) suggests that the variation in correct rates is more pronounced within classes in high-poverty schools.

Table 2: Class-level student performance in high- and low-poverty schools

	Open Rate	MC Correct Rate	
		Mean	SD
	(1)	(2)	(3)
high_poverty	-0.0686***	-0.0836***	0.0227***
	(0.0042)	(0.0050)	(0.0024)
logged_class_size	-0.0348***	-0.0011	0.0195***
	(0.0075)	(0.0089)	(0.0020)
Class Grade FE	✓	✓	✓
Observations	11,099	11,099	11,078
R^2	0.06674	0.11903	0.05974
Adjusted R^2	0.06582	0.11816	0.05880

Notes: This table presents the findings regarding the performance gap between high-poverty and low-poverty schools. Columns (1), (2), and (3) present the results of three class-level performance measures: the average assignment open rate, the average multiple-choice question correct rate, and the standard deviation of the multiple-choice question correct rate. We only include classes that have at least one non-differentiated assignment.

Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$

The above results provide evidence of a performance gap between high-poverty and low-poverty schools. Students in high-poverty schools, on average, exhibit lower performance levels compared to their counterparts in low-poverty schools. Additionally, classes in high-poverty schools show a greater variation in performance within the class. These findings highlight the challenges faced by students in high-poverty schools and the importance of addressing the performance disparities between different socioeconomic settings.

3.2 Evidence of Differentiation Effectiveness

In the previous section, we established the presence of a performance gap between high-poverty and low-poverty schools. Now, we turn our attention to assessing the effectiveness of differentiation in improving student performance.

To start, we investigate whether there are performance differences between differentiated and non-differentiated assignments. Specifically, we examine the open rates for each assignment and compare the open rates between the two types of assignments using the following regression model:

$$open\_rate_{icj} = \theta_i + \kappa_c + time_{icj} + \beta_1 if\_diff_{icj} + \beta_2 if\_diff_{icj} \times high\_poverty_{ic} + \epsilon_{icj}, \qquad (2)$$

where $open\_rate_{icj}$ is the open rate of assignment j assigned by teacher i in class c, θ_i, κ_c, and $time_{icj}$ are the teacher, class, and time fixed effects, if_diff_{icj} is a dummy variable indicating whether assignment j is differentiated. β_1 and β_2 are the variables of interest: β_1 and $\beta_1 + \beta_2$ represent the difference in open rate for differentiated assignment compared to that of non-differentiated ones for low-poverty and high-poverty groups, respectively.

Column (1) in Table 3 reports the results. We find that differentiated assignments are associated with 11.33% (13.01%) higher open rates compared to non-differentiated ones for low-poverty (high-poverty) groups. This suggests that students are more likely to open the assignments when they are assigned differentiated ones, and the effect is more pronounced for students from high-poverty schools.

One potential concern in the previous analysis is the potential selection bias, as students who receive differentiated assignments may differ systematically from those who do not. To address this issue, we can conduct a student-assignment level analysis and control for student fixed effects. However, it is important to note that we do not always observe students' opening decisions for all assignments. For non-differentiated assignments, we have complete information as we know that all students in the class received the assignment. We can infer the students who received the assignment but did not open it. However, for differentiated assignments, when the number of students who opened the assignment is smaller than the number of students who were assigned, we do not have performance information (correct rate) for those students who did not open the assignment. It is unclear whether they were not assigned in the first place or if they were assigned but chose not to open it. To partially address this issue, we focus on the other performance measure where we are able to account for student fixed effects. This allows us to control for individual student characteristics that could influence assignment performance. We will directly address the missing opening decisions in section 4.3 to provide a more comprehensive analysis.

Conditional on students opening the assignment, we observe student-level multiple-choice question correct rate. We conduct the following student-assignment-level analysis to examine whether student performance differs for differentiated assignments. The specification is as follows:

$$\begin{aligned} performance_{icjs} =& \theta_i + \kappa_c + \mu_s + time_{icj} + \beta_1 if\_diff_{icj} + \beta_2 if\_diff_{icj} \times high\_poverty_{ic} + \\ & \beta_3 difficulty\_level_{icj} + \beta_4 logged\_num\_MCQ_{icj} + \epsilon_{icj} \end{aligned} \tag{3}$$

where $performance_{icjs}$ represents student s's performance on assignment j assigned by teacher i in class c, μ_s is the student fixed effect, $difficulty\_level_{icj}$ is the difficulty level of assignment j measured by the grade level of the article, and $logged\_num\_MCQ_{icj}$ is the logged number of multiple choice questions in assignment j, and ϵ_{icj} is the error term.

Column (2) in Table 3 present the results of the student-assignment-level analysis. The findings reveal that differentiated assignments are associated with higher correct rates (1.32%) when compared to non-differentiated assignments after accounting for the number of questions and the difficulty level of the assignment. Additionally, the increase in the correct rate does not significantly differ between classes in high-poverty and low-poverty schools.

Thus far, our findings have indicated a correlation between differentiated assignments and increased rates of assignment engagement and correct responses to multiple-choice questions. This prompts us to consider whether this correlation signifies an improvement in students' inherent reading comprehension abilities. One plausible explanation for these observed results is that differentiated assignments compel students to dedicate greater attention and effort to their tasks. Consequently, they perform better overall, but this does not necessarily imply an actual enhancement in their reading comprehension ability. To address this concern, we investigate whether the past usage of differentiation impacts students' current performance.

To examine the potential impact of past differentiation on current student performance, we focus

Table 3: The relationship between student performance and assignment types

	Open Rate (1)	MC Correct Rate (2)
if_diff	0.1133***	0.0131***
	(0.0062)	(0.0023)
if_diff × high_poverty	0.0168*	-0.0062
	(0.0088)	(0.0050)
difficulty_level		-0.0226***
		(0.0011)
logged_num_mcq		-0.0610***
		(0.0048)
Teacher FE	✓	✓
Class FE	✓	✓
Student FE		✓
Time FE	✓	✓
Observations	203,228	2,787,558
R^2	0.56331	0.41030
Adjusted R^2	0.52456	0.35130

Notes: This table presents the effects of differentiated assignments on student performance. Columns (1) and (2) presents the results in assignment open rates and multiple-choice question correct rates, respectively.

Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$

on evaluating students using non-differentiated assignments, which are assigned to all students in the same class. This ensures that we are not comparing students based on assignments with varying difficulty levels. Within each class, we calculate the student performance in the first month and the last month by aggregating the multiple-choice question correct rates across all non-differentiated assignments the student opens during each month. We denote these aggregated rates as $first\_avg\_mc\_correct\_rate\_nondiff$ and $last\_avg\_mc\_correct\_rate\_nondiff$, respectively. These variables serve as proxies for student performance at the beginning and the end of their platform usage period. To measure the level of differentiation experienced by each student, we calculate the percentage of differentiated assignments out of all assignments they opened before the last month, denoted as pct_diff. We then investigate how changes in student performance are associated with the degree of differentiation they received during this period. We control for the total number of assignments opened by the student and the average difficulty level of non-differentiated assignments in the last month. The regression specification is as follows:

$$\begin{aligned} last\_avg\_mc\_correct\_rate\_nondiff_s =& \theta_i + \kappa_c + \gamma_t + \alpha_1 logged\_num\_assignments_s + \\ & \alpha_2 first\_avg\_mc\_correct\_rate\_nondiff_s + \alpha_3 pct\_diff_s + \\ & \alpha_4 pct\_diff_s \times first\_avg\_mc\_correct\_rate\_nondiff_s + \\ & \alpha_5 last\_avg\_difflevel\_nondiff_s + \epsilon_s \end{aligned} \tag{4}$$

where θ_i, κ_c, and γ_t are teacher, class, and time fixed effects, respectively, $logged\_num\_assignments$ is the logged number of assignments opened by the student before the last month, $avg\_difflevel\_nondiff$ is the average difficulty of non-differentiated assignments opened by the student. The variables of interest are α_3 and α_4 where α_3 represents the main effect of differentiated assignment percentage on student performance, and α_4 represents the interaction effect between the percentage of differentiated assignments and initial student performance.

Table 4: Past usage of differentiation on student performance

	last_avg_mc_correct_rate_nondiff	
	Low Poverty (1)	High Poverty (2)
logged_num_assignments	0.0791***	0.0753***
	(0.0039)	(0.0037)
first_avg_mc_correct_rate_nondiff	0.1601***	0.1478***
	(0.0082)	(0.0084)
pct_diff	0.0690***	0.1101***
	(0.0220)	(0.0239)
first_avg_mc_correct_rate_nondiff × pct_diff	-0.1614***	-0.1815***
	(0.0219)	(0.0239)
last_avg_difflevel_nondiff	-0.0283***	-0.0256***
	(0.0036)	(0.0028)
Teacher FE	✓	✓
Class FE	✓	✓
Time FE	✓	✓
Observations	137,789	66,368
R^2	0.33686	0.33722
Adjusted R^2	0.28248	0.28043

Notes: This table presents the effects of past usage of differentiation on students' current performance. Columns (1) and (2) present the results for students from low- and high-poverty schools, respectively.

Significance levels: *** p ≤ 0.01, ** p ≤ 0.05, * p ≤ 0.10

Table 4 presents the results for low-poverty and high-poverty schools in columns (1) and (2) respectively. The estimated coefficients for α_3 are positive and statistically significant for both poverty groups, indicating that a higher usage of differentiation is associated with improved student performance. Furthermore, the negative coefficients for α_4 suggest that the positive effect of differentiation is particularly pronounced for students with lower initial performance.

In sum, we find evidence supporting the effectiveness of differentiation: 1) differentiated assignments are associated with better student performance compared to non-differentiated ones, and 2) a higher percentage of differentiated assignments in the past is associated with better current performance. However, it is important to note that the assignment of differentiated tasks is not random, which introduces endogeneity concerns and limits our ability to establish a causal relationship between the usage of differentiation and student performance improvement.

3.3 Evidence of Teachers' Endogenous Differentiation Usage

Teachers play a crucial role in the implementation of differentiation, and therefore, understanding its effectiveness requires accounting for their strategies. One intuitive expectation is that differentiation would be particularly beneficial in larger classes, where a one-size-fits-all approach is less likely to meet the diverse needs of students. Similarly, differentiation may be more advantageous in classes with greater variation in student performance, as it can address individual needs more effectively. In this section, we examine the relationship between a teacher's differentiation strategy and both class size and student performance variation. We find a positive association between a teacher's usage of differentiation and class size, as well as student performance variation, for both low-poverty and high-poverty groups. This suggests that teachers are more inclined to implement differentiation in larger classes and when there is greater heterogeneity in student performance. Next, we delve deeper into the factors influencing the allocation of differentiated assignments to students. Interestingly, we find contrasting patterns between teachers from the low-poverty group and those from the high-poverty group. Teachers from the low-poverty group tend to assign more differentiated assignments to students with lower performance on average. This indicates an effort to provide additional support to struggling students and potentially close the performance gap. However, this trend does not hold for teachers in the high-poverty group. The difference suggests that teachers from different socioeconomic backgrounds may have different preferences and priorities when it comes to implementing differentiation in their classes.

When do teachers use differentiation?

We aggregate the assignment decisions made by teachers at the monthly level for each class. To capture the differentiation practices, we calculate the percentage of differentiated assignments assigned by the teacher for every class in a given month. Additionally, we measure the average student performance within the class and the variation of student performance within the class during each month. To calculate the average student performance within the class, we first compute the average multiple-choice correct rate across students for each non-differentiated assignment assigned by the teacher in that month. We then aggregate these averages over all non-differentiated assignments to obtain the overall average student performance for the class in that month. Similarly, we determine the variation of student performance within the class by calculating the standard deviation of the multiple-choice correct rate for each non-differentiated assignment assigned by the teacher in that month. We then aggregate these standard deviations over all non-differentiated assignments to obtain the overall variation of student performance within the class for the month. To examine the relationship between the teacher's differentiation decision for the class and the average student performance and standard deviation of performance within the class, we regress the differentiation decision on these variables. Specifically, we focus on the most recent month in which the teacher assigned non-differentiated assignments before the current month. We control for class size as well as fixed effects for the teacher, time, and class grade to account for any potential confounding factors.

$$\begin{aligned} pct\_diff_{ict} = &\theta_i + \gamma_t + class\_grade_{ic} + m_1 sd\_correct\_rate\_nondiff_{ic,t-1} + \\ &m_2 avg\_correct\_rate\_nondiff_{ic,t-1} + m_3 logged\_class\_size_{ic} + \epsilon_{ict} \end{aligned} \tag{5}$$

where θ_i, γ_t, and $class\_grade_{ic}$ are teacher, time, and class grade fixed effects, respectively, $sd\_correct\_rate\_nondiff_{ic,t-1}$ is the standard deviation of student performance within class c in the previous period, $avg\_correct\_rate\_nondiff_{ic,t-1}$ is the average student performance of class c in the previous period, $logged\_class\_size$ is logged class size of class c, and ϵ_{ict} is the error term.

We run the regression for teachers from high-poverty and low-poverty schools separately, and report the results in Table 5. The positive and significant estimate of m_3 implies that teachers are more likely to use differentiation when they have a bigger class. The positive and significant estimate of m_1 suggests that controlling for the class size, teachers are more likely to use differentiation when the performance variation within the class is larger for both poverty groups.

Table 5: The Relationship Between Class-Level Performance and Teachers' Differentiation Usage

	pct_diff	
	Low Poverty	High Poverty
	(1)	(2)
sd_mc_correct_rate_nondiff_lag	0.0584*	0.1039***
	(0.0278)	(0.0226)
avg_mc_correct_rate_nondiff_lag	-0.0010	0.0006
	(0.0006)	(0.0008)
logged_class_size	0.0553***	0.0245**
	(0.0119)	(0.0100)
Teacher FE	✓	✓
Class Grade FE	✓	✓
Time FE	✓	✓
Observations	26,546	13,421
R^2	0.43029	0.40781
Adjusted R^2	0.34727	0.32370

Notes: The table presents the relationship between class-level performance and teachers' usage of differentiation. Columns (1) and (2) shows the results for classes from low- and high-poverty schools.

Significance levels: *** p $\leq$ 0.01, ** p $\leq$ 0.05, * p $\leq$ 0.10

Who is more likely to receive differentiated assignments?

After we have shown that teachers' differentiation strategy is associated with student performance variation within the class, a natural question to ask is which students are more likely to receive differentiated assignments. We zoom into the student-level data, and similar to the previous analysis, we aggregate the student assignment information at a monthly level and calculate two variables: the percentage of differentiated assignments out of all assignments opened by each student, and the student's relative performance compared to the class average. The relative performance is measured as the difference between the student's average multiple-choice question correct rate for non-differentiated assignments and the class's average multiple-choice question correct rate for non-differentiated assignments in each period. We then regress the percentage of differentiated assignments in each period on the relative performance of the students in the previous period while controlling for teacher, class, and time fixed effects:

$$pct\_diff_{st} = \theta_i + \kappa_c + \gamma_t + b_1 rlt\_avg\_correct\_rate\_nondiff_{s,t-1} + \epsilon_{st} \tag{6}$$

where θ_i, κ_c, and γ_t are teacher, class, and time fixed effects, respectively, pct_diff_{st} is the percentage of differentiated assignments student s opened in period t, $rlt\_avg\_correct\_rate\_nondiff_{s,t-1}$ is the relative performance of student s in the previous period, and ϵ_{st} is the error term.

Table 6: The Relationship Between Student Relative Performance in Class and Differentiation

	pct_diff	
	Low Poverty (1)	High Poverty (2)
rlt_avg_correct_rate_nodiff_lag	-0.0016** (0.0007)	0.0009 (0.0007)
Teacher FE	✓	✓
Class FE	✓	✓
Time FE	✓	✓
Observations	457,056	218,567
R^2	0.57235	0.52444
Adjusted R^2	0.56211	0.51269

Notes: The table presents the impact of student relative performance within the class on the percentages of differentiated assignments they receive. Columns (1) and (2) shows the results for classes from low- and high-poverty schools.

Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$

Based on the results presented in Table 6, we observe that students with relatively lower performance in the class are more likely to receive differentiated assignments. However, this relationship is significant only for classes in the low-poverty group. This finding suggests that while both high- and low-poverty teachers are more inclined to use differentiation when there is greater variation in student performance, their specific differentiation implementation may differ. This could be driven by the various preferences of teachers from different socioeconomic segments.

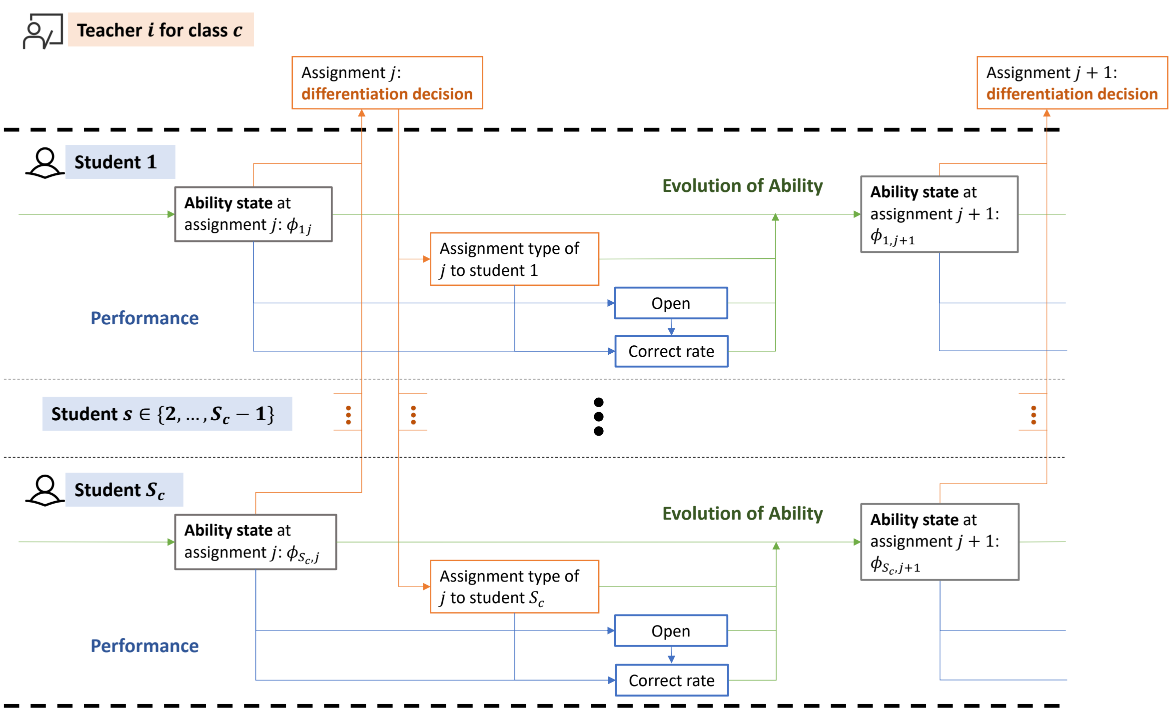
4 Model

4.1 Model Overview

We propose a comprehensive structural model that addresses several limitations associated with the previous analysis. Firstly, we recognize that the assignment received by each student is not exogenous, and failing to account for teacher usage and implementation may introduce bias into the results. Secondly, student performance is influenced by the assignment they receive, making it difficult to obtain a fair evaluation of student ability based solely on observed performance. Furthermore, student correct rates are only observed when the student opens the assignment, which further complicates the assessment of student abilities.

We then provide an overview of our model. The model we propose is centered around the student's ability state and its evolution. We aim to capture the two-way relationship between observed student performance and the teacher's differentiation decisions. Figure 2 shows the conceptual framework of our model.

Figure 2: Conceptual Framework



Our model consists of three components. The first component is student performance, which is influenced by several factors. The observed student performance can be affected by their underlying ability state. When a student receives an assignment, the student can decide whether to open and if so, we observe the correct rate of the student's answers. Both the student's open decision and correct rate reflect their underlying ability state. In addition, student performance is subject to the assignments they receive. For example, the difficulty level of the assignment can impact the observed student performance, as more challenging tasks may lead to lower performance. Moreover, external factors such as socioeconomic status can also influence student performance. For instance, students from disadvantaged backgrounds may face additional barriers that impact their ability to perform well.

The second component is the evolution of student ability states. We aim to capture how a student's ability state changes over time in response to various factors, such as the specific assignment they receive and how they interact with these assignments, i.e., their engagement and performance on the assignments. By modeling the evolution of ability states, we can gain insights into how student learning progresses over time. In addition, it enables us to evaluate the effectiveness of different interventions. For instance, we can use our model to simulate how a student's ability state would evolve under different scenarios, such as receiving differentiated assignments.

The third component is the teachers' differentiation decisions for a class of students. We consider the following three factors that may influence a teacher's decision on whether to use differentiation and how to use it. First, teachers may consider the expected effectiveness of differentiation when deciding whether to differentiate. As certain types of differentiation may be more effective for some students than others, teachers may consider whether a particular student would benefit from differentiation based on their ability state.

Second, teachers may also assign different importance to student progress resulting from differentiation. When teachers assign importance to differentiation, they acknowledge the significance of tailoring assignments to meet the specific needs of different students. At the same time, they may also have preferences or instructional priorities that lead to teachers prioritizing certain student segments. For example, some may prioritize additional support for struggling students while others focus more on challenging high-achieving students using differentiated assignments. While teacher preferences in differentiation can be influenced by factors such as instructional philosophy, previous experiences, and professional training, our model captures the variations in these preferences without further dissecting the specific factors. Due to limited information available on teachers, we recognize that individual educators may prioritize different aspects of differentiation based on their unique perspectives and context. Specifically, our model accommodates teachers' preferences and priorities in implementing differentiation by allowing them to assign higher importance to certain students based on their underlying ability states. This approach enables us to capture and account for the variations in teachers' preferences when implementing differentiation. Given that a teacher's prioritization of certain students can be a sensitive issue and may occur unconsciously, closely observing their behaviors can be crucial in gaining insights into their motivations.

Lastly, it is important to consider the constraints that teachers may face, including limited time and resources. Teachers who face significant time and resource limitations may find it more challenging to fully utilize the differentiation tool. These constraints, coupled with the ease of use of the differentiation tool, directly impact the costs that teachers need to incur when implementing differentiation.

We first introduce the model setup and then discuss each part of the model in detail.

4.2 Model Setup

In our model, we focus on teacher i and their decisions regarding differentiation for class c. We assume that the timing of assignments is exogenous and use j to denote each assignment of the class. We aim to model the teacher's differentiation decisions for the class for each assignment j, denoted as $d_{cj} \in \{0, 1\}$. If assignment j is non-differentiated, then all students in this class received the same non-differentiated assignment, we use $z_{sj} = nd$ to denote the type of assignment received by student s in this class on assignment j. If assignment j is differentiated, then the type of assignment received by student s is $z_{sj} \in \{l, m, h, n\}$, which belongs to one of the four types of differentiated assignments easier, medium, challenging, and no assignment, respectively. In addition, we use ϕ_{sj} to denote student s's ability level which is observable to teachers. Given student s is assigned with an assignment $z_{sj} \neq n$, we use O_{sj} and Y_{sj} to denote whether the student opens the assignment and the multiple choice correct rate conditional on opening. Table 7 summarizes the notation.

Table 7: Summary of Notation

	Description
i	Teacher ID
c	Class ID
s	Student ID, $s \in \{1, \ldots, S_c\}$
j	Assignment ID, $j \in \{1, \ldots, J_c\}$
d_{cj}	Binary variable indicating whether assignment j by teacher i to class c is differentiated.
z_{sj}	Type of assignment received by student s for assignment j, $z_{sj} = nd$ if $d_{cj} = 0$ and $z_{sj} \in \{l, m, h, n\}$ if $d_{cj} = 1$, where l, m, h and n stand for easier, medium, challenging, and no assignment.
ϕ_{sj}	Student s's ability state before assignment j, $\phi_{sj} \in \{1, \ldots, K\}$
O_{sj}	Binary variable indicating whether student s opened assignment j.
Y_{sj}	Multiple choice correct rate for assignment j by student s.

Notes: Assignment timing are assumed to be exogenous. Therefore, assignment ID can be viewed as time ID.respectively.

4.3 Student Performance

Teacher i assigns J_c assignments in total to students in class c. For each assignment $j \in \{1, \ldots, J_c\}$, if student s received assignment j, i.e., $z_{sj} \neq n$, up to two performance outcomes of the student are observed: whether the student opened the assignment, and the score (i.e., the multiple-choice questions correct rate) conditional on opening. We use $O_{sj} \in \{0,1\}$ to denote if student s opened assignment j, and $Y_{sj} \in [0,1]$ to denote the score student s received. We use a latent utility approach to model students' opening decisions. Let U^O_{sj} be student s's latent utility for opening assignment j, and student s would open the assignment ($O_{sj} = 1$) if $U^O_{sj} > 0$. The latent utility can be written as:

$$U^O_{sj} = \tau^O_{t(c,j)} + \beta^O_{c0}(\phi_{sj}) + \beta^O_{c1}(\phi_{sj})d_{cj} + \epsilon^O_{sj}. \tag{7}$$

In equation 7, $\tau^O_{t(c,j)}$ captures the time fixed effects (quarterly), $\beta^O_{c0}(\phi_{sj})$ captures the intrinsic tendency of a student of state ϕ_{sj} in class c taught by teacher i to open an assignment, and $\beta^O_{c1}(\phi_{sj})$ represents the effect of the assignment being a differentiated one on the open utility of a student with type ϕ_{sj}. We allow these parameters to be teacher-class specific, which enables us to define student states differently for each class. This flexibility ensures that the model can account for the unique learning profiles and requirements of students across various classes. The reduced-form analysis regarding assignment open rate shows that differentiated assignments tend to have higher open rates by the students compared to non-differentiated ones. Therefore, although ReadWorks does not explicitly indicate whether an assignment is differentiated to students, they may learn about whether the assignment is a differentiated one through other channels, such as communication with their teachers. This may affect students' open decisions. For instance, if a student knows that an assignment is differentiated, they may feel more motivated to engage with it, as they understand that the teacher is paying extra attention to their individual needs. Both $\beta^O_{c0}(\phi_{sj})$ and $\beta^O_{c1}(\phi_{cj})$ depend on the student's underlying ability state, denoted as ϕ_{sj}. We discuss the evolution of ϕ_{sj} in section 4.4.

Assuming student s has opened the assignment ($O_{sj} = 1$), we can observe the score, Y_{sj}, which represents the percentage of correctly answered multiple-choice questions:

$$Y_{sj} = \tau^Y_{t(c,j)} + \beta^Y_{c0}(\phi_{sj}) + \beta^Y_{c1}(\phi_{sj})I\{z_{sj} = l\} + \beta^Y_{c2}(\phi_{sj})I\{z_{sj} = m\} + \beta^Y_{c3}(\phi_{sj})I\{z_{sj} = h\} + \epsilon^Y_{sj}. \tag{8}$$

In equation 8, $\tau^Y_{t(c,j)}$ captures the time fixed effects (quarterly), $\beta^Y_{c0}(\phi_{sj})$ captures a student's baseline score that depends on the underlying ability state, ϕ_{sj}, and a student who has higher ability states would have a higher baseline score. Similar to equation 7, $\beta^Y_{c1}(\phi_{sj})$, $\beta^Y_{c2}(\phi_{sj})$, and $\beta^Y_{c3}(\phi_{sj})$ capture the effect of three types of differentiated assignment on the student performance measured by the correct rate, since the performance would also be affected by the difficulty level of the differentiated assignment after the student opens the assignment.

In addition, we can allow for correlations between the two error terms ϵ_{sj}^O and ϵ_{sj}^Y. Specifically, we assume

$$\epsilon_{sj}^O \sim N(0,1) \tag{9}$$

$$\epsilon_{sj}^Y = \sigma_{YO}\epsilon_{sj}^O + \nu_{sj}^Y, \quad \nu_{sj}^Y \sim N(0,\sigma_Y^2) \tag{10}$$

where ϵ_{sj}^O and ν_{sj}^Y are $i.i.d.$ across s and j. Hence, the two error terms are jointly normal:

$$\begin{pmatrix} \epsilon_{sj}^O \\ \epsilon_{sj}^Y \end{pmatrix} \sim N(0,\Omega_1), \tag{11}$$

where

$$\Omega_1 = \begin{pmatrix} 1 & \sigma_{YO} \\ \sigma_{YO} & \sigma_{YO}^2 + \sigma_Y^2 \end{pmatrix}. \tag{12}$$

In this model, we assume $\sigma_{YO} = 0$ to avoid numerical integration for teachers' decisions and show that the assumption is not highly restrictive in Section 4.5.

4.4 Student Ability States

We model the student's underlying ability using a first-order discrete-time discrete-state hidden-Markov model (HMM). We denote the state of student s at the time of assignment j as ϕ_{sj}, $\phi_{sj} \in \{1,2,\ldots,K\}$. For identification, we order the states from 1 to K, with K being the highest ability as HMM is invariant to state permutation. Specifically, as the correct rate is the most straightforward proxy for student ability state, and $\beta_{c0}^Y(\phi_{sj})$ represents the baseline correct rate, we assume $\beta_{c0}^Y(\phi_{sj})$ increases with the state ϕ_{sj}, i.e., $\beta_{c0}^Y(1) \le \beta_{c0}^Y(2) \le \ldots \le \beta_{c0}^Y(K)$.

We capture the evolution of ability states using a student- and time-specific state transition matrix:

$$Q_{sj} = \begin{pmatrix} q_{sj}(1,1) & \cdots & q_{sj}(1,K) \\ \vdots & \ddots & \vdots \\ q_{sj}(K,1) & \cdots & q_{sj}(K,K) \end{pmatrix}. \tag{13}$$

where each element in the matrix $q_{sj}(\phi,\phi')$ is the probability that student s transitions from state ϕ before assignment j to state ϕ' before assignment j'. Following Netzer et al. (2008) and Ma et al. (2015), we use a threshold model to account for the non-homogeneous state transition since the ability states are ordered from the lowest to the highest. Specifically, we consider an ordered probit model where a transition between states occurs if the propensity for transition passes a certain threshold level. We specify a set of threshold values as boundaries between states and denote them as $\mu_c(\phi, \phi')$, where $\phi \in \{1, 2, \ldots, K\}$, $\phi' \in \{1, 2, \ldots, K-1\}$, and $\mu_c(\phi, \phi') \leq \mu_c(\phi, \phi''), \forall \phi' < \phi''$. In addition, we assume a student's transition propensity is affected by the type of assignment received by the student and the student's performance given the assignment received. We use g_{sj} to denote the unobserved propensity and use $\boldsymbol{\rho}_s(\phi)$ to capture the effect of different factors on the propensity for the transition from state ϕ:

$$\begin{aligned} g_{sj} =& \bar{g}_{sj} + \epsilon^{\rho}_{sj} \\ =& \bar{\rho}^{O}_{sj} O_{sj} + \bar{\rho}^{Y}_{sj}(z_{sj}) Y_{sj} + \epsilon^{\rho}_{sj}, \end{aligned} \tag{14}$$

where

$$\begin{aligned} \bar{\rho}^{O}_{sj} =& \rho_{c0}(\phi_{sj}), \\ \bar{\rho}^{Y}_{sj}(z_{sj}) =& \rho_{c1}(\phi_{sj}) + \rho_{c2}(\phi_{sj}) I\{z_{sj} = l\} + \rho_{c3}(\phi_{sj}) I\{z_{sj} = m\} + \rho_{c4}(\phi_{sj}) I\{z_{sj} = h\}, \end{aligned} \tag{15}$$

$\bar{\rho}^{O}_{sj}$ captures the effect of assignment opening on state transition propensity and $\bar{\rho}^{Y}_{sj}(z_{sj})$ captures the effect of student performance, specifically the correct rate, of various types of assignment on the state transition propensity. ϵ^{ρ}_{sj} is the error term that follows a standard normal distribution. Note that we have $Y_{sj} = 0$ when $O_{sj} = 0$ by default. This implies that there is no systematical difference in state transition processes between the situation where a student was given an assignment but did not open it and the situation where the student did not receive any assignment at all.

The state transition probabilities in equation 13 can be written as follows:

$$\begin{cases} q_{sj}(\phi, 1) = F\left(\mu_c(\phi, 1) - \bar{g}_{sj}\right) \\ q_{sj}(\phi, \phi') = F\left(\mu_c(\phi, \phi') - \bar{g}_{sj}\right) - F\left(\mu_c(\phi, \phi' - 1) - \bar{g}_{sj}\right), \quad \forall \phi' \in \{2, \ldots, K-1\} \\ q_{sj}(\phi, K) = 1 - F\left(\mu_c(\phi, K-1) - \bar{g}_{sj}\right). \end{cases} \tag{16}$$

where $F(\cdot)$ is the cumulative distribution function for standard normal distribution.

Finally, we denote the probability that a customer starts from state ϕ as $q_{s0}(\phi)$. In our sample, the first assignment for 89% of classes is a non-differentiated one. Therefore, we restrict our sample to those classes where the first assignment is a non-differentiated assignment and use student performance based on the first assignment to augment student state before the first assignment. Specifically, we assume noninformative prior for each student's initial state and calculate the posterior distribution of the state $q_{s0}(\phi) = q_{s0}(\phi|O_{s1}, Y_{s1})$.

4.5 Teachers' Differentiation Decisions

For class c taught by teacher i, we assume there are J_c exogenously given slots to give out assignments, and teacher i makes differentiation decisions for each of the assignment slots, $j \in \{1, 2, \ldots, J_c\}$. We model the teacher's differentiation decision as a two-stage process. First, teacher i decides whether to differentiate for assignment j to class c, and we use $d_{cj} \in \{0, 1\}$ to denote the first-stage differentiation decision where $d_{cj} = 0$ stands for non-differentiated assignment and $d_{cj} = 1$ stands for differentiated assignment. Next, if assignment j is non-differentiated, i.e., $d_{cj} = 0$, all students in class c taught by teacher i would receive the same non-differentiated assignment, and we use $z_{sj} = nd$ to denote the type of assignment received by student s as non-differentiated when $d_{cj} = 0$. If assignment j is differentiated, i.e., $d_{cj} = 1$, teacher i needs to decide the type of differentiated assignment to assign to every student in class c, denoted as $z_{sj} \in \{l, m, h, n\}, \forall s \in \{1, 2, \ldots, S_c\}$. l, m, h, and n represent assignments of varying levels of difficulty compared to non-differentiated assignments, with l representing an easy assignment, m representing a medium-level assignment (or similar level to non-differentiated assignment), h representing a difficult assignment, and n representing no assignment.

To summarize, in the first stage, teacher i decides $d_{cj} \in \{0, 1\}$. In the second stage, if $d_{cj} = 0$, then we have $z_{sj} = nd, \forall s \in \{1, 2, \ldots, S_c\}$; if $d_{cj} = 1$, teacher i needs to determine $z_{sj} \in \{l, m, h, n\}$ for every student in class c.

As discussed in section 4.1, teachers' differentiation decisions can be influenced by multiple factors, such as their perceptions of the anticipated effectiveness of differentiation, their beliefs and incentives related to the implementation of differentiation, and the potential costs associated with time and resource limitations. In addition, these factors may be incorporated into different stages of differentiation decisions in our model. We use a latent utility approach to model both stages of teachers' differentiation decisions.

We begin by discussing the expected student progress.

4.5.1 Expected Student Progress

We assume the student's ability state is known to the teacher before giving out each assignment. For student s and assignment j, teacher i forms an expectation for student open decision if the teacher gives student s the assignment with type z_{sj}: $Pr(O_{sj} = 1|z_{sj})$. Combined with equation 7, we have

$$Pr(O_{sj} = 1|z_{sj}) = F\left(X^O_{sj}(z_{sj})\beta^O_{sj}\right), \tag{17}$$

where $F(\cdot)$ represents the cumulative density function of standard normal distribution.

In addition, teacher i forms an expectation of student progress given a specific assignment type. We use $EP_{sj}(z_{sj})$ to denote the expected probability of transitioning to a higher state (staying in the current state for those who are currently in the highest state). $EP_{sj}(z_{sj})$ can be used as a proxy for the expected student progress given assignment type z_{sj}. For student s whose ability state before assignment j is ϕ_{sj}, the expected progress of the student receiving assignment type z_{sj} is

$$EP_{sj}(z_{sj}) = \begin{cases} \boldsymbol{E}\left[\sum_{\phi' > \phi_{sj}} q_{sj}(\phi_{sj}, \phi') \middle| z_{sj}\right] & \text{if } \phi_{sj} < K \\ \boldsymbol{E}\left[\sum_{\phi' = \phi_{sj}} q_{sj}(\phi_{sj}, \phi') \middle| z_{sj}\right] & \text{if } \phi_{sj} = K \end{cases} \tag{18}$$

For the ease of notation, we define $\mu_c(K, K) = \mu_c(K, K-1)$ and rewrite the student expected progress as

$$\begin{aligned} &\boldsymbol{E}\left[\sum_{\phi' > \phi_{sj}} q_{sj}(\phi_{sj}, \phi') \middle| z_{sj}\right] \\ =& \iiint_{\epsilon^O_{sj} > -X^O_{sj}(z_{sj})\beta^O_{sj}, \epsilon^\rho_{sj} > \mu_c(\phi_{sj}, \phi_{sj}) - \bar{g}_{sj}} f(\epsilon^\rho_{sj}) f(\epsilon^Y_{sj}, \epsilon^O_{sj}) d\epsilon^\rho_{sj} d\epsilon^Y_{sj} d\epsilon^O_{sj} + \\ & Pr(O_{sj} = 0|z_{sj}) \int_{\epsilon^\rho_{sj} > \mu_c(\phi_{sj}, \phi_{sj}) - \bar{g}_{sj}} f(\epsilon^\rho_{sj}) d\epsilon^\rho_{sj} d. \end{aligned} \tag{19}$$

where the first and second terms represent the probability of student s transitioning to higher states after assignment j given that 1) student s opened assignment j, and 2) student s did not open it, respectively. We rewrite the integration region of the first term as

$$\begin{aligned} &\epsilon^O_{sj} > -X^O_{sj}(z_{sj})\beta^O_{sj} \\ &\epsilon^\rho_{sj} + \bar{\rho}^Y_{sj}\rho_{YO}\epsilon^O_{sj} + \bar{\rho}^Y_{sj}\epsilon^Y_{sj} > \mu_c(\phi_{sj}, \phi_{sj}) - \left(\bar{\rho}^O_{sj} + \bar{\rho}^Y_{sj}(z_{sj})X^Y_{sj}(z_{sj})\beta^Y_{sj}\right) \end{aligned} \tag{20}$$

When $\sigma_{YO} = 0$, equation 19 can be written as:

$$
\begin{aligned}
&EP_{sj}(z_{sj}) = \boldsymbol{E}\left[\sum_{\phi' > \phi_{sj}} q_{sj}(\phi_{sj}, \phi') \middle| z_{sj}\right] \\
=&Pr(O_{sj} = 1|z_{sj}) \left(1 - F\left(\frac{\mu_c(\phi_{sj}, \phi_{sj}) - \left(\bar{\rho}^O_{sj} + \bar{\rho}^Y_{sj}(z_{sj}) X^Y_{sj}(z_{sj}) \beta^Y_{sj}\right)}{\sqrt{1 + (\bar{\rho}^Y_{sj}\sigma_Y)^2}}\right)\right) + \\
&Pr(O_{sj} = 0|z_{sj}) \left(1 - F\left(\mu_c(\phi_{sj}, \phi_{sj})\right)\right).
\end{aligned} \tag{21}
$$

where $F(\cdot)$ is the CDF of standard normal distribution.

To use equation 21 and avoid numerical integration, we set σ_{YO} to zero during our model estimation. However, we also performed a robustness check where we removed the constraint on σ_{YO} and did not involve teacher differentiation decisions. We believe that our assumption is not highly restrictive, as the estimated value for σ_{YO} is small, less than 0.1.

4.5.2 Teachers' Second-stage Decision: how to differentiate?

We start with the second stage of a teacher's differentiation decision when the teacher decides to differentiate. First, the teacher forms an expectation of the effectiveness of differentiation for each student, which is represented by the expected progress of this student with different assignment types. Second, teachers may have different preferences when differentiating, the same progress from different students may bring different utility to a teacher. We allow teachers' utility from the same progress to vary across student ability states. Third, teachers incur a net cost for finding an assignment of a certain type for each student on the ReadWorks platform.

Formally, if teacher i decides to differentiate in class c on assignment j, i.e., $d_{icj} = 1$, the type of differentiated assignments received by student s for assignment j is $z_{sj} \in \{l, m, h, n\}$. We use l, m, and h to denote easier, medium, and more challenging differentiated assignments compared to non-differentiated assignments. n stands for no assignment given for assignment j slot. We use $V_{sj}(z)$ to denote the teacher's utility from giving assignment j of type z to student s:

$$
V_{sj}(z) = \begin{cases} b_c(\phi_{sj}) EP_{sj}(z) - w_c + w_{sjz} & \text{if } z \in \{l, m, h\} \\ b_c(\phi_{sj}) EP_{sj}(z) + w_{sjz} & \text{if } z = n \end{cases} \tag{22}
$$

where $b_c(\phi_{sj})$ denotes the weight associated with student s's expected progress with assignment j.

We allow the weight to vary across students' states to capture teachers' differential valuation of the same progress of students in various states. In addition, teacher i incurs a cost $w_c - w_{sjz}$ to find the assignment of type z for student s. w_c is the mean cost that varies across assignment types. w_{sjz} represents the random cost teacher i incurs to find the right assignment of type z for student s for assignment j, and we assume it follows a standard type-1 extreme value distribution. We assume that teachers do not look into different assignments before they decide whether to differentiate in the first stage and as a result, w_{sjz} is only observable for teachers after teacher i decides to differentiate in the second stage.

4.5.3 Teachers' First-stage Decision: whether to differentiate? ($d_{cj} \in \{0, 1\}$)

In the first stage, teacher i decides whether to use differentiation. We incorporate the following components that may affect teachers' decisions. The first component is the difference between the expected utility from differentiating assignment j in the second stage and the expected utility from non-differentiated assignment j. Recall that conditional on a teacher using differentiation for an assignment, the teacher's second-stage decision involves the effectiveness of differentiation, teacher preferences, and differentiation cost on ReadWorks. Therefore, the first component entering the teacher's first-stage decision essentially entails the difference between the effectiveness of differentiation and no differentiation regarding student expected progress, teacher preferences, as well as the differentiation cost on the ReadWorks platform. The second component represents the net utility of teacher i from outside options. Specifically, since we only observe teachers' activities on ReadWorks but nothing outside the platform, and only around 34% of the classes have at least one differentiated assignment, we use the second factor to capture the net utility teacher obtained from outside options.

We now put it in mathematical form and write teacher i's utility in the first stage deciding whether to differentiate in assignment j as follows,

$$U_{cj} = \bar{U}_{cj} + e_{cj} = \frac{1}{|S_c|} \sum_{s \in S_c} \left\{ E\left[\max_{z \in \{n,h,m,l\}} V_{sj}^*(z) \right] - b_c(\phi_{sj}) EP_{sj}(nd) \right\} - UO_{cj} + e_{cj} \tag{23}$$

where the first term measures the difference of utilities from differentiating assignment j and no differentiation on assignment j averaged across all students in the class, UO_{cj} represents the net utility of outside option for class c taught by teacher i at time t, and e_{cj} represents the randomness of the outside option that follows a logistic distribution.

The net utility of the outside option has two parts, the class-specific part, and the time-specific part:

$$UO_{ct} = UO_{c,0} + UO_{t(c,j)}, \tag{24}$$

where $UO_{t(c,j)}$ captures the common shock.

Teacher i's differentiation decision on assignment j in class c is determined as follows:

$$d_{cj} = \begin{cases} 1 & \text{if } U_{cj} > 0 \\ 0 & o.w. \end{cases}$$

In equation 23, the first term is obtained by taking an average of utility gain of differentiation across S_c students in class c. We assume the teacher forms an expected utility from differentiation because the cost of giving differentiated assignments of a certain type is not realized in the first stage. We write utility of differentiation from student s on assignment j with type z in equation 22 as

$$V_{sj}(z) = \bar{V}_{sj}(z) + w_{sjz}.$$

Then the expected utility of differentiation from student s on assignment j would be an expected maximum utility associated with different types of differentiated assignments,

$$E\left[\max_{z\in\{n,h,m,l\}} V_{sj}(z)\right] = \sum_{z\in\{n,h,m,l\}} \bar{V}_{sj}(z) \times \frac{\exp(\bar{V}_{sj}(z))}{\sum_{z'\in\{l,m,h,n\}} \exp(\bar{V}_{sj}(z'))}. \tag{25}$$

Meanwhile, the expected utility with no differentiation from student s on assignment j is,

$$b_c(\phi_{sj})EP_{sj}[z = nd]. \tag{26}$$

The utility gain of differentiation from student s can then be expressed as the difference between equations 25 and 26.

4.5.4 Log-likelihood of observing teachers' differentiation decisions

The likelihood of observing d_{cj} and $z_{sj} \forall s \in S_c$ can be written as:

$$L(\{z_{sj}\}_{s\in S_c}) = L(d_{cj}, \{z_{sj}\}_{s\in S_c}) = \Pi \left(\frac{1}{1+\exp(\bar{U}_{cj})}\right)^{I\{d_{cj}=0\}} \left(\frac{\exp(\bar{U}_{cj})}{1+\exp(\bar{U}_{cj})}\right)^{I\{d_{cj}=1\}}$$
$$\Pi_{s\in S_c}\Pi_{z\in\{n,l,m,h\}} \left(\frac{\exp(\bar{V}_{sj}(z))}{\sum_{z'\in\{n,l,m,h\}}\exp(\bar{V}_{sj}(z'))}\right)^{I\{z_{sj}=z\}I\{d_{cj}=1\}}$$

The log-likelihood is

$$\begin{aligned} LL(d_{cj}, \{z_{sj}\}_{s\in S_c}) = \Bigg\{ & I\{d_{cj}=0\} \times \log\left(\frac{1}{1+\exp(\bar{U}_{cj})}\right) + \\ & I\{d_{cj}=1\} \times \log\left(\frac{\exp(\bar{U}_{cj})}{1+\exp(\bar{U}_{cj})}\right) + \\ & \sum_{s\in S_c}\sum_{z\in\{n,l,m,h\}} I\{z_{sj}=z\} \times \log\left(\frac{\exp(\bar{V}_{sj}(z))}{\sum_{z'\in\{l,m,h,n\}}\exp(\bar{V}_{sj}(z'))}\right)\Bigg\} \end{aligned}$$

4.6 Missing information about assignment type

One caveat of our data is that we do not always observe the type of assignment a student receives. We start with the information we do observe in the data. For each assignment j, we observe whether it is a differentiated one, i.e., d_{cj}. In addition, we observe the student performance record, i.e., the correct rate only when the student opened the assignment. Therefore, when the assignment is non-differentiated, i.e., $d_{cj} = 0$, we know for sure that the student has received the assignment, $z_{sj} = nd$, and if we find no record of this student, it means that the student did not open it $O_{sj} = 0$. However, when the assignment is differentiated, i.e., $d_{cj} = 1$, when we do not observe the performance record of a student s the student is either not assigned or is assigned but did not open. Therefore, when $d_{cj} = 1$, $O_{sj} = 0$, for student s that does not have a performance record, the probability that student s receive a differentiated assignment j of type z_{sj} can be written as:

$$Pr(z_{sj} = z|O_{sj} = 0) = \begin{cases} \dfrac{Pr(z_{sj})Pr(O_{sj}=0|z_{sj}=z)}{Pr(z_{sj}=n)+\sum_{z'\in\{l,m,h\}}Pr(z_{sj}=z')Pr(O_{sj}=0|z_{sj}=z')}, & \text{if } z \in \{l,m,h\}, \\ \dfrac{Pr(z_{sj}=n)}{Pr(z_{sj}=n)+\sum_{z'\in\{l,m,h\}}Pr(z_{sj}=z')Pr(O_{sj}=0|z_{sj}=z')}, & \text{if } z = n. \end{cases}$$

We augment the missing assignment type in our Bayesian estimation procedure.

4.7 Heterogeneity

We denote each teacher-class specific parameter as λ_c

$$\lambda_c = \lambda_c^L LowPov_c + \lambda_c^H HighPov_c, \tag{27}$$

where $LowPov_c$ equals 1 if teacher i comes from a low-poverty school, $HighPov_c$ equals 1 if teacher i comes from a high-poverty school. λ_c^L and λ_c^H are class-specific terms for those in low-poverty and high-poverty schools, respectively. To account for unobserved heterogeneity, we assume that the class-specific terms are drawn from population-level normal distributions,

$$\begin{aligned} \lambda_c^L &\sim N(\bar{\lambda}^L, \sigma^2_{\lambda^L}), \\ \lambda_c^H &\sim N(\bar{\lambda}^H, \sigma^2_{\lambda^H}). \end{aligned} \tag{28}$$

λ_c denotes the intercepts in student performance equations ($\beta^O_{c0}(\phi)$ and $\beta^Y_{c0}(\phi)$) and the threshold parameters for the state transition ($\mu_c(\phi, \phi')$). For other parameters in the student performance and state transition equations, we only allow for observed heterogeneity but not unobserved heterogeneity (i.e., $\sigma_{\lambda^L} = \sigma_{\lambda^H} = 0$). Similarly, we allow the parameters in the teacher's differentiation decisions to have observed heterogeneity only. The reason we do not allow for unobserved heterogeneity is that as the main independent variable for teachers' differentiation decisions, the expected progress does not vary for students with the same ability state in the same class at the same time. Therefore, we leverage the variation of student expected progress across classes and the variation over time for the identification of teachers' differentiation decision variables. The only exception is the net utility for the outside option $UO_{c,0}$. In addition to the observed heterogeneity, we allow for unobserved heterogeneity. However, since around 34% of the classes have no differentiated assignments at all, we assume the unobserved heterogeneity has two discrete segments to capture such patterns.

5 Identification and Estimation

We first discuss the identification of parameters. For student performance parameters, the intrinsic student performance (the state-dependent intercept in the open utility and correct rate functions) is identified through the tendency to open assignments and achieve a certain level of correct rate by students of each state. The differentiation parameters in the performance equations are identified from the relationship between a student's performance and the type of assignments received by the students.

For the student ability state transition part, the identification of student ability states and intrinsic state transition probabilities, i.e., the thresholds for the ordered probit model relies on changes in a student's performance trajectories over time. Consider a student who rarely opens any assignments and performs poorly with low correct rates on the rare occasions that the student opens the assignment, then starts to actively open the assignments and give answers that achieve higher correct rates. This implies the existence of different states, and the length of the occasions with distinct patterns indicates the intrinsic tendency to change states. Furthermore, the state transition parameters are identified through the relationship between state transition patterns and covariates including the teacher's assignment decisions and the realized student performance on these assignments.

For the teacher differentiation decision part, for students with each ability state, the weight parameters are identified through the relationship between the student's expected progress and whether the student receives a differentiated assignment when the teacher decides to differentiate. Since the current model only allows for class-level heterogeneity but not student-level heterogeneity, the expected student progress for students in the same class and the same state is the same. Therefore, we leverage the expected student progress variation across different classes in the same socioeconomic status to identify the weight parameters. Additionally, the net cost of finding a differentiated assignment of a certain type is identified by teachers' intrinsic tendency to use a certain type of differentiated assignment. In sum, the variation from the implementation of differentiation helps us identify the parameters that enter the teachers' second-stage decisions. Consequently, the net outside utility parameter that enters teachers' first-stage differentiation decisions is then identified by the teachers' intrinsic tendency to use differentiation for each class. In addition, as the differentiation decisions are first made at the class level and then at the student level, and therefore, for a student, the variation of the student ability of other students in the class would provide the variation of the differentiation assignments for the focal student.

We estimate the parameters using Markov Chain Monte Carlo (MCMC). In our model, we use data augmentation to draw the student ability state at each assignment slot, the open utility for students when they are given assignments, and the missing assignment type information. We use a combination of Gibbs sampling with Metropolis-Hastings to estimate the parameters.

6 Results

We first show the estimation results for the student performance and state transition parameters in section 6.1. This would allow us to evaluate the potential effectiveness of differentiation. Next, we report the estimation results for teachers' differentiation decisions in section 6.2, which allows us to have a better understanding of teacher usage of the differentiation tool.[5]

6.1 Effectiveness of differentiation

We report the estimation results for student performance parameters in Table 8. Panel A shows the open utility equation estimates. The intercepts for each state represent the average tendency to open an assignment across all classes within the respective socioeconomic segment. These intercepts provide valuable insights into the inherent tendency to engage with non-differentiated assignments. The results indicate that state 1 students have an intrinsic open rate of approximately 38% for non-differentiated assignments. On the other hand, state 2 and state 3 students exhibit an intrinsic open rate exceeding 90%. In addition, the positive and significant estimate of if_diff suggests that students across all states are more inclined to open an assignment when it is differentiated. It is consistent with our empirical evidence that differentiated assignments have higher open rates compared to non-differentiated ones. This implies that students can tell whether an assignment is differentiated or not, even in the absence of direct information within the assignment. As a result, when students perceive an assignment as tailored to their individual needs, they are more inclined to actively engage with it, indicating a preference for personalized attention from their teachers.

Panel B shows the estimates in the correct rate equation. The intercepts for each state represent the average correct rate student can get for a non-differentiated assignment across all classes within the respective socioeconomic segment. State 1 students tend to achieve approximately 5% correct rate, while state 2 students typically achieve around 50%, and state 3 students surpass 85%. For the correct rate equation, we further control for the difficulty level of the differentiated assignment using the difficulty level of non-differentiated assignments as a benchmark. Consistent with our intuition, students are more likely to have a higher correct rate when working on easier differentiated assignments and a lower correct rate when they are assigned more challenging assignments.

The results in Table 8 show how differentiation affects students' observed performance. However, to truly understand its impact, we need to examine how students' abilities change with and

[5]The estimation results are based on the 563 classes in the second grade and the number of student states is assumed to be three. The model using the full sample and models with alternative specifications are in progress.

Table 8: Estimation Results for Student Performance Parameters

	Low Poverty			High Poverty		
	state 1	state 2	state 3	state 1	state 2	state 3
Panel A: open utility						
intercept	-0.292***	1.375***	2.242***	-0.309***	1.725***	2.218***
if diff	2.639***	2.602***	0.646***	1.79***	1.651***	0.863***
Time FE			✓			
Panel B: correct rate						
intercept	0.052***	0.527***	0.893***	0.065***	0.493***	0.851***
diff l	0.088***	0.312***	-0.108***	0.059***	0.188***	0.045***
diff m	-0.053***	-0.033***	-0.036***	0.015	-0.02***	0.005
diff h	0.193***	-0.315***	-0.101***	-0.061	-0.283***	-0.138
Time FE			✓			

Notes: The table reports the estimated effects of differentiation on student performance for high-poverty and low-poverty schools. Panel A presents the results for open utility, indicating how differentiation affects students' utility in accessing assignments. Panel B presents the results for correct rate, showing the impact of differentiation on students' performance in terms of correct answers.

Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$

without differentiation. While adjusting the difficulty level of assignments can manipulate observed performance, what matters more is the actual change in students' ability states. Next, we present the results of state transition.

Table 9 reports the parameter estimates for state transition. For students in low-poverty schools, at states 1, 2, and 3, the unconditional probability of remaining in the same state for the next assignment is approximately 90.5%, 44.9%, and 63.0% respectively. On the other hand, for students in high-poverty schools, the corresponding unconditional probability is 91.0%, 45.2%, and 50.6%. Regardless of socioeconomic background, these findings suggest that lower-ability states are more persistent or "stickier" than higher-ability states for both socioeconomic segments. In other words, it is more challenging for students with lower achievement levels to improve and transition to higher states compared to high-achieving students transitioning to lower states. Furthermore, the results indicate that student abilities are more likely to evolve gradually rather than undergo drastic changes. The comparison between the high-poverty and low-poverty groups suggests that it is particularly challenging for students in high-poverty schools to improve and transition to higher-ability states.

Conditional on a student opening the assignment, their correct rate does indeed impact the state transition. Generally, a higher correct rate on the current assignment increases the probability of transitioning to a higher ability state. Moreover, given the same observed correct rate, a student could have a higher probability of transitioning to a higher state when the assignment is more difficult. In other words, even with the same observed performance, tackling more challenging assignments presents a greater opportunity for students to progress to higher states of achievement.

Table 9: Unconditional transition probability

	Low Poverty			High Poverty		
From/To State	state 1	state 2	state 3	state 1	state 2	state 3
state 1	0.905	0.075	0.02	0.91	0.069	0.021
state 2	0.169	0.449	0.381	0.253	0.452	0.295
state 3	0.115	0.255	0.63	0.182	0.312	0.506

Notes: The table presents the unconditional transition probability matrix for students from high-poverty and low-poverty schools. The calculation is based on the average threshold parameters ($\mu_c(\phi, \phi')$) across all classes in each socioeconomic segment.

Table 10: Conditional transition parameter

	Low Poverty			High Poverty		
	state 1	state 2	state 3	state 1	state 2	state 3
Open	1.368***	-0.108***	-0.223***	1.049***	-0.092***	-0.052***
CorrectRate	0.092*	0.234***	0.263***	0.777***	0.233***	0.226***
CorrectRate × diff l	-0.809***	-0.088***	-0.008***	-2.286***	-0.062***	-0.029***
CorrectRate × diff m	4.467***	0.015***	0.028***	-0.797***	0.019***	0.028***
CorrectRate × diff h	-0.036	0.106***	0.047***	2.608***	0.086***	0.077***

Notes: The table reports the impact of student performance on state transition, which varies for student at different ability states and students from high- and low-poverty schools. The impact of the correct rate also varies based on the type of the assignment.

Significance levels: *** p $\leq$ 0.01, ** p $\leq$ 0.05, * p $\leq$ 0.10

Table 10 presents the results of the impact of student performance on state transitions. The effect varies for students at different ability states and from high-poverty and low-poverty schools. Students at state 2 and state 3 from both high-poverty and low-poverty schools experience a negative and statistically significant effect when opening the assignment with a 0 correct rate. This suggests that starting with a low performance level hinders their chances of transitioning to a higher state. However, as the correct rate of the assignment increases, the probability of transitioning to a higher state also increases. Moreover, the magnitude of this effect becomes more pronounced as the difficulty level of the differentiated assignments increases. In contrast, for students at state 1, simply opening the assignment has a positive impact on their transition to a better state.

The effect of a specific type of differentiated assignment can be understood by considering the interaction between two opposing forces. Taking a more challenging assignment as an example, there are two factors at play. Firstly, assigning a difficult task often leads to a lower average correct rate, indicating that students may struggle more and achieve a lower level of correctness, on average. However, on the other hand, tackling a more difficult assignment also implies a higher weight assigned to the correct rate. This means that correct responses carry greater significance in determining students' progression to higher ability states. As a result, the impact of differentiated assignments is a combination of these two forces—the potential decrease in average correctness and the increased importance of correct responses—which collectively influence students' advancement to higher levels of achievement.

Table 11: The Impact of Differentiation on Expected Student Progress

	Low Poverty			High Poverty		
Pct	state 1	state 2	state 3	state 1	state 2	state 3
baseline ($EP(z)$)	10.71	38.84	62.51	9.87	31.92	51.15
$\Delta EP(nd)$	14.40	0.50	0.40	12.05	0.77	5.13
$\Delta EP(d)$	38.70	0.55	0.93	25.76	0.88	6.13
$\Delta EP(d) - \Delta EP(nd)$	24.30	0.05	0.53	13.71	0.11	1.00

Notes: The table presents the change in expected progress (EP) when students are assigned non-differentiated and differentiated assignments. The baseline represents the expected probability of a student transitioning to a higher state (or remaining at the highest state if they are already at the highest state) when no assignment is given. $\Delta EP(nd)$ represents the change in expected student progress when the student receives a non-differentiated assignment, while $\Delta EP(d)$ represents the change in expected student progress when the student receives a differentiated assignment that yields the maximum increase among the three levels (l, m, h), i.e. $\max_{z\in\{l,m,h\}} \Delta EP(z)$.

In Table 11, we examine the effects of different assignment types on student state transitions, shedding light on the benefits of differentiated assignments for students at various ability states in both high-poverty and low-poverty schools. The analysis compares the expected progress when a student is assigned a non-differentiated assignment to the maximum benefit derived from differentiated assignments. The expected progress is defined as the expected probability of transitioning to a higher state, with the highest state representing the probability of staying at the highest state when already there. We establish the baseline using the expected probability when no assignment is given. Subsequently, we calculate the change in expected progress for non-differentiated assignments compared to the baseline and likewise for differentiated assignments, denoted as $\Delta EP(nd)$ and $\Delta EP(d)$, respectively. By subtracting $\Delta EP(nd)$ from $\Delta EP(d)$, we measure the impact of differentiated assignments on student expected progress. The results demonstrate that for state 1 students in both poverty groups, the impact of differentiated assignments on expected progress is substantial, at 24.3% and 13.7%, respectively. However, the magnitude diminishes for state 2 and state 3 students, with figures of 0.05% and 0.11% for state 2, and 0.11% and 1.0% for state 3, for low-poverty and high-poverty schools, respectively. These findings highlight the varying degrees of impact that differentiated assignments have on student expected progress across different ability states.

6.2 Teachers' usage of differentiation

We provide the parameters for teachers' differentiation usage decisions in Table 12, 13, and 15. In Table 12, we present the estimates for the importance weight assigned to the progress of each student ability state, indicating teachers' preferences for different student groups. Additionally, Table 13 reports the net cost associated with assigning three different types of differentiated assignments on ReadWorks. These estimates allow us to calculate the expected probability of a student receiving a differentiated assignment (i.e., $z \neq n$) conditional on the teacher's decision to use differentiation in the first stage.

Table 12: Teacher weights on student expected progress

	Low Poverty			High Poverty		
	state 1	state 2	state 3	state 1	state 2	state 3
weight (b)	0.146***	28.283***	9.757***	0.107***	7.408***	0.807***

Notes: The table reports the weights that are put on student expected progress for students at different ability states by teachers from both low-poverty and high-poverty schools.

Significance levels: *** p ≤ 0.01, ** p ≤ 0.05, * p ≤ 0.10

Table 13: Net Cost of Giving Assignment on ReadWorks

	Low Poverty	High Poverty
Net Cost (w)	8.192***	5.026***

Notes: The table reports the net cost of giving a differentiated assignment to a student for teachers from both low-poverty and high-poverty schools.

Significance levels: *** p ≤ 0.01, ** p ≤ 0.05, * p ≤ 0.10

The resulting probabilities, presented in Table 14, provide insights into teacher preferences for students of different ability states when implementing differentiation. Conditional on teachers choosing to differentiate in the first stage, students in state 2 and state 3 are more likely to receive differentiated assignments compared to students in state 1. This pattern holds true for both high-poverty and low-poverty schools. Specifically, state 3 students from high-poverty schools have a higher likelihood of receiving differentiated assignments (66.4% compared to 62.4% for low-poverty schools), indicating that teachers in these schools prioritize differentiation for higher-achieving students. On the other hand, state 2 students from low-poverty schools are more likely to receive differentiated assignments (74.5% compared to 68.5% for high-poverty schools), suggesting that teachers in low-poverty schools may place greater emphasis on supporting students in the intermediate ability range.

Table 14: Expected probability of receiving differentiated assignment conditional on differentiation

	Low Poverty			High Poverty		
	state 1	state 2	state 3	state 1	state 2	state 3
Prob	0.234	0.745	0.624	0.231	0.685	0.664

Notes: The table presents the probability of a student at each ability state receiving a differentiated assignment at the second stage when the teacher decides to differentiate in the first stage.

Table 15 provides the parameter estimates for the net utility of outside options, which captures the preference of teachers for not implementing differentiation in their classes. As we observe that many teachers never attempt differentiation in their classes, we allow classes to be drawn from two segments, and those classes have not differentiated assignments likely belong to segment 2. This segment has a higher net utility from outside options, indicating a reluctance to adopt differentiation strategies. Notably, the net outside utility is larger for teachers in high-poverty schools for both segments.

Table 15: Net Outside Utility

	Low Poverty	High Poverty
segment 1	-2.643***	-1.472***
segment 2	2.496***	3.252***

Notes: The table reports the net outside utility at teachers' first-stage decisions. There are two segments for classes in both low-poverty and high-poverty schools.

Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$

Combining the parameter estimates from the second stage of teachers' differentiation decision with the net outside utility estimates in Table 15, we can calculate the probability of teachers

Table 16: Probability of Differentiation

	Low Poverty	High Poverty
segment 1	0.539 (22%)	0.420 (23%)
segment 2	0.052 (78%)	0.014 (77%)

Notes: The table reports the probability of differentiation at the first stage for both segments from low-poverty and high-poverty schools. The percentages of classes for each segment are included in the parentheses.

choosing to differentiate at the class level in the first stage, as shown in Table 16. We find that, for both poverty groups, classes in segment 1 are more likely to utilize differentiation frequently, while those in segment 2 rarely differentiate. Overall, teachers from high-poverty schools are less likely to use differentiation, and this pattern holds true for both segments. Furthermore, a similar proportion of classes in high-poverty schools fall into segment 1 (22%) compared to low-poverty schools (23%).

7 Counterfactual Analysis

We conduct the following three counterfactual analyses. In the first counterfactual analysis, we aim to understand the potential effectiveness as well as the actual effectiveness of differentiation on student ability. In the second counterfactual analysis, we explore how reducing the cost associated with differentiation on ReadWorks influences teachers' utilization and implementation of differentiated instruction. Additionally, we investigate the subsequent effects on student ability resulting from changes in teachers' practices. The third counterfactual analysis centers around enhancing teachers' recognition of the value of student progress achieved through differentiation in addition to cost reduction. Similar to the second analysis, we examine how teachers' utilization of differentiation and the evolution of student abilities are affected by the increased emphasis on valuing differentiated learning outcomes for teachers from high-poverty schools.

Potential and actual effectiveness of the differentiation tool

To investigate the full potential of differentiation on student performance and the actual effectiveness of the differentiation tool, we simulate the student performance evolution when a) *All non-diff*, where all assignments are non-differentiated; b) *Current*, which represents the assignment differentiation based on the current parameter estimates and c) *All diff*, where all assignments are differentiated except for the first assignment. In the *All diff* scenario, we assume that each student receives the differentiated assignment that maximizes their expected progress, allowing us to examine the full potential of differentiation on student performance.

For each class, we simulate the progress of assignments for four additional assignments, in addition to the initial non-differentiated assignment, for all three scenarios using individual MCMC draws. Our focus is on the distribution of student ability states within the class after these five assignments. We analyze the student ability distribution after five assignments for all three scenarios, and the results are presented in Table 17. This allows us to compare the effectiveness of differentiation in improving student performance across different assignment scenarios.

Table 17: Effectiveness of the Differentiation Tool–Student Ability Distribution

	Low Poverty			High Poverty		
	state 1	state 2	state 3	state 1	state 2	state 3
initial dist	0.286	0.287	0.428	0.341	0.293	0.366
All non-diff	0.348	0.252	0.400	0.453	0.257	0.290
Current	0.343	0.252	0.404	0.434	0.265	0.301
All diff	0.228	0.287	0.484	0.364	0.292	0.344

Notes: This table presents the average student ability distribution after four assignments for both low-poverty and high-poverty school classes under three different assignment scenarios.

In Table 17, The first row presents the average student ability distribution at the first assignment for both low-poverty and high-poverty classes. We observe that high-poverty school classes generally have a higher percentage of students in state 1 and a lower percentage of students in state 3 compared to low-poverty school classes. When all assignments are non-differentiated in *All non-diff* scenario, we find that after four assignments, students on average experience a decline in their ability states. This decline is more pronounced in high-poverty school classes. However, when we consider the usage and implementation of differentiation observed in the data in the *current* scenario, we observe a small but beneficial effect in terms of preventing students from falling to lower states. With the usage and implementation observed in the data, we see it is benefitial in terms of preventing more students fall to lower states, however, the effect scale is small. In the *all diff* scenario, where we fully leverage the potential of differentiated assignments, we find that the tool has the ability not only to prevent students from slipping to lower states but also to boost them to state 3. This effect is particularly evident in low-poverty classes. This exercise demonstrates the substantial potential effectiveness of the differentiation tool. However, the actual effectiveness is limited, likely due to the limited usage of differentiation by teachers.

Reducing differentiation cost

We investigate how reducing the cost of differentiation affects teacher behaviors and student ability evolution. The platform can reduce the cost by refining the design of the differentiation tool to make it more effective and accessible. Several approaches can be employed to achieve this goal. For example, the platform could try to implement algorithms or features that automatically pick differentiated assignments based on the difficulty level chosen by teachers which may greatly reduce the time and effort required by teachers. By automating this process, the tool can reduce the burden on teachers to manually adapt and modify assignments.

Specifically, we explore the impact of reducing the cost of differentiation on ReadWorks (w) by 50% and 100%. We investigate the probability of teachers using differentiation in the first stage and the resulting student ability distribution after five assignments. Panel A in Table 18 presents the probability of differentiation usage at the class level, while Panel A in Table 19 presents the student ability state distribution after four assignments under different counterfactual scenarios.

We find that reducing the cost of differentiation increases its usage for both high-poverty and low-poverty classes. However, the increase in usage is more substantial for classes from low-poverty schools. When the cost is reduced by 100%, the probability of differentiation usage is 37.3% for high-poverty classes, compared to 83.7% for low-poverty classes. Correspondingly, when examining the student distribution after four assignments, we observe substantial benefits for students from low-poverty schools. They are prevented from slipping to lower ability states and are encouraged to progress to higher ability states. However, the impact on students from high-poverty schools is relatively limited. While both low-poverty and high-poverty classes benefit from the cost reduction, it also exacerbates the existing gap between high-poverty and low-poverty classes. The reduced cost further widens the disparity in the usage and effectiveness of differentiation between these two socioeconomic segments.

Combination of cost reduction and enhancing teachers' recognition of the value of student progress from differentiation

We explore potential interventions that can mitigate the widening gap between the socioeconomic segments. In addition to cost reduction, the platform may also work on enhancing teacher valuation of the student progress from differentiation. Recognizing and appreciating the impact of

Table 18: Cost Reduction–Usage of Differentiation

	Low Poverty	High Poverty
Panel A: Cost reduction		
CR by 0% (current)	0.154	0.091
CR by 50%	0.352	0.171
CR by 100%	0.837	0.373
Panel B: Cost reduction + Valuation enhancement (high-poverty)		
CR by 0% & VE by 200%		0.191
CR by 50% & VE by 200%		0.392
CR by 100% & VE by 200%		0.722

Notes: This table presents the average probability of using differentiation for both low-poverty and high-poverty school classes under different counterfactual scenarios regarding cost reduction.

differentiation on student growth and achievement can further motivate teachers to embrace and implement differentiation. The platform may consider providing comprehensive professional development opportunities and training sessions specifically tailored to differentiation, highlighting and sharing success stories of teachers using differentiation, and providing teachers with access to data-driven evidence of the effectiveness of differentiation to further strengthen their appreciation of its impact.

We investigate the combined effect of cost reduction and valuation enhancement on the usage of differentiation in high-poverty schools. Specifically, we focus on teachers from high-poverty schools to explore the potential way to mitigate education inequity. Specifically, we increase the importance high-poverty school teachers assign to student progress (b_c) by 200% in addition to the different levels of cost reduction and investigate teachers' probability of using differentiation in the first stage, and student ability distribution after 4 assignments. Panel B in Table 18 presents the probability of differentiation usage at the class level and panel B in Table 19 presents the student ability state distribution after four assignments under different counterfactual scenarios for classes from high-poverty classes.

We find that when both cost reduction and valuation enhancement are implemented, the usage of differentiation increases more significantly. Specifically, with a 100% cost reduction combined with valuation enhancement, the probability of differentiation usage in high-poverty schools reaches 72.2%. This represents a substantial increase from the 37.3% observed with cost reduction alone. As a result of this increased usage, we also observe greater benefits for students from high-poverty segments. Particularly, there is a more substantial impact in terms of preventing students from slipping to lower ability states. These findings suggest that providing targeted training to high-poverty schools to enhance teachers' valuation of student progress from differentiation could be an effective strategy. By focusing not only on cost reduction but also on improving teachers' perception of the value of differentiation, we may be able to mitigate the potential widening of the gap between high-poverty and low-poverty schools.

Table 19: Cost Reduction and Valuation Enhancement for High Poverty Schools–Student Ability Distribution

	Low Poverty			High Poverty		
	state 1	state 2	state 3	state 1	state 2	state 3
Panel A: Cost reduction						
initial pct	0.286	0.287	0.428	0.341	0.293	0.366
CR by 0% (current)	0.343	0.252	0.404	0.452	0.258	0.290
CR by 50%	0.304	0.265	0.431	0.441	0.262	0.297
CR by 100%	0.240	0.283	0.477	0.417	0.271	0.312
Panel B: Cost reduction + Valuation enhancement (high-poverty)						
initial pct				0.341	0.293	0.366
CR by 0% & VE by 200%				0.434	0.265	0.301
CR by 50% & VE by 200%				0.409	0.274	0.317
CR by 100% & VE by 200%				0.374	0.288	0.339

Notes: This table presents the average student ability distribution after 4 assignments for both low-poverty and high-poverty school classes under different counterfactual scenarios regarding cost reduction and valuation enhancement.

8 Conclusion

In this paper, we study the impact of a digital differentiation tool on student learning outcomes, taking into account the usage and implementation by teachers. With the increasing presence of educational technology products, there has been a growing interest in digital tools that facilitate differentiation in education. These tools hold the potential to improve student learning outcomes and address educational disparities. However, the effectiveness of such tools can vary significantly due to the complexities involved in their implementation. One key factor contributing to this variation is the incorporation of teacher usage and implementation. The design of the digital differentiation tool alone is not sufficient; it is equally important to understand how teachers utilize and implement the tool in their classes. Our study fills this gap by explicitly incorporating teachers' usage and implementation when evaluating the effectiveness of the digital differentiation tool.

Additionally, we investigate whether the effectiveness of the tool and the patterns of teacher usage and implementation differ across socioeconomic segments. This analysis allows us to explore the role of the digital differentiation tool in addressing educational disparities and identify potential interventions to bridge the gap.

We develop a comprehensive structural model that incorporates a hidden Markov framework to capture the underlying student ability evolution and a two-stage decision process for teachers' differentiation decisions. Our findings indicate that the digital differentiation tool has the potential to benefit students from both high-poverty and low-poverty schools. However, the actual effectiveness of the tool is hindered by the limited usage of teachers from both socioeconomic segments. Furthermore, we observe that teachers from different socioeconomic backgrounds exhibit differential preferences when implementing differentiation, with teachers in low-poverty schools potentially prioritizing medium-achieving students to a greater extent than their counterparts in high-poverty schools. Through counterfactual analyses, we emphasize the importance of not solely focusing on product design but also providing targeted training and support for teachers, especially those in high-poverty schools, to enhance the effectiveness of the differentiation tool. By addressing the differential preferences and usage patterns of teachers across socioeconomic segments, we can better leverage the digital differentiation tool to bridge educational disparities and improve student learning outcomes.

Our study provides several managerial insights for educators and EdTech platforms. Firstly, it highlights the significance of considering teachers' usage and implementation when assessing the effectiveness of digital differentiation tools. This underscores the importance of promoting tool adoption among teachers, particularly those in high-poverty schools, by improving tool design, raising awareness about its benefits, and providing comprehensive training programs. Secondly, continuous assessment and evaluation of the tool's impact are crucial for refining and enhancing its efficacy. This iterative process ensures that the differentiation tool remains relevant, effective, and aligned with the evolving needs of the education landscape. Lastly, fostering partnerships between EdTech platforms and educational institutions can facilitate the widespread usage and implementation of digital differentiation tools, ultimately improving student learning outcomes and addressing educational disparities.

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