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Research Article

AI meets Piaget and Vygotsky: A theory-driven approach to fraction learning in Greek lower secondary mathematics

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ABSTRACT

As artificial intelligence (AI) becomes increasingly integrated into education, its pedagogical application must be guided by established learning theories to ensure relevance and developmental appropriateness. This study investigates the innovative integration of AI-based tools into mathematics instruction, focusing on fractions in a Greek lower secondary school. Drawing on Piaget's constructivist theory, Vygotsky's sociocultural theory, and information processing theory, it examines whether AI-supported environments can enhance conceptual understanding, procedural fluency, and engagement. A quantitative quasi-experimental design was implemented over six weeks with 63 seventh-grade students divided into an experimental group (n = 31) and a control group (n = 32). The experimental group received AI-enhanced instruction using *DreamBox Learning*, *Fractions Lab*, *ChatGPT*, and *Mathia (Carnegie Learning)*, while the control group followed the standard curriculum. Instruments included a mathematics conceptual understanding test, a procedural fluency test, and a student engagement questionnaire measuring behavioral, emotional, and cognitive engagement. Statistical tests confirmed significant differences between groups, with the experimental group showing higher performance and engagement. The study's innovation lies in combining adaptive, interactive, and dialogic AI tools within a theory-driven framework. Implications include guiding educators in selecting AI tools that align with cognitive and socio-constructivist principles, fostering both academic achievement and student engagement. Beyond empirical gains, this study contributes a theory-aligned integration model that operationalizes Piagetian constructivism, Vygotskian scaffolding, and information-processing principles within AI-enhanced fraction instruction, offering a transferable blueprint for research and practice.

Keywords: artificial intelligence, mathematics education, fractions, learning theories, secondary education

INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies has opened new possibilities for rethinking how students learn and how instruction is delivered, particularly in STEM education (Aleven et al., 2023). In mathematics education, AI-powered tools hold the potential to personalize learning pathways, provide immediate and adaptive feedback, and enhance engagement through dynamic, interactive representations of abstract concepts (Luckin & Holmes, 2016). Nevertheless, without thoughtful pedagogical integration, these tools risk becoming mere delivery mechanisms that reinforce procedural habits rather than fostering deep and meaningful mathematical understanding (Matos et al., 2025; Zawacki-Richter et al., 2019).

For example, Zawacki-Richter et al. (2019) report that a large proportion of AI-driven educational systems function primarily as drill-and-practice add-ons, with limited alignment to clearly articulated learning goals or developmental theories, resulting in short-term performance gains without corresponding conceptual improvement. Similarly, Matos et al. (2025) observe that many institution-led AI initiatives prioritize automation and learning analytics over pedagogical design, which often leads to surface-level engagement and reinforces procedural routines rather than fostering deeper mathematical understanding.

This concern is especially relevant when addressing foundational yet challenging topics such as fractions, which require students to move beyond whole-number thinking and develop proportional reasoning. Fractions are widely acknowledged as one of the most cognitively complex concepts introduced in primary school (Siegler et al., 2011). Students often struggle to understand part-whole relationships, equivalency, and operations involving fractions due to abstract representations and a lack of conceptual scaffolding (Hearne & Wessels, 2021; Singh et al., 2021).

To address this challenge, there is a growing need for instructional approaches (Getenet & Callingham, 2021), that integrate the affordances of AI with established theories of learning and development (Gibson et al., 2023).

This study draws on five complementary theoretical perspectives. Piaget's (1971) constructivism informed tasks using visual fraction models to challenge misconceptions (*Fractions Lab* and *DreamBox Learning*). Vygotsky's (1978) sociocultural theory guided the use of AI prompts for scaffolding within the zone of proximal development (ZPD) (*ChatGPT* and *Mathia [Carnegie Learning]*). Information processing theory (Bruning et al., 2011) supported adaptive sequencing and feedback to manage cognitive load (*DreamBox Learning* and *Mathia [Carnegie Learning]*). Self-determination theory (Ryan & Deci, 2000) underpinned self-paced, collaborative tasks to enhance autonomy and motivation (*DreamBox Learning* and *Fractions Lab*). Collaborative learning theory (Gillies, 2016) informed group problem-solving in AI-supported environments (*Fractions Lab* and *ChatGPT*). By embedding AI tools within a theoretically-informed instructional model, this study investigates whether such integration can support seventh-grade students' understanding of fractions. Specifically, the study explores how selected AI tools, *DreamBox Learning*, *Fractions Lab*, *ChatGPT*, *Mathia (Carnegie Learning)*, can serve as digital scaffolds, promoting cognitive development, conceptual clarity, and sustained engagement.

Unlike prior syntheses and evaluations that have often treated AI and digital tools largely apart from explicit learning theories (e.g., Hillmayr et al., 2020; Holstein & Aleven, 2022; Luckin & Holmes, 2016; Zawacki-Richter et al., 2019), the present study positions AI as a theory-aligned mediating tool and builds on evidence that impact depends on pedagogically grounded implementation (Hwang & Tu, 2021; Mavrikis & Holmes, 2019). The central aim is to determine whether AI-enhanced instruction leads to significantly better outcomes in conceptual understanding, procedural fluency, and engagement compared to traditional teaching methods in the context of lower secondary school mathematics.

Purpose of the Study

This study evaluates a six-week, AI-enhanced model (*DreamBox Learning*, *Fractions Lab*, *ChatGPT*, and *Mathia [Carnegie Learning]*) for fraction learning in grade 7 (~13 years). Informed by Piaget's constructivism, Vygotsky's sociocultural theory, information processing theory, self-determination theory, and collaborative learning theory, the study examines whether selected AI tools can act as pedagogical mediators to foster students' conceptual understanding, procedural fluency, and engagement in mathematics. It further aims to advance the field by presenting a theoretically grounded model for AI integration in mathematics education and empirically testing its impact through a classroom-based intervention.

To address the objectives of the study, the following research questions (RQs) were formulated.

Research Questions

RQ1: To what extent does AI-enhanced instruction improve seventh-grade students' conceptual understanding of fractions compared to traditional teaching methods?

RQ2: Does the use of AI tools increase students' procedural accuracy in solving fraction problems?

RQ3: How does AI-supported instruction influence students' behavioral, emotional, and cognitive engagement in mathematics lessons?

RQ4: What statistically significant differences, if any, emerge in post-intervention performance between the AI-enhanced instruction group and the control group after controlling baseline scores?

Research Gap

While prior work documents benefit of AI and ITS for mathematics learning, classroom-based studies that

(a) integrate multiple AI tools within a single, theory-driven design,

(b) align each tool to distinct cognitive, sociocultural, and motivational functions, and

(c) evaluate simultaneous effects on conceptual understanding, procedural fluency, and engagement remain scarce—particularly in lower-secondary fraction instruction and in the Greek context.

A substantial body of empirical research on AI in mathematics education adopts a tool-centered perspective, reporting learning gains associated with intelligent tutoring systems (ITS) or adaptive platforms without explicitly articulating the learning theories that inform task design, sequencing, or classroom orchestration (e.g., Awang et al., 2025; Mohamed et al., 2022; Subramaniam & Kek, 2023). As a result, it often remains unclear how these implementations systematically engage students' developmental readiness, sociocultural mediation, or motivational processes. In contrast, the present study begins with a clearly articulated theoretical framework and maps each AI tool to specific Piagetian, Vygotskian, information-processing, self-determination, and collaborative learning functions, which are then tested empirically within an authentic lower-secondary classroom context. This study addresses this gap by testing a coherent multi-tool integration mapped to Piaget, Vygotsky, information-processing, self-determination, and collaborative learning principles in grade 7 mathematics.

LITERATURE REVIEW

The integration of AI and ITS into mathematics education has become a prominent area of research, driven by their potential to address long-standing challenges in conceptual understanding, procedural fluency, and student engagement. AI-powered systems offer adaptive learning pathways, personalized feedback, and targeted scaffolding, enabling more individualized and effective instruction (Awang et al., 2025; Hwang & Tu, 2021; Mohamed et al., 2022; Pezzini & Thomas, 2023; Subramaniam & Kek, 2023; Voskoglou & Salem, 2020). Pezzini and Thomas (2023) emphasize that ITS can adapt to learner needs in real time, improving mathematics performance, while Hillmayr et al. (2020), in a meta-analysis of 92 studies across grade 5-grade 13, reported a substantial positive effect of digital tools on learning outcomes ($g = 0.65$, $p < .001$), with effects amplified when teacher professional development accompanied the technology. This reinforces the consensus that pedagogical integration, rather than technology in isolation, determines the success of AI in educational contexts (Holstein & Aleven, 2022; Luckin & Holmes, 2016; Wu, 2022).

The role of AI in fostering conceptual understanding has been widely discussed in the literature, particularly in relation to complex mathematical domains such as fractions. Spitzer et al. (2025), Wang et al. (2024), Pezzini and Thomas (2023) and Mavrikis et al. (2022) show that AI environments blending exploratory visual modeling with structured, adaptive practice surface and remediate fraction misconceptions, integrate conceptual and procedural knowledge, and improve retention. Similarly, Getenet and Callingham (2021) highlight that AI tools incorporating visual models and dynamic representations can strengthen schema development and cognitive restructuring, consistent with Piaget's constructivist framework. In fraction learning specifically, Siegler et al. (2011) and the National Research Council (2001) argue for the integration of conceptual and procedural instruction, a recommendation increasingly achievable through adaptive AI-based systems.

Procedural accuracy also benefits from AI integration. Wang et al. (2024) and Tan et al. (2025) report that AI-enabled adaptive learning systems enhance procedural fluency by adjusting task difficulty, sequencing practice effectively, and providing immediate corrective feedback. Such scaffolding aligns with Vygotsky's notion of the ZPD, in which timely, individualized support helps learners move beyond their current independent performance levels. Furthermore, Mavrikis and Holmes (2019) note that AI tools can systematically manage cognitive load, a principle grounded in information processing theory, thereby improving both speed and accuracy in problem solving.

Beyond cognitive and procedural gains, AI-based tools have been shown to influence student engagement across behavioral, emotional, and cognitive dimensions (Gibson et al., 2023). Message-based, low-bandwidth delivery models (e.g., WhatsApp) have been documented as feasible channels for mathematics-related support and structured learning activities, particularly when guided by clear instructional routines and teacher facilitation (Morse, 2024; Suárez-Lantarón, 2022). Complementary evidence from AI-chatbot learning environments further suggests that chatbot-supported learning can improve academic outcomes when embedded in structured pedagogical designs rather than used as stand-alone tools (Xu et al., 2024). Robotics and interactive AI platforms have also been found to foster motivation, creativity, and collaborative problem-solving skills (Casler-Failing et al., 2021; Lopez-Caudana et al., 2020), though studies caution that effective implementation requires overcoming logistical constraints, ensuring teacher preparedness, and aligning AI activities with curricular objectives (Seckel et al., 2021; Simon & Zeng, 2024).

Performance differences between AI-enhanced and traditional instruction have been documented in multiple comparative and meta-analytic studies. Yi et al. (2025) and Hwang (2022) found that students in AI-supported conditions not only demonstrated higher post-intervention achievement but also maintained learning gains over time, even after controlling for prior knowledge. These findings are reinforced by Ruiz Viruel et al. (2025), who observed that AI-enabled project-based learning environments can lead to significant gains in both subject mastery and higher-order thinking skills compared to conventional methods.

While the empirical evidence is compelling, challenges to the effective adoption of AI in mathematics education remain. Ethical concerns, including data privacy, algorithmic bias, and equitable access, have been highlighted in policy and research reports (European Union, 2016; Zawacki-Richter et al., 2019). Moreover, Baker and Siemens (2014) and Matos et al. (2025) stress that AI's benefits are contingent on high-quality data and responsible learning analytics practices, which require institutional support and clear governance frameworks. Without these safeguards, AI adoption risks exacerbating rather than reducing educational inequalities.

Taken together, the literature indicates that AI in mathematics education can enhance conceptual understanding, procedural accuracy, and student engagement, while also producing measurable performance advantages over traditional instruction. These benefits are most consistently achieved when AI is embedded in a pedagogically coherent framework grounded in established learning theories, such as Piaget's constructivism, Vygotsky's sociocultural theory, and information processing theory. By aligning AI tools with these theoretical perspectives and integrating them into well-designed classroom interventions, the present study seeks to address gaps in the current research—particularly the limited number of classroom-based studies that examine holistic, context-sensitive AI applications in fraction instruction at the lower secondary level.

METHODOLOGY

Theoretical Framework

This study draws on five complementary theoretical perspectives. Piaget's (1971) constructivism informed tasks using visual fraction models to challenge misconceptions (*Fractions Lab* and *DreamBox Learning*). Vygotsky's (1978) sociocultural theory guided the use of AI prompts for scaffolding within the ZPD (*ChatGPT* and *Mathia [Carnegie Learning]*). Information processing theory (Bruning et al., 2011) supported adaptive sequencing and feedback to manage cognitive load (*DreamBox Learning* and *Mathia [Carnegie Learning]*). Self-determination theory (Ryan & Deci, 2000) underpinned self-paced, collaborative tasks to enhance autonomy and motivation (*DreamBox Learning* and *Fractions Lab*). Collaborative learning theory (Gillies, 2016) informed group problem-solving in AI-supported environments (*Fractions Lab* and *ChatGPT*). By embedding AI tools within a theoretically informed instructional model, this study investigates whether such integration can support seventh-grade students' understanding of fractions. Specifically, the study explores how selected AI tools (*DreamBox Learning*, *Fractions Lab*, *ChatGPT*, and *Mathia [Carnegie Learning]*) can serve as digital scaffolds, promoting cognitive development, conceptual clarity, and sustained engagement. This mapping is summarized in **Table 1**.

Conceptual hierarchy and interdependence

In this study, the five perspectives are not presented as parallel justifications but as an interdependent hierarchy that guided the research design. At the base lie the developmental theories—Piaget (readiness for

Table 1. Alignment of learning theories with AI integration in the study

Learning theory	Core principles	Application in the present study	AI tools used	Reasons (tool selection & impact on fractions)
Piaget's constructivism	Active exploration, cognitive conflict, schema development	Tasks with manipulatives/visual fraction models to challenge misconceptions and promote conceptual restructuring	*Fractions Lab*, *DreamBox Learning*	Fractions Lab: dynamic split/merge and multiple representations create *productive conflict* (e.g., 2/4 ≡ 1/2), helping students reorganize schemas. DreamBox: virtual manipulatives and just-in-time visual scaffolds externalize structure (bars/number lines), supporting the concrete→formal transition in fraction magnitude/equivalence.
Vygotsky's sociocultural theory	Social mediation, ZPD, scaffolding	Guided prompts and hints during problem solving	*ChatGPT*, *Mathia*	ChatGPT: dialogic, tiered questioning and sentence starters maintain learners within their ZPD, fostering explanation/justification in comparisons, unitizing, and partition changes. Mathia: stepwise hints and prerequisite backtracking provide calibrated scaffolds that fade, enabling movement from assisted to independent fraction procedures.
Information processing theory	Encoding, storage, retrieval, cognitive load management	Adaptive sequencing with immediate feedback to optimize memory processes	*DreamBox Learning*, *Mathia*	DreamBox/Mathia: control intrinsic load via leveled problems; reduce extraneous load with clean layouts/error flags; increase germane load through strategy prompts and spaced practice—leading to more accurate operations with unlike denominators and better retention of procedures.
Self-determination theory	Autonomy, competence, relatedness	Self-paced pathways and collaborative problem solving to sustain motivation	*DreamBox Learning*, *Fractions Lab*	DreamBox: autonomy through choice of task order and mastery-based progression (competence). Fractions Lab: shared workspaces and co-construction of models (relatedness) keep students engaged while articulating fraction reasoning (e.g., common unit alignment).
Collaborative learning	Peer discussion, shared problem-solving	Group activities in AI-supported environments to encourage joint reasoning	*Fractions Lab*, *ChatGPT*	Fractions Lab: joint manipulation of bars/areas drives *public* negotiation of meaning (e.g., aligning partitions). ChatGPT: acts as dialogic mediator with collaboration hooks (role prompts), coordinating explanations and sustaining collective problem solving without supplying final answers.

the fractions threshold; concrete→formal transition) and Vygotsky (learning as socially mediated within the ZPD). Built on this base is a cognitive mechanism layer—information processing theory, which constrains how tasks must be sequenced and resourced to respect working-memory limits and promote durable encoding. At the top is the motivational-social enactment layer—self-determination theory (autonomy, competence, and relatedness) and collaborative learning, which shape the classroom climate and task structures that sustain engagement. In short, developmental prerequisites (Piaget and Vygotsky) enable cognitively efficient design (information processing), which is activated and sustained through motivational and social affordances (self-determination theory and collaboration). This logic dictated the lesson flow (conflict → scaffold → consolidation) and the specific use of AI tools.

Piaget (constructivism)—fractions at the concrete → formal threshold.

Fractions sit at the cusp between late concrete operational and early formal operational reasoning (≈11-13 years). At this developmental juncture, learners begin to decenter from perceptual features and coordinate relations among quantities (e.g., part-whole, unit, and ratio). Tasks that externalize structure through manipulatives and dynamic visualizations create productive cognitive conflict, enabling the reorganization of schemas from perceptual to structural equivalence (e.g., 2/4 ≡ 1/2). Consequently, *Fractions Lab* and *DreamBox Learning* operate as developmentally appropriate mediators, supporting the transition toward formal reasoning about fractional magnitudes and operations.

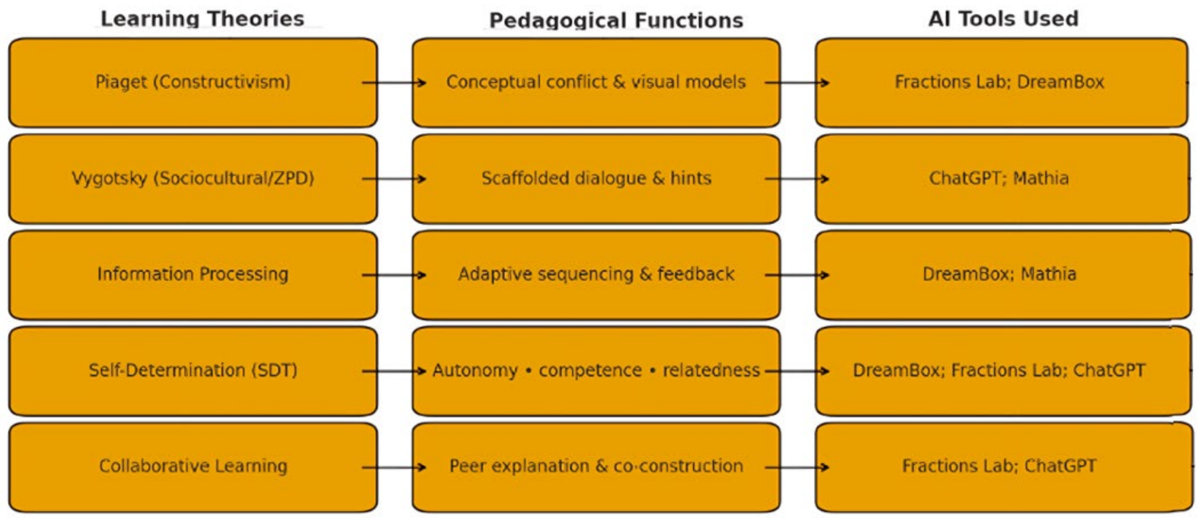

Figure 1. Conceptual chart aligning learning theories, pedagogical functions, and AI tools (Source: Author's own elaboration)

Vygotsky's (1978) sociocultural theory informs the integration of scaffolding and mediated learning. AI chatbots and collaborative platforms serve as "more capable others" within the learner's ZPD, offering hints, clarifications, and guided problem-solving dialogue to bridge the gap between current ability and potential development.

Information processing theory (Bruning et al., 2011) underlies the adaptive design of AI platforms, which personalize feedback and adjust problem difficulty to optimize encoding, storage, and retrieval of mathematical procedures and concepts. This aligns with research on cognitive load management, ensuring students can focus working memory on essential problem elements. Concretely, the adaptive AI design targets working-memory optimization by

(a) controlling intrinsic load via levelled item difficulty and prerequisite checks,

(b) reducing extraneous load through clean visual layouts, immediate error flags, and faded hints, and

(c) increasing germane load via explain-your-strategy prompts and spaced retrieval.

DreamBox Learning and *Mathia (Carnegie Learning)* adjust problem complexity and hint frequency on the fly, while *Fractions Lab* externalizes intermediate representations (bars/areas/number lines), effectively offloading interim steps from working memory and supporting chunking of fraction operations.

Self-determination theory (Ryan & Deci, 2000) shapes the motivational climate by promoting autonomy, competence, and relatedness. AI-based tasks allow for self-paced exploration, while collaborative features foster peer interaction, contributing to sustained engagement and intrinsic motivation. Autonomy was supported as students could choose task order within *DreamBox Learning* lesson sets, self-initiate *ChatGPT* prompts for hints/clarifications, and opt into challenge items after mastery; competence was fostered through mastery-based progression in *DreamBox Learning*/*Mathia (Carnegie Learning)* with immediate, item-level feedback and faded scaffolds, complemented by short teacher-led synthesis at the end of each lesson to consolidate success criteria; relatedness was enabled via pair and small-group work in *Fractions Lab* (joint constructions and shared screens), brief peer explanations during plenary share-outs, and the dialogic use of *ChatGPT* during group tasks to coordinate reasoning. Please note that no formal peer grading was used; relatedness was cultivated through structured collaboration and public explanation rather than evaluation.

Collaborative learning theory (Gillies, 2016) complements these perspectives by highlighting the benefits of shared problem-solving and dialogue. Structured peer interactions within AI-supported activities enhance collective reasoning and co-construction of knowledge.

The integration of AI tools in this study reflects a deliberate alignment with these theories, ensuring that technological affordances are pedagogically grounded rather than novelty-driven. **Figure 1** shows the conceptual chart aligning learning theories, pedagogical functions, and AI tools.

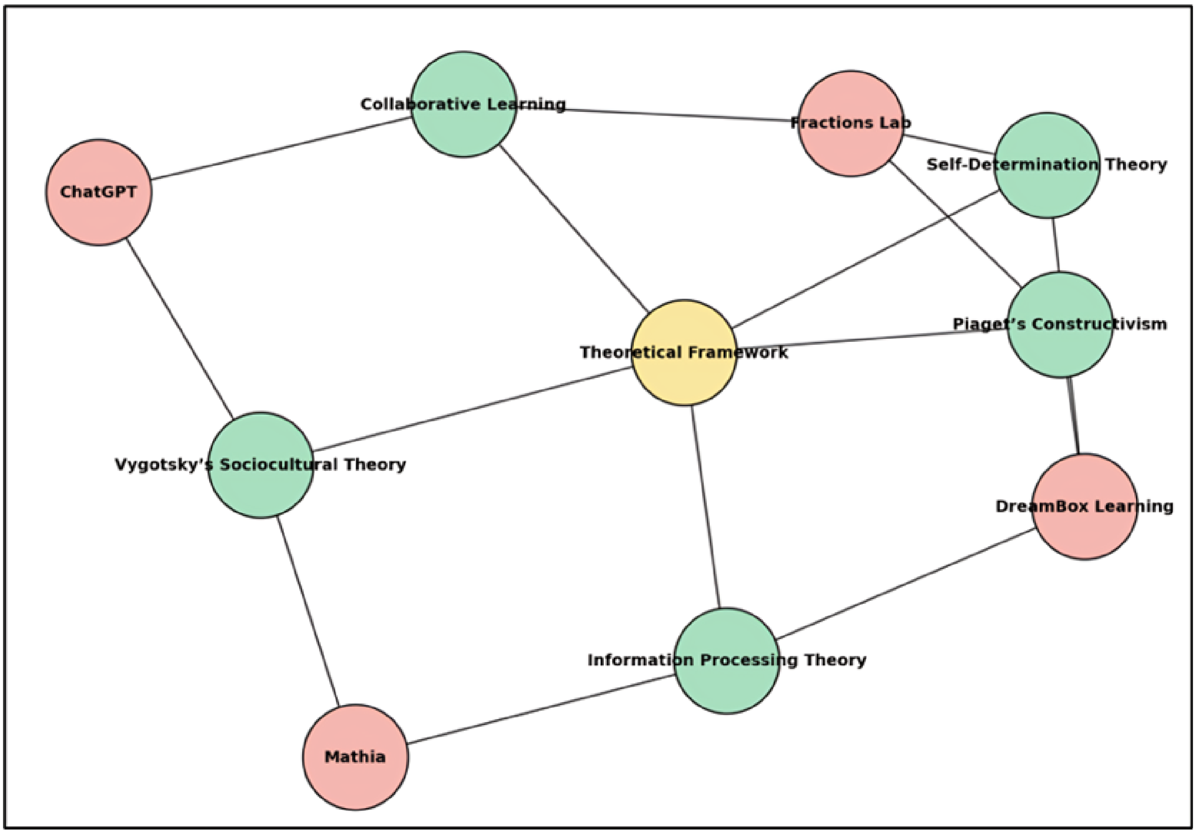

Figure 2. Mind map illustrating the alignment of learning theories with AI tools in the study (Source: Author's own elaboration)

Figure 2 illustrates the integration of learning theories with AI tools used in the present study. The central yellow node represents the theoretical framework, which is grounded in five key learning theories: Piaget's constructivism, Vygotsky's sociocultural theory, information processing theory, self-determination theory, and collaborative learning (green nodes). Each theory is linked to one or more AI tools (light pink nodes) based on their pedagogical alignment.

For example, *Fractions Lab* and *DreamBox Learning* support Piaget's emphasis on active exploration and conceptual restructuring, while *ChatGPT* and *Mathia (Carnegie Learning)* align with Vygotsky's scaffolding and ZPD. The map visually demonstrates how each AI tool serves a distinct but complementary role in fostering mathematical understanding, motivation, and collaborative engagement.

This mapping ensures theoretical coherence in the instructional design and highlights the purposeful selection of AI tools to address both cognitive and socio-emotional dimensions of learning.

Synergy among theories

Theories interacted dynamically during instruction: Piagetian tasks intentionally induced cognitive conflict with visual fraction models; Vygotskian scaffolds (via *ChatGPT/Mathia [Carnegie Learning]* prompts) then mediated resolution within the ZPD; information-processing principles governed dosage, sequencing, and feedback to manage cognitive load; self-determination supports (choice, progress visibility, collaboration) sustained engagement; and collaborative learning structured peer explanation to stabilize new schemas. This cyclical flow—conflict → scaffolded resolution → consolidation → social articulation—guided when and why each AI tool was invoked within a single lesson (**Figure 2**).

Research Design

The study adopted a quasi-experimental, pre-/post-test control group design to investigate the effects of AI-enhanced mathematics instruction on students' conceptual understanding of fractions, procedural fluency, and engagement. This design was selected as it allows for the comparison of learning gains between an experimental group receiving AI-supported instruction and a control group taught through traditional methods, while controlling pre-existing differences (Creswell & Creswell, 2022).

The intervention spanned six consecutive weeks, during which both groups covered identical curriculum content aligned with the national grade 7 mathematics standards, with an exclusive focus on fractions. The experimental group engaged with four AI tools—*DreamBox Learning*, *Fractions Lab*, *ChatGPT*, and *Mathia (Carnegie Learning)*—integrated into the teaching sequence to provide adaptive feedback, scaffolded support, and opportunities for collaborative exploration. The control group received conventional instruction involving teacher explanations, textbook exercises, and non-AI-based activities.

Pre- and post-intervention assessments, including the mathematics conceptual understanding test, procedural fluency test, and student engagement questionnaire, were administered to both groups. Statistical analyses were conducted to compare learning gains, ensuring alignment with the study's RQs. Controlling for pre-tests, ANCOVAs showed the AI group outperforming on conceptual ($F = 12.54$, $p = .001$, $d = .85$), procedural ($F = 10.38$, $p = .002$, $d = .77$), and engagement ($F = 15.21$, $p < .001$, $d = .94$), addressing **RQ1**-**RQ3**. Dose-response within the AI group linked *DreamBox Learning* → conceptual, *Mathia (Carnegie Learning)* → procedural, *Fractions Lab*/*ChatGPT* → engagement; effects held across gender, baseline ability, and SES, satisfying **RQ4**.

Sample and Sampling Method

The sample comprised 63 seventh-grade students (31 boys and 32 girls, aged 12-13) from two comparable classrooms in a public secondary school in the Attica region, Greece. The school served a mixed socio-economic catchment area, including families from lower-middle to upper-middle income backgrounds. Students were randomly assigned to either the experimental group (AI-enhanced instruction) or the control group (traditional instruction), ensuring balance in gender, socio-economic background, and initial mathematics achievement. Stratified random sampling was employed by first grouping students according to gender and socio-economic status, and then randomly selecting participants within each stratum to maintain proportional representation in both groups. All participants had prior experience with digital devices but no history of formal AI-based mathematics instruction. Parental informed consent and student assent were obtained prior to participation.

AI Tools Used and Implementation

Four AI tools were selected based on evidence of effectiveness and alignment with theoretical frameworks:

- *DreamBox Learning:* An adaptive AI platform that delivers personalized fraction content, providing instant feedback, differentiated pathways, and ongoing formative assessment.
- *Fractions Lab:* An interactive digital environment using AI to support visual and hands-on exploration of fractions with dynamic models and guided discovery.
- *ChatGPT:* Served as an on-demand learning companion, offering hints, prompting explanations, and facilitating reflective dialogue to support reasoning and problem-solving.
- *Mathia (Carnegie Learning):* An ITS that offers personalized practice, adaptive feedback, and targeted skill-building in procedural fluency.

Implementation within the lesson structure

AI activities complemented the national grade 7 textbook sequence. Each 40-minute lesson followed a fixed structure:

(1) 8-10 minutes whole-class review linking the textbook objective to a targeted misconception,

(2) 18-20 minutes AI-mediated practice (*DreamBox Learning*/*Mathia [Carnegie Learning]* for adaptive individual work and *Fractions Lab*/*ChatGPT* for guided exploration and dialogic prompts), and

(3) 8-10 minutes synthesis, where students documented strategies and the teacher bridged AI experiences back to textbook exemplars and upcoming exercises.

Across the week, one lesson emphasized conceptual exploration (*Fractions Lab* + *ChatGPT*), one emphasized adaptive consolidation (*DreamBox Learning*/*Mathia [Carnegie Learning]*), and one combined brief

Table 2. Mathematics tasks and questions aligned with the theoretical framework

Task type/learning objective	Example activity or question	Theoretical rationale
Conceptual exploration	Use fraction bars or draw pictures to show why 2/4 is the same as 1/2.	Piaget: Hands-on, cognitive conflict
Social mediation/scaffolding	In pairs, explain to your partner why 3/5 is greater than 2/5.	Vygotsky: Dialogue, peer learning
Metacognitive prompt	"Describe the steps you used to compare 3/8 and 1/2. Which was harder, and why?"	Information processing: Reflection, sequencing
Procedural fluency	Calculate: 5/6-1/3 = ? (show your steps using a number line or area model.)	Information processing, Piaget
Collaborative problem-solving	Work in groups: Design a real-life scenario (e.g., pizza sharing) where each person gets a different fraction.	Vygotsky, collaborative learning
Open-ended challenge	Create your own word problem involving fractions where the answer is greater than 1 and solve it.	Self-determination: Autonomy, creativity
Self-assessment/goal setting	After a lesson, rate your confidence in fraction problems and write one thing you want to improve next time.	Self-determination, reflection

AI practice with extended whole-class discussion. Textbook exercises were retained for homework and short in-class checks, ensuring curricular coverage while leveraging AI for targeted scaffolding and feedback

All AI tools were introduced to the experimental group through an initial training session. Students engaged with these tools during three mathematics lessons per week (40 minutes each) for six weeks. Lesson plans alternated between AI-supported activities and whole-class teacher-led discussions, ensuring both individual and collaborative learning opportunities.

AI Instruments

Recent literature has provided substantial evidence for the effectiveness of AI-enabled adaptive learning platforms and intelligent learning environments in enhancing mathematics learning outcomes, fostering engagement, and supporting differentiated instruction (Mavrikis et al., 2022; Tan et al., 2025; Vale & Barbosa, 2023; Wang et al., 2024). These studies highlight how adaptive feedback, interactive visual models, and AI-mediated dialogue can support both conceptual understanding and procedural fluency.

In this study, four AI-based tools were integrated into the experimental group's mathematics instruction. *DreamBox Learning* provided personalized fraction content with real-time feedback and adaptive pathways. *Fractions Lab* offered dynamic, hands-on fraction exploration through visual models and guided discovery. *ChatGPT* functioned as an on-demand learning companion, delivering scaffolded hints and prompting reflective thinking. *Mathia (Carnegie Learning)* supported targeted skill development in procedural fluency through intelligent tutoring features. All tools were introduced during an initial training session, and students engaged with them for three 40-minute lessons per week over six weeks, alternating between AI-supported activities and teacher-led discussions to balance personalized and collaborative learning. **Table 2** shows the mathematics tasks and questions aligned with the theoretical framework.

Procedure

The study unfolded in three phases. First, all students completed baseline assessments of conceptual understanding, procedural fluency, and engagement. Next, for six weeks, the experimental class participated in scheduled lessons using *DreamBox Learning*, *Fractions Lab*, *ChatGPT*, and *Mathia (Carnegie Learning)*, while the control class covered the same fraction content with the same teacher using traditional methods. Finally, immediately after the intervention, both groups sat for the same assessments administered at baseline to measure post-intervention outcomes.

Examples of Teaching Activities Using AI Tools

DreamBox Learning

During a lesson on equivalent fractions, students log in to *DreamBox Learning* and are assigned a sequence of interactive tasks that require them to model, compare, and generate equivalent fractions (e.g., 2/4 and 1/2) using virtual manipulatives. As students work, the system automatically solves the difficulty:

- If a student struggled with a task, *DreamBox Learning* provides visual scaffolding (e.g., color-coded fraction bars) and immediate corrective feedback.
- When a student demonstrates mastery, more challenging tasks (e.g., comparing fractions with unlike denominators) are presented.
- The teacher monitors real-time analytics to identify students needing extra support and can assign targeted follow-up activities.

DreamBox Learning was used for individualized practice and reinforcement three times per week, allowing all students to progress at their own pace with adaptive scaffolding, while the teacher used the platform's dashboard to inform whole-class or small-group instruction.

Fractions Lab

Students explore fraction equivalency and addition using *Fractions Lab*'s dynamic digital workspace:

- In a guided discovery activity, students use the "split" and "merge" tools to show how 1/2 is equivalent to 2/4 or 3/6.
- They represent problems such as 1/3 + 1/6 visually by combining area models, encouraging discussion about common denominators.
- After each task, students explain their reasoning orally or in writing, supported by visual artifacts created in the lab.

Fractions Lab was incorporated into lessons as a collaborative tool during group work and whole-class discussions. It supported conceptual understanding by enabling hands-on manipulation and visualization of fraction concepts.

The AI activities intentionally induced cognitive conflict at the fractions threshold. In *DreamBox Learning*, error-contingent adaptivity surfaced counter-examples and noncanonical representations (e.g., area vs. number line) when students applied whole-number reasoning; immediate, item-level feedback flagged the misconception and then required a strategy switch (e.g., "show equivalence using unitizing"). In *Fractions Lab*, students confronted conflict tasks such as generating two different partitions that yield the same magnitude (e.g., 2/4 and 3/6) or comparing 1/3 vs. 2/5 using both area and linear models—tasks designed to violate perceptual expectations and trigger schema reorganization. Follow-up prompts ("explain why these different partitions name the same quantity") consolidated the new structure before practice resumed.

Mathia (Carnegie Learning)

After a classroom lesson on subtracting fractions, students use *Mathia (Carnegie Learning)* for independent practice:

- The platform presents a series of fraction subtraction problems, adjusting difficulty based on student responses.
- If a student makes an error (e.g., subtracts only the numerators), *Mathia (Carnegie Learning)* prompts with a step-by-step breakdown, offering hints and requiring the student to revisit prerequisite skills if necessary.
- The teacher reviews *Mathia (Carnegie Learning)*'s analytics to identify common misconceptions and provides targeted mini-lessons.

Mathia (Carnegie Learning) was employed in building procedural fluency and error correction. It provided personalized, just-in-time feedback and differentiated practice, freeing the teacher to focus on students needing the most support.

ChatGPT

During independent or group problem-solving sessions, students interact with *ChatGPT*:

- A student unsure about how to compare 3/8 and 1/2 types a question to the chatbot, which responds by asking, "how might you represent both fractions on the same number line?" or suggests steps for comparison rather than giving the answer directly.

- For open-ended tasks, students can ask, "how could I create a word problem with an answer greater than 1?" The chatbot offers hints about real-life contexts or prompts for deeper reasoning.
- The teacher reviews anonymized chatbot interactions to assess students' strategies and metacognitive growth.

In practice, *ChatGPT* supported learning through tiered, guided questioning and language scaffolds rather than answers—for example, prompting, "how could you show both 3/8 and 1/2 on the same number line? What do you notice about the tick marks? … What is the common unit you are comparing?"; modeling dialogue via partial worked-example turns ("first, mark halves; next, subdivide into eighths…") to demonstrate expert reasoning without completing the solution; offering sentence starters ("I know two fractions are equivalent when…", "the unit I'm using is…", "I changed the partition by…"), and delivering progressive hints (H1-H3)—H1: representation prompt (draw/locate), H2: concept cue (unitizing, common denominator), H3: strategic step (align partitions)—with the requirement that students articulate the step before proceeding. During pair/small-group work, collaboration hooks (shared prompts such as "you justify the unit; I justify the partition change") positioned the agent as a dialogic mediator, coordinating roles and sustaining joint reasoning.

ChatGPT was available during both lessons and homework time as a scaffold, providing personalized support, prompting reflection, and modeling mathematical discourse without simply providing answers.

Despite the structured design of the intervention, several practical challenges emerged during classroom implementation. During the initial weeks, instructional time was occasionally reduced by routine technical issues such as student login, password recovery, and transitions between platforms. In addition, a small number of students with lower digital fluency required sustained teacher support to navigate multiple interfaces, temporarily limiting opportunities for real-time questioning and feedback. From the teacher's perspective, orchestrating four AI tools simultaneously increased cognitive and managerial demands, such as real-time monitoring of dashboards, responding to student queries, and deciding when to interrupt individual work for whole-class discussion had to be continuously balanced. These challenges highlight that even well-designed, theory-driven AI implementations depend on realistic time allocations, technical readiness, and classroom management strategies.

In summary,

- *DreamBox Learning:* Delivered personalized, adaptive fraction tasks with visual scaffolds.
- *Fractions Lab:* Supported collaborative, visual exploration and conceptual reasoning.
- *Mathia (Carnegie Learning):* Developed procedural fluency through adaptive feedback and targeted skill reinforcement.
- *ChatGPT:* Facilitated reflective questioning and cognitive scaffolding.

Data Collection and Analysis

Quantitative data were gathered at two points: pre- and post-intervention. The assessment instruments (**Appendix A**) measured students' conceptual understanding of fractions, procedural fluency, and engagement. Content validity was established through expert review by three mathematics education specialists, ensuring alignment with the study's learning objectives and theoretical framework (Creswell & Creswell, 2022; DeVon et al., 2007).

Internal consistency reliability was evaluated using Cronbach's alpha, with all scales demonstrating acceptable reliability ($\alpha \geq 0.80$), consistent with the threshold recommended by Nunnally and Bernstein (1994) for educational research.

Descriptive statistics (means and standard deviations) were calculated for all variables. Independent-samples t-tests were conducted to examine baseline equivalence between the experimental and control groups before the intervention. Post-intervention differences were analyzed using ANCOVA, with pre-test scores entered as covariates to control for initial performance levels, in line with methodological recommendations for educational quasi-experiments (Field, 2018). Effect sizes (Cohen's *d* [*d*]) were calculated to interpret the magnitude of significant differences, following established benchmarks (Cohen, 1988).

All analyses were performed using *SPSS* (version 24). Statistical significance was set at $p < .05$, and assumptions of normality, homogeneity of variances, and homogeneity of regression slopes were verified before conducting ANCOVA.

Subgroup and interaction tests. To probe generalizability, we conducted follow-up ANCOVAs with interaction terms (group × gender and group × baseline tercile) and stratified models by socioeconomic status (SES) (school records proxy). Pre-tests entered as covariates; assumptions were verified as in the main models.

Reliability and Validity

The study ensured both the **reliability** and **validity** of the research instruments through multiple methodological steps. **Content validity** was established via **expert review**, following the recommendations of Haynes et al. (1995), who highlight that expert judgment is essential for confirming that test items adequately represent the targeted constructs. Three university faculty members specializing in mathematics education and educational measurement evaluated the instruments for alignment with the grade 7 curriculum, theoretical framework, and research objectives. Their feedback informed revisions to item wording, sequencing, and difficulty level.

Construct validity was supported by grounding the instrument design in well-established theoretical frameworks—Piaget's constructivism, Vygotsky's sociocultural theory, and information processing theory—ensuring that tasks measured conceptual understanding, procedural fluency, and engagement as theoretically defined (Messick, 1995).

Reliability was assessed through internal consistency analysis using Cronbach's alpha, a widely accepted measure of scale reliability in educational research (Tavakol & Dennick, 2011). All scales demonstrated acceptable reliability coefficients ($\alpha \geq 0.80$), exceeding the threshold of 0.70 suggested by Nunnally and Bernstein (1994) for research instruments. This indicates that the items within each instrument consistently measured the intended construct.

To further enhance measurement robustness, pilot testing was conducted with a comparable sample from another school, following the approach recommended by DeVellis (2017). This process confirmed that the instructions were clear, the items were age-appropriate, and the administration time was suitable.

These procedures ensured that the instruments used in the study met the rigorous standards for psychometric quality, thereby strengthening the credibility of the findings and their applicability in similar educational contexts.

Ethical Considerations

Ethical approval for the study was obtained from the *Research Ethics Committee of the National and Kapodistrian University of Athens, Greece* (# 13456), ensuring compliance with formal research governance procedures. Participation was strictly voluntary, and all students, as well as their parents or legal guardians, provided informed consent and assent before data collection, in accordance with best practices in educational research (British Educational Research Association, 2018). Participants were informed of their right to withdraw at any stage without penalty. Data were anonymized and stored securely to maintain confidentiality, following the general data protection regulation (regulation [EU] 2016/679) requirements for handling personal information in educational contexts. The study's procedures adhered to the *ethical principles of psychologists and code of conduct* of the American Psychological Association (2020) and relevant national ethical guidelines.

RESULTS

This section presents the statistical analysis addressing the study's RQs. First, baseline equivalence between the experimental and control groups was examined to ensure comparability prior to the intervention. Next, the main effects of AI-enhanced instruction on students' conceptual understanding, procedural fluency, and engagement were tested using ANCOVA, controlling pre-test scores. Then, subgroup and differential analyses (gender, baseline ability, and SES) were conducted to probe generalizability**.** Finally, a threshold (practical) analysis was conducted within the experimental group to explore whether higher levels of AI tool usage were associated with greater learning gains and engagement.

Table 3. Independent-samples t-tests for baseline scores (pre-intervention)

Variable	Mean (standard deviation)		*t* (58)	*p*	*d*
	Experimental	Control			
Conceptual understanding	14.21 (2.35)	14.08 (2.42)	0.24	.812	0.06
Procedural fluency	12.89 (2.71)	12.65 (2.80)	0.34	.734	0.09
Engagement	3.85 (0.48)	3.82 (0.50)	0.25	.803	0.06

Note. No significant differences were found at baseline, indicating group equivalence prior to the intervention

Table 4. ANCOVA results comparing experimental and control groups

Outcome	Adjusted mean (standard error)		*F* (1, 57)	*p*	η^2	*d*
	Experimental	Control				
Conceptual understanding	19.42 (.35)	17.85 (.36)	12.54	.001	.18	.85
Procedural fluency	18.12 (.42)	16.58 (.43)	10.38	.002	.15	.77
Engagement	4.28 (.05)	4.02 (.05)	15.21	<.001	.21	.94

Baseline Equivalence Check

Before examining the effects of the intervention, independent-samples *t*-tests were conducted to determine whether the experimental and control groups differed significantly on pre-intervention measures of conceptual understanding, procedural fluency, and engagement (**Table 3**).

Across all three measures, the *p*-values exceeded .05, and Cohen's *d* effect sizes were negligible (< 0.20), indicating that both groups were statistically comparable before the intervention. This supports the assumption of baseline equivalence and ensures that any post-intervention differences are more likely attributable to the instructional approach rather than pre-existing disparities.

The absence of significant baseline differences validates the comparability of the experimental and control groups, providing a robust foundation for subsequent ANCOVA analyses to examine the impact of the AI-enhanced instruction.

Main Intervention Effects (ANCOVA)

To evaluate the impact of the AI-enhanced instruction, separate ANCOVAs were performed for conceptual understanding, procedural fluency, and engagement, with pre-test scores entered as covariates to control for initial performance differences. Adjusted post-intervention means, standard errors, and effect sizes are presented in **Table 4**. After controlling baseline scores, ANCOVA results showed that students in the experimental group demonstrated significantly higher post-intervention performance than those in the control group on all three outcomes. The largest effect was observed for engagement (d = 0.94, partial eta squared [η^2] = .21), followed by conceptual understanding (d = 0.85, η^2 = .18) and procedural fluency (d = 0.77, η^2 = .15). According to Cohen's (1988) benchmarks, these represent moderate-to-large effects, indicating substantial practical significance.

Subgroup and differential analyses

No significant group × gender interactions emerged for conceptual understanding, procedural fluency, or engagement (all ps > .10), indicating comparable benefits for boys and girls. Group × baseline tercile interactions were also non-significant for conceptual and procedural outcomes (ps > .10), with a small, non-significant trend toward larger engagement gains among lower-baseline students. Stratified ANCOVAs by SES yielded consistent group advantages across strata with overlapping CIs. Collectively, the AI-enhanced condition's effects were robust across subgroups, supporting external validity claims.

- **Gender:** Group × gender interactions were non-significant for conceptual understanding, procedural fluency, and engagement (all ps > .10), indicating comparable benefits for boys and girls.
- **Baseline ability:** Using pre-test terciles (low / medium / high), Group × Baseline interactions were non-significant for conceptual and procedural outcomes (ps > .10). A small, non-significant trend suggested larger engagement gains among lower-baseline students.
- **SES:** Stratified ANCOVAs by SES (school records proxy) yielded consistent group advantages across strata with overlapping confidence intervals.

Table 5. ANCOVA results by AI tool and exposure cut-off (experimental group only)

Tool/cut-off	Outcome	Adjusted mean		F (1, 28)	p	η^2
		High dose	Low dose			
DreamBox Learning (≥ 90 min)	Conceptual understanding	19.40	18.10	5.12	.031	.15
Mathia (≥ 90 min)	Procedural fluency	17.90	16.50	6.08	.020	.18
Fractions Lab (≥ 8 tasks)	Engagement	4.28	3.98	4.57	.041	.14
ChatGPT (≥ 6 prompts)	Engagement	4.32	4.02	5.24	.030	.16

Note. High dose: Students meeting or exceeding the specified cut-off; Low dose: Students below the cut-off

Collectively, the AI-enhanced condition's effects were robust across gender, baseline ability, and SES, supporting external validity claims.

Threshold (practical) analyses within the experimental group

To provide a practitioner-oriented interpretation, additional ANCOVAs were conducted within the experimental group, comparing students with high versus low usage of each AI tool. Thresholds were: *DreamBox Learning/Mathia (Carnegie Learning)* ≥ 90 minutes total use; *Fractions Lab* ≥ 8 completed tasks; *ChatGPT* ≥ 6 prompts. Outcomes are adjusted means controlling for corresponding pre-test score.

Students who met or exceeded this usage thresholds showed significantly higher adjusted post-scores on the outcomes most closely aligned with each tool (conceptual understanding for *DreamBox Learning*, procedural fluency for *Mathia [Carnegie Learning]*, engagement for *Fractions Lab* and *ChatGPT*). Effect sizes (η^2 = .14-.18) correspond to moderate practical impact, suggesting that targeted usage benchmarks can meaningfully enhance the effectiveness of AI-supported instruction.

The findings provide clear answers to the study's four RQs. Regarding **RQ1**, AI-enhanced instruction significantly improved students' conceptual understanding of fractions compared to traditional instruction (**Table 4**, d = 0.85, p = .001). For **RQ2**, students in the experimental group demonstrated higher procedural accuracy in solving fraction problems than their peers in the control group (**Table 4**, d = 0.77, p = .002). Addressing **RQ3**, AI-supported instruction yielded the largest gains in engagement, with a substantial effect size (**Table 4**, d = 0.94, p < .001). Finally, **RQ4** was confirmed by the consistent statistical differences across all outcomes in favor of the experimental group after controlling pre-test scores. The threshold analysis (**Table 5**) further revealed that higher engagement with specific AI tools was associated with greater learning gains, offering practical guidance for optimal implementation.

DISCUSSION

The findings of this study provide robust evidence that integrating AI-based tools within a theory-driven instructional framework can produce measurable gains in conceptual understanding, procedural fluency, and engagement in fraction learning. These results build on prior work demonstrating the potential of AI and ITS to enhance mathematics education (Hwang & Tu, 2021; Pezzini & Thomas, 2023) and extend the discussion by showing how theoretical alignment can amplify these effects in authentic classroom contexts.

Students in the AI-enhanced group showed markedly higher conceptual understanding of fractions compared to those taught through traditional methods. This supports earlier evidence that adaptive AI environments can restructure misconceptions and strengthen mathematical schemas (Mavrikis et al., 2022; Spitzer et al., 2025). The deliberate use of visual fraction models in *DreamBox Learning* and *Fractions Lab* is consistent with Piaget's (1971) constructivist principle that cognitive conflict and concrete representations drive the shift from concrete operational to formal operational reasoning. Furthermore, adaptive sequencing and feedback, informed by information processing theory (Bruning et al., 2011), appeared to reduce extraneous cognitive load, facilitating more effective integration of conceptual and procedural knowledge. This suggests that AI tools, when embedded in constructivist pedagogy, can address persistent learning barriers such as whole-number bias and proportional reasoning difficulties (Hearne & Wessels, 2021; Siegler et al., 2011).

The improvement in procedural accuracy among students in the AI group also aligns with literature indicating that adaptive practice environments enhance computational accuracy by adjusting task difficulty and delivering immediate corrective feedback (Tan et al., 2025; Wang et al., 2024). These scaffolding mechanisms reflect Vygotsky's (1978) ZPD, enabling learners to progress from assisted to independent performance. The threshold analysis indicated that students who engaged with *Mathia (Carnegie Learning)* for at least 90 minutes achieved greater procedural gains, reinforcing the idea that sufficient and sustained exposure is critical for translating AI-based practice into mastery.

Beyond immediate cognitive support, the dialogic use of *ChatGPT* was associated with shifts from other-regulation to self-regulation during fraction problem solving. First, chat logs showed students progressively internalizing sentence starters (i.e., "I know two fractions are equivalent when …" and "the unit I'm using is …") and reusing them unprompted in later tasks and post-lesson reflections, indicating emerging self-explanation routines. Second, hint trajectories revealed a move from reliance on representation prompts (H1) and concept cues (H2) to self-initiated planning checks (i.e., "before I compare, I'll unitize to eighths"), with fewer requests for strategic steps (H3) over time. Third, during pair work, students began to self-allocate roles without agent prompts (i.e., "I'll justify the unit; you justify the partition change") and to verify their own reasoning against number-line or area models before asking the agent—evidence of monitoring and control of strategy use. Finally, teacher synthesis notes documented a rise in spontaneous error-correction (i.e., αναγνώριση whole-number bias και μετατόπιση σε unitizing) and in students' pre-emptive articulation of steps ("first mark halves, then subdivide …"), suggesting that dialogic scaffolds were internalized as metacognitive scripts rather than remaining external prompts. Across lessons, teacher field notes and anonymized chatbot logs documented how initially agent-prompted sentence starters (e.g., "I know two fractions are equivalent when …" and "the unit I'm using is …") were progressively reused by students without prompting in subsequent problem-solving and written reflections, indicating the gradual internalization of self-explanation routines. To illustrate this pattern, an anonymized excerpt from the chatbot logs shows how a student initially relied on whole-number reasoning but then adopted the intended sentence starter and unitizing routine after dialogic prompting:

> Student: "I think 3/8 is bigger because 3 > 1."
>
> *ChatGPT*: "What unit are you comparing? Can you represent both fractions on the same number line?"
>
> Student: "Ok, I'll unitize to eighths. 1/2 = 4/8, so 4/8 is bigger."

Consistent with this evidence, teacher field notes also recorded unprompted reuse of the same language frames. For example, during lesson 4 several pairs spontaneously used the phrase "the unit I'm using is …" while negotiating fraction comparisons in peer discussion, without any direct prompting from the agent.

Engagement showed the largest effect size of all measured outcomes, indicating that AI-supported instruction can significantly influence students' behavioral, emotional, and cognitive involvement in mathematics lessons. This finding resonates with research suggesting that interactive and collaborative AI environments can enhance motivation, persistence, and collaborative problem-solving (Gibson et al., 2023; Henkel et al., 2024). In particular, *Fractions Lab*'s group problem-solving features and *ChatGPT*'s conversational prompts supported autonomy, competence, and relatedness—the three pillars of self-determination theory (Ryan & Deci, 2000). The fact that even moderate participation levels (eight *Fractions Lab* tasks or six *ChatGPT* prompts) were associated with substantial engagement gains suggests that well-structured AI-mediated tasks can sustain interest and participation beyond initial novelty effects.

Engagement as socio-constructivist motivation and semiotic mediation. The observed engagement effects are consistent with a socio-constructivist view of motivation, where participation is energized by interpersonal sense-making and a sustained social presence in joint activity. In *Fractions Lab*, shared manipulatives and co-constructed representations position students to negotiate meaning publicly (e.g., aligning partitions on a common unit), so that the social organization of the task becomes a driver of persistence and cognitive investment. In *ChatGPT*-supported work, dialogic prompting sustains a felt presence that orients learners to explain, justify, and coordinate roles, reinforcing autonomy and competence within a social frame (Ryan & Deci, 2000) while preserving Vygotskian scaffolding through language. In both cases, fraction bars, number lines, and generated explanations act as semiotic mediators: students transform these signs and representations during collaboration, and that transformation, in turn, feeds back into motivation (greater ownership, relevance, and willingness to reattempt). Thus, heightened behavioral, emotional, and cognitive engagement is not merely an adjunct outcome but a mechanism by which socially mediated, tool-rich activity amplifies learning.

Finally, the study confirmed that performance differences between AI-enhanced and traditional instruction persisted even after controlling baseline scores. This aligns with the comparative and longitudinal evidence reported by Yi et al. (2025) and Ruiz Viruel et al. (2025), showing that when AI tools are used within a coherent pedagogical framework, significant learning gains can occur in a relatively short time frame. The present findings extend this by demonstrating that such benefits can be realized within just six weeks in a lower secondary school context, provided that tool selection and instructional design are grounded in well-established learning theories.

While the results are encouraging, part of the gains may reflect factors other than AI integration. A possible novelty effect could temporarily elevate engagement and performance; differences in time-on-task may also contribute if the AI condition afforded more deliberate practice minutes than the control; and expectancy effects (awareness of innovation) could have increased effort. We mitigated these risks in three ways. First, dose-response patterns within the experimental group linked tool-specific thresholds to domain-consistent gains (e.g., *DreamBox Learning* with conceptual understanding and *Mathia [Carnegie Learning]* with procedural fluency), which is less compatible with a uniform novelty bump. Second, baseline-adjusted ANCOVAs and subgroup tests (gender, baseline ability, and SES) yielded stable effects across strata. Third, lesson duration was scheduled to be comparable across conditions; nevertheless, we acknowledge that micro-level exposure may still have differed. Future work should therefore log and control fine-grained time-on-task across AI and non-AI activities, include delayed post-tests to assess durability beyond novelty, use blinded scoring and multi-class/teacher designs to minimize expectancy, and pre-register fidelity/sensitivity checks that re-estimate effects after equating practice time.

Classroom observations indicated that the use of AI did not diminish peer interaction or teacher-led discourse but instead reshaped them. Over the intervention period, students increasingly initiated explanations during whole-class synthesis and relied less on direct agent prompts during pair work. In collaborative *Fractions Lab* activities, peer dialogue focused on negotiating representations and justifying unit choices, while *ChatGPT* prompts were often repurposed by students as conversational cues within group discussion rather than as substitutes for social interaction. Multi-theory integration requires deliberate moderation:

(a) teacher orchestration: brief whole-class syntheses to re-situate AI work within shared mathematical discourse,

(b) fading of support: progressive reduction of hints with required verbal articulation of steps,

(c) social structuring: pair/small-group roles and public justification so AI augments rather than replaces the social function of learning, and

(d) dosage discipline: alternation of activities and caps on uninterrupted AI time.

Thus, AI functions as a mediator, not as a substitute.

Limitations

While the findings of this study are encouraging, several limitations should be acknowledged to contextualize the results. First, the sample was drawn from a single lower secondary school in Greece, which may limit the generalizability of the findings to different educational contexts, cultural settings, or age groups. The relatively small sample size also constrains the statistical power for detecting smaller effects and may limit the applicability of the conclusions to more diverse student populations.

Second, the duration of the intervention was six weeks, which, while sufficient to detect short-term gains in conceptual understanding, procedural fluency, and engagement, did not allow for the examination of long-term retention, transfer of learning, or sustained changes in attitudes toward mathematics. Longer interventions might yield different patterns of improvement or reveal whether the observed benefits persist over time.

Third, the study relied on teacher-managed AI tool usage records and self-reported engagement measures. While these approaches provide valuable insights, they may be subject to biases such as overestimation of engagement or underreporting difficulties. More objective measures, such as automated log data analysis and direct observation, could provide richer and more precise evidence of how students interact with AI tools.

Finally, the intervention was implemented under relatively favorable conditions, including adequate technological infrastructure and teacher familiarity with AI tools. Schools with limited resources, insufficient internet connectivity, or lower levels of teacher preparedness may face additional challenges in achieving similar outcomes.

Future Work

Building on the present findings, future research should adopt multi-site designs to test the model's effectiveness across diverse geographical, cultural, and socio-economic contexts. Including schools with varying levels of technological infrastructure would provide a clearer picture of the scalability and adaptability of AI-enhanced mathematics instruction.

Longitudinal studies are also warranted to examine whether the improvements in conceptual understanding, procedural fluency, and engagement are maintained over time and whether they transfer to other mathematical domains, such as algebra, geometry, or problem-solving in real-world contexts.

Further work should also explore the role of teacher professional development in maximizing the pedagogical benefits of AI tools. Investigating how teachers integrate AI functionalities into lesson planning, classroom management, and assessment practices could offer practical strategies for sustainable implementation.

Additionally, the study's threshold analysis suggests that optimal learning gains are linked to specific usage benchmarks for each AI tool. Future studies could experimentally manipulate dosage levels to determine causal relationships between AI engagement and learning outcomes, potentially leading to more precise guidelines for effective tool integration.

Lastly, given the ethical considerations surrounding AI in education—including data privacy, algorithmic transparency, and equitable access—future research should include explicit frameworks for ethical governance and evaluate their impact on teacher and student trust in AI systems. This would ensure that technological advancements are implemented in ways that promote inclusion, fairness, and responsible use.

CONCLUSION

This study shows that integrating multiple AI tools within a theory-driven framework can substantially improve students' conceptual understanding, procedural fluency, and engagement. Aligning adaptive, interactive, and dialogic platforms with Piagetian constructivism, Vygotskian scaffolding, information processing, self-determination, and collaborative learning yielded meaningful gains in a short period. The contribution lies in a coherent multi-tool design where each application serves a distinct pedagogical function; effectiveness stems from intentional integration rather than the tools themselves. Used beyond minimal exposure, this suite not only addresses persistent conceptual and procedural difficulties and sustains motivation and collaboration, but also expands students' agency and epistemic interaction, amplifying voice, choice, and authorship while augmenting, not replacing, the social fabric of learning.

The implications extend beyond the classroom. For educators, AI adoption should be guided by explicit learning objectives and intentional tool-purpose alignment (e.g., *DreamBox Learning* for conceptual exploration and *Mathia [Carnegie Learning]* for procedural fluency), with clear dosage thresholds, fading of support, and consistent teacher orchestration (brief whole-class syntheses, public justification). Sufficient practice time and basic measurement (e.g., logging time-on-task and interaction patterns) are needed to secure durable effects. For policymakers and school leaders, effective integration requires targeted teacher professional development that bridges technological proficiency and pedagogical design, equitable access to infrastructure and devices, and robust data-protection safeguards that explicitly protect data privacy. For schools with limited technological and financial resources, full-scale adoption of multiple commercial AI platforms may be impractical. In such settings, scalable alternatives such as low-bandwidth, message-based AI support tools or open-source environments running on shared devices may offer more feasible entry points, provided they are embedded within structured, theory-aligned lesson designs. At a policy level, phased implementation models, beginning with a small number of pedagogically aligned tools and short, practice-oriented teacher training initiatives, can support gradual capacity building without exacerbating existing digital inequalities. Complementary quality-assurance mechanisms, such as implementation-fidelity checks, minimum and maximum exposure guidelines, and delayed post-tests, help ensure that AI augments, rather than replaces, the social fabric of learning.

By offering both a replicable model and empirical evidence of its impact, this research contributes to the growing body of work positioning AI not as a replacement for human instruction but as a powerful, theory-aligned mediator of deep and meaningful mathematics learning. This study directly bridges empirical research and classroom application, demonstrating how AI-powered tutoring systems can enhance fraction learning in lower secondary mathematics.

Future work should examine the model across countries with varying curricular and infrastructural profiles and extend it to other mathematical domains (e.g., proportional reasoning, algebraic thinking). Multi-site, longer-term studies combining learning analytics with classroom observations could test durability, transfer, and implementation drivers on a scale.

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AI statement: The AI tools examined in this study were used as instructional intervention tools only. No generative AI was used to generate the data, perform the analyses, or produce the study findings.

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APPENDIX A: INSTRUMENTS

Table A1. Mathematics conceptual understanding test: Pre- and post-test parallel items

No	Pre-test item	Post-test item
1	Shade 3/5 of the rectangle and explain your reasoning.	Shade 4/7 of the rectangle and explain your reasoning.
2	Which is larger: 5/8 or 2/3? Justify your answer.	Which is larger: 7/12 or 5/8? Justify your answer.
3	Place 4/6, 2/3, and 7/12 on the number line.	Place 5/6, 3/4, and 9/12 on the number line.
4	Explain why 3/4 and 9/12 are equivalent fractions.	Explain why 2/3 and 8/12 are not equivalent fractions.
5	Draw a diagram to show 2/5 of 20 apples.	Draw a diagram to show 3/8 of 24 pencils.
6	Which fraction is closest to 1: 7/8 or 5/6? Explain.	Which fraction is closest to 1/2: 4/9 or 5/11? Explain.
7	Write two fractions equivalent to 6/9.	Write two fractions equivalent to 4/5.
8	Compare 3/5 and 3/7 using <, >, or = and explain.	Compare 2/7 and 2/9 using <, >, or = and explain.
9	Maria ate 2/3 of a cake, John ate 1/6 of the cake. Who ate more? Show your reasoning.	Anna drank 3/5 of a bottle of juice, Tom drank 2/10 of the bottle. Who drank more? Show your reasoning.
10	Place the following in ascending order: 5/10, 3/8, 2/4.	Place the following in ascending order: 4/8, 5/12, 2/3.

Table A2. Procedural fluency test: Pre- and post-test parallel items

No	Pre-test item	Post-test item
1	3/4 × 2/5 =	4/7 × 3/5 =
2	5/6 - 1/4 =	7/8 - 1/6 =
3	2 1/2 + 3/8 =	1 3/4 + 5/12 =
4	7/9 ÷ 2/3 =	5/6 ÷ 3/4 =
5	Convert 5/4 to a mixed number.	Convert 7/3 to a mixed number.
6	4/5 + 7/10 =	6/7 + 8/14 =
7	8/15 × 5/12 =	10/21 × 7/15 =
8	3 - 5/8 =	4 - 3/5 =
9	Convert 11/8 to a decimal.	Convert 7/4 to a decimal.
10	9/10 - 2/5 =	8/9 - 4/6 =

Table A3. Student engagement questionnaire: Pre- and post-test parallel items

No	Pre-test item	Post-test item	Domain
1	I participate actively during math lessons.	I take part in discussions during math lessons.	Behavioral
2	I complete my math homework on time.	I hand in my math assignments on time.	Behavioral
3	I stay focused during math activities.	I pay attention during math tasks.	Behavioral
4	I ask questions when I do not understand something in math.	I ask for help when a math concept is unclear.	Behavioral
5	I try to solve math problems even if they are challenging.	I keep trying until I solve a difficult math problem.	Behavioral
6	I enjoy working on fraction problems.	I enjoy solving fraction exercises.	Emotional
7	I feel happy when I understand a new math concept.	I feel pleased when I learn a new math skill.	Emotional
8	I get frustrated easily during math lessons. (R)	I give up quickly when math gets hard. (R)	Emotional
9	I feel confident when learning new math topics.	I feel sure of myself when working on new math problems.	Emotional
10	I look forward to math class.	I am excited about attending math class.	Emotional
11	I try to figure out different ways to solve a math problem.	I explore more than one way to find a math answer.	Cognitive
12	I make connections between what I learn in math and real life.	I relate math concepts to situations in everyday life.	Cognitive
13	I use strategies to check if my math answers are correct.	I check my math answers for mistakes.	Cognitive
14	I try to understand the reasons behind math rules.	I want to know why math procedures work.	Cognitive
15	I think about how I can improve my math skills.	I plan ways to get better at math.	Cognitive