

Secondary Teachers' Perceptions of Utilizing AI-Facilitated Small Groups: A Mixed-Methods Study

Daisy Cabler, PhD

Contact: daisyhill12@yahoo.com

Abstract

This mixed-methods study examined secondary math and English teachers' perceptions of using artificial intelligence to facilitate differentiated small groups in the post-pandemic learning environment. The researcher collected teachers' reflections, conducted interviews, and analyzed Likert-scale data to form a comprehensive view of their perceptions of this pedagogical practice after delivering a professional development (PD) workshop on using AI tools to deliver small-group learning in a variety of secondary contexts. After collecting and analyzing the data, the researcher found that secondary teachers had positive perceptions of AI's ability to support differentiated learning. However, when comparing qualitative and quantitative data, the researcher found that teachers need ongoing coaching in areas like prompting and output refinement to feel fully confident in their abilities. Overall, the results suggest a need for further training and that the professional should remain the cornerstone of classroom decision-making.

Introduction

Teachers have varying perceptions of the role of artificial intelligence (AI) in the classroom (Lindner et al., 2026). As student needs have rapidly changed since the pandemic, researchers and educational leaders have looked to AI as a potential aid to help teachers differentiate instruction and support teachers' classroom needs (Hashem et al., 2024). This mixed-methods study explored how secondary English language arts (ELA) and Math teachers adapted AI tools for differentiated small-group instruction after professional development (PD) and examined how their perceptions of these tools evolved through this experience.

As K-12 schools continue to address learning gaps that have widened in the wake of the COVID-19 pandemic, educators are seeking innovative instructional methods that not only meet diverse student needs but also support meaningful learning gains (Hashem et al., 2024). By analyzing secondary ELA and math teachers' responses to reflective prompts, interview questions, and a Technology Acceptance Model (TAM) survey, the study aimed to understand how teachers took what they learned in PD about AI-facilitated small group instruction in the classroom and adapted it to fit their own style, content, and pedagogical practices.

Research Question and Theoretical Frameworks

The study aimed to answer the question, "What are secondary ELA and math teachers' perceptions of adapting AI tools for differentiated small group instruction following professional development?" The study integrated two main theoretical frameworks. Tomlinson's Theory of Differentiation and Vygotsky's Zone of Proximal Development (ZPD) offer powerful frameworks for exploring the integration of AI-facilitated small group instruction. Both theories highlight the value of peer interaction, guided support, and active engagement in learning (McLeod, 2024; Tomlinson, 2014). By emphasizing how students grow through collaboration and tailored scaffolding, these frameworks support group learning experiences and help meet individual students' academic needs in meaningful, developmentally appropriate ways (McLeod, 2024; Tomlinson, 2014), making this instructional method a viable strategy to study to support teachers in supporting student academic recovery post-pandemic.

Vygotsky's Zone of Proximal Development

Vygotsky's ZPD refers to a zone where students can achieve skills that are too difficult to master or complete on their own but can be done with guidance from a more knowledgeable person (McLeod, 2024). The idea of the ZPD hinges on one crucial factor: the presence of a more knowledgeable other (MKO). This zone, the ZPD, bridges the gap between students' current abilities and future capabilities (McLeod, 2024). Vygotsky believed that the ZPD "is the space between current teaching knowledge and potential new levels with assistance" (McLeod, 2024).

When students try to complete a task just out of their grasp, an MKO can give them enough of a "boost to achieve the task" (McLeod, 2024). In the small group learning strategy, teachers serve as the MKO because they can work more intimately with students and provide more targeted support. With the teacher serving as an MKO, the students in the small group are likely to achieve tasks that they would not have been able to complete using traditional instructional

methods. MKOs in the form of AI-facilitated differentiated instruction allow a teacher to adapt instruction to bridge learning gaps in their students.

Vygotsky's ZPD also supports small-group work with an MKO to help students master new skills (McLeod, 2024). Collaborative ZPD challenges original interpretations of Vygotsky's ZPD. Instead of focusing on asymmetry (a more knowledgeable individual and a less knowledgeable individual), collaborative ZPD takes a symmetrical approach in which peers co-construct knowledge regardless of expertise level (McLeod, 2024). According to McLeod (2024), collaborative ZPD recognizes that learning is not merely a transmission of knowledge from one individual to another but a process of co-construction where all participants contribute to and benefit from the interaction. This challenges the notion of a fixed expert-novice dichotomy, acknowledging that even within peer groups, roles can be fluid, with individuals taking turns leading, questioning, and supporting each other.

In summary, students can build their own ZPD by working collaboratively with peers at similar skill levels, especially when the group includes an expert, such as a teacher. By combining both interpretations of Vygotsky's ZPD, students can be grouped by similar skill levels in peer-based small groups, where they engage in meaningful dialogue and co-construct knowledge with appropriate scaffolds and with a teacher present as an MKO.

Within these groups, students scaffold each other's learning, explain concepts, and challenge one another's thinking, deepening their own understanding. At the same time, the teacher acts as the MKO, leading the group by providing targeted guidance, clarifying misunderstandings, or introducing more complex tasks that push students beyond their current abilities. This combination lets students benefit from both small-scale peer interaction, which fosters collaborative problem-solving, and teacher support, which provides expert scaffolding within the ZPD. Through structured rotations between independent practice and teacher intervention, students balance independence and support, gradually taking on more responsibility for their learning while receiving the guidance they need to reach the next level of cognitive development.

Tomlinson's Theory of Differentiation

Tomlinson's theory of differentiation emphasizes intentionally grouping students to maximize engagement, learning, and growth for all learners (Tomlinson, 2014). Groupings are designed based on students' readiness levels, interests, and learning profiles, ensuring that each student receives tasks that are appropriately challenging and accessible (Tomlinson, 2014). In ability-based small groups, the teacher remains central to shaping group dynamics and fostering productive interaction (Tomlinson, 2014). While students in a group may share similar readiness levels, they can still bring diverse perspectives, learning styles, and strengths (Tomlinson, 2014).

Within this framework, students take on active roles as both learners and teachers, engaging in peer explanations, shared problem-solving, and collaborative meaning-making. Tasks are designed to stretch each learner's capacity while providing necessary scaffolds, encouraging students to support one another and develop critical thinking skills. Technology can be integrated as a tool to enhance differentiation by streamlining assessment, informing grouping decisions, and providing targeted resources. In this way, tools such as AI-facilitated platforms and digital

materials complement the teacher's role as a facilitator, allowing for more responsive and flexible instruction. By purposefully designing groups and leveraging both student strengths and technology, teachers can create a dynamic learning environment in which all learners are appropriately challenged and supported, making this strategy a tool teachers can adapt and use in their post-pandemic classrooms.

Combining Frameworks

Together, Tomlinson's theory of differentiation and Vygotsky's ZPD provide a cohesive lens for understanding how AI-facilitated small group instruction may close learning gaps. Tomlinson's theory of differentiation frames the learning environment as one in which students benefit from intentionally designed instruction and flexible grouping (Tomlinson, 2014), which aligns with the study's use of AI to form and support targeted learning groups. ZPD complements this by explaining why students in these groups are more likely to progress when supported just beyond their current ability levels, particularly in a peer-driven, scaffolded environment. (McLeod, 2024; Tomlinson, 2014). While Tomlinson's theory of differentiation and Vygotsky's ZPD provide the conceptual lens for the study, the quantitative strand draws on Davis's (1989) Technology Acceptance Model to measure the perceptual precondition for that design to succeed. TAM therefore does not compete with the two primary frameworks but operationalizes a necessary first step: teacher adoption must occur before differentiated; ZPD-informed grouping can take place. Together, the three frameworks support the study's goal: to examine how teachers adapt AI tools for differentiated small-group instruction following PD.

Literature Review

Post-Pandemic Challenges in Education

The education system in the United States faces unprecedented challenges in educating students in a post-pandemic environment. Students are performing at lower levels than they were before the pandemic and have many more behavioral and mental health challenges (Zhang & Story, 2022). Emerging data suggest that the pandemic was associated with learning loss and reveal unparalleled declines in students' math and reading abilities (Golden et al., 2023).

Recent data from the 2024 National Assessment of Educational Progress (NAEP), known as *The Nation's Report Card*, reveal continued academic decline among U.S. secondary students in both reading and mathematics. According to the National Center for Education Statistics (NCES), the average twelfth-grade reading score in 2024 was 3 points lower than in 2019, continuing a long-term downward trend and marking the lowest reading score recorded since 1992; overall, average reading scores have declined 10 points since the assessment began. Similarly, the 2024 NAEP mathematics assessment showed that the average twelfth-grade mathematics score was 3 points lower than in 2019, reflecting ongoing post-pandemic learning loss. In both subjects, scores declined across the 10th, 25th, 50th, and 75th percentiles, while performance at the 90th percentile remained relatively stable, indicating that lower- and middle-performing students experienced the most significant declines, while the highest-performing students were largely insulated from loss.

Additionally, the U.S. rate of chronic absenteeism was around 31% in the 2021-2022 school year and was 28% in the 2022-2023 school year (U.S. Department of Education, 2025). Chronic absenteeism is associated with increased disengagement from learning and decreased interactions with peers and other caring adults, which makes teachers' jobs increasingly difficult. For students already performing at or below grade level, missed instructional time compounds existing learning gaps and undermines efforts to remediate unfinished learning. As a result, teachers face the difficult realities of learning in post-pandemic instructional environments.

In the 2021–22 school year, many teachers returned to a more typical routine but still had high expectations for themselves and their students. They needed to address pandemic-related learning loss, support students' behavior and mental health, and provide challenging lessons that met current grade-level standards (Pressley et al., 2024). As student behavior and mental health needs have intensified since the pandemic, teachers have assumed roles as both academic instructors and emotional support providers. In many secondary classrooms, educators have served as first responders to student distress, addressing emotional crises, behavioral escalations, and social challenges in real time while trying to maintain rigorous, grade-level academic expectations.

Wendy Reinke, a Curators' Distinguished Professor in Educational, School and Counseling Psychology, vice chancellor for research, and a co-director of the Missouri Prevention Science Institute, who is researching why teachers are leaving the classroom in the post-pandemic era, stated in an interview about the research, "If teachers struggle, instruction suffers, and students don't learn as they should. When there aren't enough teachers, schools may hire uncertified staff or increase class sizes, making effective instruction and learning less likely. Disruptive behavior also spreads — kids in disorderly classrooms carry those habits into the next grade" (Stann, 2025). These challenges require scalable, efficient instructional interventions.

Differentiated Small Group Instruction

Traditional whole-class instruction remains widespread, especially in secondary settings, yet mounting evidence from recent research underscores its limitations in addressing diverse learning needs post-COVID. As classrooms now include wider variations in student readiness and academic skill gaps (Golden et al., 2023; National Center for Education Statistics, n.d.; Zhang & Story, 2022), whole-group models can inadvertently deepen disparities and impede recovery efforts. Whole-group instruction assumes that students begin lessons with similar background knowledge and learning needs. However, post-pandemic learning loss has produced classrooms with significant differences in student abilities, making uniform pacing and content delivery ineffective for many learners. In fact, whole-group instruction is not closing learning gaps post-COVID because it does not address significant learning loss and widened opportunity gaps, especially for disadvantaged students, as reported by teachers experiencing low instructional effectiveness (Namkung et al., 2022). This strategy assumes students are at similar readiness levels and leaves many middle- and low-performing students further behind.

Curriculum pacing guides are intended to help teachers and schools cover the required standards, but they often prioritize course completion over student readiness and mastery. When pacing pressure overrides formative evidence of student learning, teachers are compelled to move

forward despite gaps in foundational understanding, leading to minimal depth but maximum breadth of coverage. Formative assessment, a cornerstone of flexible learning (Tomlinson, 2014), encourages teachers to frequently analyze student achievement and build a classroom responsive to students' needs. Evidence from a study of Michigan school districts indicates that traditional schooling structures impede flexible pacing, which is essential for competency-based education (Sutherland et al., 2023). Rigid pacing guides followed without question can disproportionately disadvantage students already below grade level and widen performance gaps within a cohort.

One way to address these issues is by utilizing teacher-led targeted small groups (Tomlinson, 2014). This study focused on implementing intensive small-group instruction to encourage academic growth in post-pandemic educational environments. Research shows that high-dosage tutoring effectively boosts math and reading skills, especially for struggling K–12 students, and advocates encourage adopting evidence-based programs for lasting improvement (Zhang & Storey, 2022). Differentiated small-group instruction could be a promising approach to addressing academic regression and widening learning gaps (Tomlinson, 2014) in post-pandemic classrooms because it allows teachers to provide targeted, responsive instruction aligned to students' specific needs, unlike traditional whole-class instruction, which often struggles to accommodate wide variances in student readiness. When students receive additional support in small-group settings with MKOs, they can achieve more because they are working in their ZPD. Supported by data-informed decision-making and AI-driven assessment and planning tools, small-group instruction offers a scalable way to promote academic recovery while maintaining instructional coherence within the core classroom setting.

While much of the research on small group instruction has focused on elementary populations, emerging evidence supports its effectiveness in secondary contexts. For example, a 2023 study in Florida found that differentiated small groups in a 9th-grade mathematics course improved students' grades and overall math progress (Timar, 2023). This study also found that while small-group instruction helped advanced students progress faster while supporting targeted learners, it is significantly more time-consuming than typical whole-class approaches (Timar, 2023). Additionally, Haelermans (2022) confirmed in a study from the Netherlands that performance improvements are most pronounced when instruction is carefully differentiated to match students' learning strategies. While current evidence shows promise, researchers caution that more research on differentiated small groups in secondary settings is needed because existing research in those settings is limited.

Teacher-Technology Adoption and AI Integration

Teachers' adaptations of technology processes are often guided by Davis's (1989) Technology Acceptance Model. When teachers better understand the technology's perceived usefulness (PU) and perceived ease of use (PEOU), they can make more informed decisions about whether to adopt it in their instructional contexts. Other variables also determine how, or whether, teachers adopt new technology. The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), predicts behavioral intention to use technology and actual usage behavior. The theory's four core constructs are performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). This theory is particularly useful in studies of AI adoption in schools, where teacher behavior is shaped by systematic

constraints. As noted in the study's theoretical framework, TAM served as the guiding model for the quantitative instrument, measuring perceptual conditions, PEOU and PU, that determine whether teachers adopt the AI-facilitated practices framed by Tomlinson and Vygotsky's models.

Successful PD profoundly affects both the TAM and UTAUT models. Though not an original construct in TAM, PD functions as an external variable that influences both PU and PEOU. When teachers are exposed to best practices, introduced to practical applications, and given guided information on how to use the tools effectively, their PU and PEOU change because their perceptions of usefulness and ease change, which then influence intention and actual use.

PD has a much more direct role in UTAUT. PD fits best under the facilitating conditions construct because it refers to the degree to which teachers believe organizational and technical support exists (Venkatesh et al., 2003). PD plays an explicit role because it shows that the district or school supports implementation, provides resources, offers training, and makes help accessible. If teachers perceive strong facilitating conditions, they are more likely to use the technology. PD also influences other UTAUT constructs. When PD shows instructional gains, it strengthens beliefs that the tool improves performance (Venkatesh et al., 2003). Modeling effective practice can reduce perceived difficulty, which affects effort expectancy (Venkatesh et al., 2003). Finally, if leadership mandates or suggests PD, it reinforces norms and expectations around use (Venkatesh et al., 2003). Like any new technology, these theories are applicable to AI adoption and PD contexts, as AI is a new and evolving technological component in education.

Artificial Intelligence in Education

Many researchers, such as Haelermans (2022) and Timar (2023), acknowledge that the differentiated small group approach can be time-consuming for teachers and requires careful implementation. Teachers can use AI to help create and run successful small-group instruction by analyzing various data points that support individualized learning.

Grouping students based on ability allows for differentiated instruction, where tasks can be designed to be appropriately challenging for each group while maintaining a level of difficulty that encourages growth. The teacher's use of AI to track progress over time makes these groupings dynamic, adjusting as students improve or face challenges and ensuring the groups remain responsive to students' evolving needs.

Teachers can use AI to analyze diagnostic and formative data because it provides personalized, data-driven insights into student learning through advanced performance monitoring and targeted interventions. The educator's use of AI technologies to analyze sets of student performance data enables them to identify learning patterns (Akavova et al., 2023), generate AI-enabled visual representations of student progress and provide personalized feedback (Liao et al., 2024), and predict student performance and enable timely interventions (Lopez-Meneses et al., 2025). By helping teachers analyze student data, AI as an instructional tool can alleviate some of the stressors of small-group instruction. This boosts teacher effectiveness and efficiency by ensuring differentiated small groups are accurate, data-informed, and based on real-time data. Additionally, using raw data in AI models without identifying information can reduce subjective

bias in grouping decisions, making it an ideal tool for teachers to use in the group formation process.

AI can also play a pivotal role in scaffolding the learning process for each ability-based group. This involves providing real-time, context-specific support that targets the needs of the group and individual learners. Using AI to deliver differentiated small-group instruction aligns closely with educational scaffolding by operationalizing Vygotsky's ZPD and Tomlinson's theory of differentiation through adaptive, personalized learning pathways that complement human instruction. Current research indicates that AI systems provide timely feedback, differentiated supports, and opportunities for self-regulated learning, enabling learners to progress incrementally from assisted to independent performance. By dynamically adjusting task difficulty and instructional prompts based on learner performance, AI supports skill acquisition while building confidence, effectively mirroring the gradual release of responsibility central to ZPD-based scaffolding models. (Al-Hamadi & Yousef, 2025; Wan Hamedi et al., 2025). For example, AI can offer tailored resources, such as guided notes, prompts, hints, or examples, designed to scaffold learning activities in ways that align with each group's academic ability. AI can also support formative assessments, track student responses, and adjust support as needed.

Formatively assessing students, evaluating ongoing progress and data, and creating scaffolded materials for each ability-based group are crucial yet taxing elements of using the differentiated small group instructional method. Research shows AI can support this intensive scaffolding and reduce teachers' cognitive load when using intensive instructional methods. AI shows significant potential to reduce teachers' cognitive load during intensive instructional methods by automating administrative tasks and personalizing learning experiences. Many existing studies provide robust evidence for this claim. Qamar et al. (2025) found a significant negative correlation between AI tools and cognitive overload, with regression analysis showing that greater AI support directly corresponds to lower cognitive burden. Yuxin Liu (2025) specifically highlighted AI's ability to manage intrinsic, extraneous, and germane cognitive load through adaptive content delivery. Additionally, Nemani et al. (2025) further confirmed AI's effectiveness in saving teachers' time by automating tasks like report generation and providing real-time feedback. However, researchers consistently emphasize that AI should complement, not replace, human instruction and require careful implementation, ongoing teacher training, and ethical oversight.

Limitations, Risks, and Ethical Considerations of AI in Education

Despite their explored potential, AI tools in education face significant limitations and require users to acknowledge ethical concerns. ChatGPT and similar models can generate inaccurate information, exhibit cultural biases, or produce content misaligned with curriculum standards (Liu, 2023). Additionally, researchers consistently caution against complete AI autonomy. Omar et al. (2025) highlighted challenges in using AI to create scaffolded materials, including static scaffolding mechanisms, over-reliance on AI, and potential algorithmic biases. Because of these limitations, AI-generated materials may lack cultural relevance or appropriate scaffolding for different ability levels and for diverse learners. The consensus suggests that AI is more effective as a collaborative tool that supports, not replaces, educators' instructional design and should be

evaluated by teachers using their professional discretion before delivering learning materials to students.

Conclusion

Recent research indicates widening academic gaps as students return to in-person classrooms, while teachers simultaneously manage increased behavioral and social-emotional demands. Differentiated small-group instruction has been shown to help address performance disparities; however, ongoing data collection, analysis of student growth, and creation of scaffolded materials make sustained implementation cognitively demanding. AI tools can streamline these processes by helping teachers analyze data, design formative assessments, and generate leveled instructional resources. With PD support, teachers can adapt AI to design and implement differentiated small group instruction more efficiently. This study therefore examines how secondary ELA and math teachers adapt AI tools for differentiated small group instruction following PD.

Methods

This study employed a convergent parallel mixed-methods design (Creswell & Plano Clark, 2018) to examine how secondary teachers adapt AI tools for differentiated instruction. In convergent designs, researchers collect quantitative and qualitative data simultaneously, analyze them separately, and then integrate them during interpretation to provide a more complete understanding of the phenomenon than either approach alone.

The mixed-methods approach was appropriate for this study because the research question requires both breadth and depth. Quantitative survey data revealed patterns in teachers' perceptions of AI usefulness and ease of use across all participants, while qualitative data from reflections and interviews provided a nuanced understanding of adaptation processes, contextual factors, and implementation experiences. The analysis and interpretation integrated these data sources, with qualitative findings helping explain quantitative patterns (e.g., why ease-of-use ratings showed greater variability than usefulness ratings).

In this design, qualitative and quantitative strands were weighted equally (QUAN + QUAL), as both were essential for addressing the research question. The quantitative strand systematically measured perceptual constructs identified in Technology Acceptance Model literature, while the qualitative strand captured adaptive practices and contextual nuances that cannot be reduced to Likert-scale items.

Participants

Participants included 10 of the 24 teachers trained in the AI-facilitated small-group instructional method. The teachers are ELA and math teachers who teach grades 6-12 in a single public school district.

The participating district serves approximately 8,000 students across 15 schools in a rural setting. The student population is 93% white, 3% Black or African American, 2% Hispanic or Latino,

and 2% two or more races (National Center for Education Statistics, 2023). Of students living in the district, 10.1% live below the poverty line, and 13% receive Supplemental Nutrition Assistance Program (SNAP) benefits (National Center for Education Statistics, 2023).

Although 24 participants were trained in the PD session and invited to participate in the study, data collection included 10 secondary ELA and math teachers. Participation in the PD session and the study were both voluntary. This sample size is appropriate given the bounded nature of this study and its descriptive, exploratory purpose (Creswell & Poth, 2018). This study did not seek statistical generalization; instead, it aimed to understand participant perceptions within a specific instructional context.

Research Setting

This study took place in a rural public school district in northern Alabama, which serves approximately 8,000 students across 15 schools (grades K-12). The district is in an Appalachian community characterized by geographic isolation, limited technology infrastructure in some areas, and socioeconomic challenges of rural settings. As noted earlier, 10.1% of families live below the poverty line, and 13% receive SNAP benefits (National Center for Education Statistics, 2023).

The district has made significant investments in instructional technology in recent years, with all secondary students receiving Chromebooks and all classrooms being equipped with projectors and internet access. However, home internet access remains inconsistent, with some students relying on school-provided hotspots. Teachers have access to a learning management system (LMS), Google Workspace for Education, and various educational technology tools, though adoption varies by teacher.

PD in this district is typically delivered in half-day sessions during teacher planning days, with follow-up support available through the district's technology and curriculum coordinators. The AI-facilitated differentiation PD that preceded this study represented the district's first formal training on AI tools for instruction, though some teachers have experimented with AI tools independently.

This study was conducted during the 2025-2026 academic year, with PD delivered in October and data collection occurring eight weeks later to allow teachers sufficient time to experiment with and adapt AI tools in their classrooms.

Sampling Procedures

Participants were recruited through purposeful criterion sampling (Patton, 2015), with the criterion being attendance at the PD session on AI-facilitated differentiated instruction delivered in October 2025. All 24 teachers who attended the PD session received an email invitation to participate in the study approximately 6 weeks after the training. The invitation explained the study's purpose, time commitment (interview, survey, and reflections), and voluntary nature. Of the 24 invited teachers, 10 agreed to participate, yielding a 42% response rate. While this response rate raises the possibility of response bias, particularly that more motivated or

successful implementers may have been more likely to participate, there is no evidence to suggest respondents differed systematically from non-respondents in terms of teaching assignment, years of experience, or access to resources.

All participants taught in the same school district, attended the same PD, and had identical access to AI tools and support structures. Inclusion criteria were attendance at the AI-facilitated differentiated instruction PD in October, currently teaching secondary grades 6-12 ELA or math, employed by Lauderdale County Schools during the study period, and willingness to participate in all 3 data collection activities (survey, interview, and reflection). No exclusion criteria were applied beyond these requirements.

Instrumentation

This study employed three complementary instruments to assess secondary teachers' perceptions and experiences with AI-facilitated differentiated instruction: (1) a modified Technology Acceptance Model (TAM) survey, (2) structured reflection prompts, and (3) semi-structured interviews. This multi-instrument approach enabled triangulation of quantitative perceptual data with qualitative descriptions of teachers' adaptation processes and experiences.

These three instruments were selected to provide complementary perspectives on teacher adaptation. The TAM survey quantified perceptual trends across participants, reflection prompts captured initial impressions and experiences, and interviews allowed for in-depth exploration of adaptation processes and contextual factors influencing implementation.

Teachers completed a modified version of Davis's (1989) Technology Acceptance Model survey delivered via Qualtrics. The instrument consisted of 28 Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree), with 14 items assessing perceived usefulness and 14 items assessing perceived ease of use.

The Technology Acceptance Model has demonstrated reliability and validity across numerous educational technology contexts, with Cronbach's alpha coefficients typically ranging from .89-.98 for perceived usefulness and .86-.98 for perceived ease of use (Scherer et al., 2019).

Items were adapted from Davis's original instrument by replacing references to generic technology systems with specific references to AI tools for differentiated instruction. For example, Davis's original item "using the system would enable me to accomplish tasks more quickly" was modified to "using AI tools for differentiated instruction enables me to accomplish tasks more quickly."

The decision to retain the full 28-item instrument, rather than using a reduced item set as in some prior TAM research, was intentional. Given the exploratory and descriptive nature of this study, the comprehensive item set allowed for nuanced examination of teachers' perceptions across multiple dimensions of usefulness and usability. This approach prioritized breadth of understanding over psychometric parsimony, which was appropriate for capturing the range of teachers' experiences with an emerging instructional technology. Appendix A provides a complete comparison between Davis's (1989) original TAM items and the modified items used in the study.

Teachers also completed five open-ended reflection prompts administered via Qualtrics. These prompts asked participants to describe their experiences implementing AI-facilitated differentiated instruction, including perceived benefits, challenges, and adaptations they made to fit their instructional contexts. The reflection prompts allowed teachers to describe their experiences in their own words before the more structured interview protocol. Table 8 includes the reflection prompts.

After the survey and reflection prompts, participants completed individual phone interviews lasting approximately 15-20 minutes. The semi-structured interview protocol included questions designed to elaborate on themes emerging from the reflection prompts and to explore teachers' adaptation processes in greater depth. Questions addressed teachers' decision-making processes, specific examples of AI use in their classrooms, perceived impact on student learning, and recommendations for PD. The semi-structured format allowed for follow-up questions and clarification while maintaining consistency across interviews. Table 1 lists the reflective prompts that teachers were asked to complete.

Table 1
Reflection Prompts

Reflection Prompts
Describe a lesson where you used an AI tool to differentiate instruction. What went well, and what challenges did you encounter?
Reflect on how the AI tools have influenced your teaching practice. Have they changed the way you plan or deliver instruction?
How do you see yourself using AI tools in your classroom moving forward? Are there specific areas or strategies you want to explore?

Participants were interviewed using the questions listed in Table 2.

Table 2
Interview Questions

Interview Questions
1. Can you describe your overall experience using the AI tools in your classroom since the PD session?
2. In what ways have you adapted your instruction using the AI tools in small group instruction? Can you give me a specific example?
3. Which aspects of the AI tools have been easy to integrate into your instruction, and which have been more challenging?
4. How have the AI tools affected your ability to differentiate instruction for students at varying skill levels?
5. How have your students responded to lessons using AI tools? Have you noticed any changes in engagement or learning outcomes?
6. How do you decide which AI-facilitated activities or features to use with specific small groups? Have you made any modifications to the tools or your plans?
7. If you could suggest improvements to the AI tools or the PD, what would they be?

Data Collection

Participation in this study was voluntary, and participants received an informed consent statement describing the study's purpose, procedures, potential risks and benefits, confidentiality protections, and their right to withdraw at any time without penalty.

Data were collected in three phases (Survey, Reflection, and Interview) during a two-week period eight weeks after the PD session. The PD session was delivered mid-semester, and data collection occurred roughly two months later, giving teachers time to adapt and implement the tools and learning strategies they learned in the session.

Data Analysis

The quantitative and qualitative data from this study were analyzed using complementary analytic approaches to provide a comprehensive understanding of teachers' perceptions and adaptations of AI-facilitated small group instructional methods.

The 28 Likert-scale items were analyzed using descriptive statistics via SPSS, with each item treated as an individual indicator of teacher perception. Mean response values were calculated for each item to summarize overall trends in participant responses. Standard deviations were also calculated for each item to capture variability in teacher responses, particularly for items where perceptions were expected to differ based on prior PD experience. No inferential statistical analyses were conducted because the survey was descriptive and exploratory.

Qualitative data were analyzed using thematic analysis (Braun & Clarke, 2006) to identify recurring patterns, themes, and contextual factors related to teachers' experiences with AI integration. Coding was inductive: codes were generated directly from teacher interviews and reflections, without predetermined categories, and refined through iterative review as patterns emerged. Codes with conceptual overlap were merged during axial review to form the four final themes. For example, easy integration, time-saving, and data-driven decision-making were collapsed into the productivity and differentiation amplifier theme; challenges prompting, refining, and aesthetics informed the ease of generation vs. difficulty of refinement theme; PD for prompting, ongoing support, and student-facing concerns were grouped into the cognitive load theme; and tool accessibility and overreliance concerns (for both students and teachers) were merged into the structural and access constraints theme.

Integration of the quantitative and qualitative data occurred during interpretation. Descriptive survey findings informed and contextualized qualitative themes, allowing interview and reflection data to elaborate on and explain patterns observed in the survey results. Once the four qualitative themes were established, they were examined in relation to the TAM constructs (PEOU and PU) to support integration with the quantitative findings. This analytic approach supported a more holistic examination of teacher perceptions and experiences by pairing numerical trends with participant narratives.

Results

This section presents findings from the quantitative survey data, qualitative reflection prompts, and semi-structured interviews. Results are organized into two parts: (1) quantitative findings from the modified TAM survey and (2) qualitative themes that emerged from the reflection prompts and interview analysis. Together, these findings address the research question: How do secondary ELA and math teachers adapt AI tools for differentiated small group instruction following professional development?

Quantitative Data

Descriptive statistics included generally positive perceptions of the system across usability, usefulness, and productivity domains. Mean scores for items related to time savings, task completion, and overall usefulness ranged from 4.0-4.4, suggesting high levels of agreement among participants. Items assessing ease of use and understanding also demonstrated high mean scores ($M \approx 4.0$), while negatively worded items related to confusion, frustration, and rigidity yielded lower mean scores ($M \approx 2.0$ -2.5). Standard deviations ranged from .63 to 1.37, indicating moderate variability in participant experiences, particularly for items related to cognitive effort and error recovery. Table 3 presents the means and standard deviations for each of the 28 modified TAM survey items.

Table 3
Survey Items' Means and SDs

Survey Item	Mean	Standard Deviation
Job Difficulty	3.3	1.252
Greater Control	3.7	1.337
Job Performance	4.0	1.274
Needs	3.8	1.135
Time Savings	4.4	.843
Accomplish Tasks Easily	4.2	.789
Supports Critical Aspects	4.2	.632
Helps Accomplish More	4.4	.843
Reduces Time on Unproductive Activities	4.3	1.059
Enhances Effectiveness	4.00	1.155
Enhances Quality of Work	3.6	1.174
Increases Productivity	4.10	1.179
Makes Job Easier	4.10	1.197
Is Useful	4.30	1.252
Often Confusing	2.40	1.265
Frequent Errors	2.50	1.269
Experience Frustration	2.40	1.174
Have to Seek Help	2.30	1.337
Requires a lot of Mental Effort	2.10	1.370
Easily Recover from Errors	3.90	.738
Find it Rigid and Inflexible	1.90	.738
Easy to make it do what I Want	3.10	1.287
Experience Unexpected Behavior	2.40	.843
Find it Cumbersome	2.10	1.197
Find it Easy to Understand	4.00	.943
Remember how to Perform Tasks	4.00	.943
Helpful Guidance	4.20	.789
Easy to Use	4.1	1.287

Qualitative Data

Teacher interviews and reflections were analyzed according to Braun and Clarke's (2006) method. After initial review, codes were formed using inductive coding to organize portions of teacher reflection and discourse. The initial codes included easy integration, challenge prompting, time saving, differentiation support, student engagement, aesthetic concern, tool accessibility, PD for prompting, PD for visual design, data-driven decisions, and overreliance concerns. After reviewing the teacher interviews and reflections and adding codes, four themes emerged. Table 4 below shows these themes.

Table 4
Qualitative Themes

	Theme
1	AI as a productivity and differentiation amplifier
2	Ease of generation vs. difficulty of refinement
3	Cognitive load is tied to experience and PD
4	Structural and access constrains limiting full use

The first theme that emerged pertained to the perceived usefulness of AI as a tool to support differentiated small group instruction. This theme was AI as a productivity and differentiation amplifier. Teachers from the study noted that using AI to inform small-group placement and to assist in creating materials “definitely improved instruction,” and that it was a “game changer for differentiation.” The second theme, ease of generation vs. difficulty of refinement, relates to the perceived ease of using AI tools. Teachers noted that generation was “easy” and “fast,” but discussed more difficulty in editing, formatting, visual design, and prompt specificity. This helps explain why survey results indicated a high mean for perceived use items, but larger standard deviations for mental effort, confusion, unexpected behavior, and ease of making the technology do what the user wants. Additionally, the third theme, cognitive load, is tied to experience and PD and added more detail about the perceived ease of use of AI tools. Teachers noted that their comfort with AI tools increased after PD and felt that teachers without PD are less confident or forget to use AI.

Finally, the fourth theme that emerged from the interviews and reflections was structural and access constraints limiting full use. Teachers noted that students do not have access to the same tools, visual design limitations limit classroom usability, and that over-reliance on AI by students is a concern. This theme accepted the high usefulness ratings but acknowledged that usefulness is limited by access, design, and classroom realities. Regarding additional needed PD, teachers in this study noted that prompting skills are a major barrier and that they would like hands-on, guided, workshop-style sessions.

The additional information provided by participants helped explain the higher variability in standard deviations for mental effort, seeking help, and confusion. At the conclusion of the thematic analysis, participants reviewed the themes to ensure that they aligned with their perceptions. This process enhanced the trustworthiness and credibility of qualitative research. Key aspects included verifying and confirming that the themes accurately represent participants' experiences and views.

Discussion

Teachers in this study consistently described motivations for adopting AI tools that align directly with the post-pandemic challenges documented in contemporary research. Participants cited needs for differentiation and opportunities to save time for meaningful tasks. These motivations mirror the empirical findings of Zhang and Storey (2022) and Golden et al. (2023), who documented significant declines in math and reading performance following the pandemic, as well as the 2024 NAEP data showing continued academic regression, particularly among lower- and middle-performing students.

The qualitative data further revealed that teachers understood their adoption of AI not as a technological experiment, but as a pragmatic response to unsustainable instructional conditions. Participants described feeling stretched between the need to address unfinished learning, support diverse student readiness levels, and maintain grade-level rigor, pressures that reflect the broader teacher burnout documented by Pressley et al. (2024) and Reinke (as cited in Stann, 2025). Teachers' motivations were not abstract or innovation-driven; they were grounded in immediate, classroom-level needs for efficiency, differentiation, and scalability.

Teachers positioned AI tools as mechanisms to operationalize differentiated small group instruction in ways that traditional whole-class models could not support. Participants described using AI to analyze student data, generate leveled materials, scaffold complex tasks, and facilitate targeted feedback, functions that align with the scaffolding principles of Vygotsky's zone of proximal development (ZPD) and Tomlinson's (2014) differentiation framework. These adaptations reflect a shift away from rigid, pacing-guide-driven instruction toward more responsive, formatively informed teaching practices.

This adaptive response also addressed a key limitation identified in the literature: whole-group instruction's inability to meet the needs of students with widely varying readiness levels (Namkung et al., 2022). By using AI to create differentiated materials and facilitate small group work, teachers attempted to reconcile the competing demands of curriculum coverage and individualized support. In doing so, they enacted instructional practices consistent with research advocating for high-dosage, targeted interventions as mechanisms for academic recovery (Zhang & Storey, 2022; Timar, 2023).

The qualitative findings strongly confirmed the quantitative trends, which indicated that teachers perceived AI as highly useful for differentiation. Teachers consistently reported that AI enabled them to deliver differentiated small-group instruction more efficiently and effectively than traditional methods would have allowed. Participants described AI as a "game changer" for differentiated instruction, leveling materials, and instructional planning. This language reflects

not only satisfaction with the technology but also recognition of its transformative potential for addressing diverse learning needs.

However, evidence also revealed that differentiation was not automatic. Teachers needed to actively curate, refine, and contextualize AI outputs to ensure alignment with student needs and learning objectives. This finding reinforced the importance of teacher expertise in mediating AI use and underscores that technology alone cannot replace professional judgment in instructional design.

Limitations

Several limitations should be considered when interpreting this study's findings. First, the quantitative analysis was intentionally descriptive rather than inferential because the study was exploratory. As a result, the findings do not support causal claims or statistical generalization beyond the study sample. This analytic approach was appropriate given the study's exploratory purpose but necessarily limits the scope of conclusions that can be drawn.

Additionally, the sample size and study context constrain the transferability of the findings. Participants were drawn from a specific educational setting, and their experiences may not reflect those of teachers in other grade levels, subject areas, or institutional environments. While qualitative findings provided depth and contextual insight, they represent the perspectives of a limited group of educators.

The study also relied on self-reported survey responses, interviews, and reflections, which are subject to response bias, social desirability, and variations in individual interpretations. The study survey had a 42% response rate. This raises the possibility of response bias, as non-respondents' perspectives may differ from those of respondents. However, all participants were drawn from the same district and had access to the same resources, minimizing systematic differences in context or support. While respondents may have been slightly more motivated than non-respondents, there is no evidence they differed meaningfully from their peers in other ways. Therefore, although the potential for response bias should be acknowledged, the sample appears reasonably representative of the larger population of interest.

Finally, the rapidly evolving nature of AI tools in education presents an inherent limitation. AI platforms' features and capabilities can change quickly, which may affect the applicability of specific findings over time. As such, interpret the results as reflecting teacher experiences with AI tools during the data collection period rather than as an enduring evaluation of specific technologies.

Conclusion

This study explored how secondary ELA and math teachers adapted AI-facilitated differentiated small-group teaching and learning strategies to their individual classroom contexts after PD. The mixed-methods study found that while teachers shared mostly positive outlooks on implementing AI, opinions varied about the perceived ease of use of AI outputs. Teachers adapted AI tools by leveraging them as productivity amplifiers that enabled efficient creation of differentiated

materials, but success in adaptation was heavily dictated by the quality of PD, structural supports, and teachers' ongoing refinement of AI-generated content.

This study provided valuable insights into teacher perceptions of using AI to differentiate instruction and demonstrates that AI can serve as a powerful tool for operationalizing established pedagogical frameworks within post-pandemic instructional contexts. However, the findings also underscore that technology alone is insufficient; effective AI adoption requires robust PD, equitable access, clear ethical guidelines, and ongoing teacher practice in curating and refining AI outputs. Future research should continue to explore the long-term impacts of AI use, the most effective professional learning models, and the ethical dimensions of AI integration to ensure these tools genuinely support, rather than complicate, the critical work of teaching.

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