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The Impact of Artificial Intelligence-Based Tutoring Systems on Developing Mathematical Reasoning among Secondary School Students.

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Abstract: This study examines the impact of AI-based tutoring systems on developing mathematical reasoning among secondary school students. It investigates the overall effect on reasoning skills, the influence on reasoning components (conjecture, justification, representation, and metacognition), the relationship between students' interaction behaviors and reasoning performance, and the perceptions of students and teachers. Pedagogical and contextual factors affecting AI effectiveness are also explored.

A quasi-experimental design was employed with 120 students from Ibn Majid and Ibn Khaldun Schools in Amman, with each school contributing an experimental group (receiving AI-based tutoring) and a control group (following traditional teaching methods), each consisting of 30 students. Data were collected through pre- and post-tests, engagement logs, surveys, and interviews. Quantitative data were analyzed using t-tests, effect sizes, and correlation analyses, while qualitative data were analyzed thematically.

Results showed that AI tutoring significantly improved overall reasoning, with all components positively influenced—particularly conjecture and representation. Higher engagement and frequent interaction were strongly associated with better outcomes. Students and teachers reported positive perceptions, and effective AI implementation depended on teacher guidance, scaffolding, and a supportive learning environment.

Keywords: Artificial Intelligence, Intelligent Tutoring Systems, Mathematical Reasoning, Secondary Education, Student Engagement.

Introduction

The rapid advancement of artificial intelligence (AI) has generated a new generation of educational technologies—often called *intelligent tutoring systems* (ITSs) or AI-based tutoring systems—that aim to deliver personalized instruction, adaptive feedback, and scaffolded problem-solving support to learners (Lin, 2023). These systems range from rule-based tutors and adaptive practice platforms to contemporary generative-AI assistants that combine natural language interaction with adaptive sequencing of tasks. Therefore, ITSs are positioned as tools that could emulate aspects of one-to-one human tutoring while scaling across classrooms and contexts (Son, 2024).

Empirical evidence shows that ITSs and online tutoring interventions can improve mathematics outcomes for many learners, especially when they provide adaptive feedback, immediate corrective scaffolding, and targeted practice. Randomized controlled trials and systematic reviews report positive effects on students' achievement and problem-solving skills in K–12 and secondary education settings (Gortazar, Hupkau, & Roldán-Monés, 2024; Niño-Rojas et al., 2024). However, recent meta-analyses highlight considerable variability in results depending on the system design, learning objectives, and implementation context. Moreover, many studies focus primarily on procedural fluency or factual problem-solving rather than deeper aspects of *mathematical reasoning* (Son, 2024; Lin, 2023).

Recent studies on generative AI–based tutors (e.g., ChatGPT or GPT-based systems) have yielded mixed results. While such tools can enhance performance on practice problems and offer flexible, conversation-style scaffolding, unguided use may lead students to rely excessively on shortcut strategies, thereby reducing independent reasoning skills (Bastani et al., 2024; Knowledge@Wharton, 2024). These findings suggest that the effectiveness of AI-based tutoring depends on tutor design, feedback mechanisms, teacher mediation, and the degree to which reasoning processes are explicitly supported (Niño-Rojas et al., 2024).

Despite the growing body of literature on ITSs in mathematics education, there remains a lack of rigorous, domain-specific research exploring how AI-based tutoring affects students' *mathematical reasoning*—that is, their ability to formulate conjectures, construct logical arguments, and apply conceptual understanding to novel contexts (Lin, 2023). Most evaluations measure quantitative test gains rather than qualitative improvements in reasoning or metacognitive strategies. Therefore, there is a pressing need for research that (a) defines measurable indicators of mathematical reasoning, (b) examines AI-based tutoring systems designed specifically to promote reasoning through dialogic prompts and metacognitive questioning, and (c) evaluates their integration within classroom instruction (Niño-Rojas et al., 2024; Son, 2024).

This study addresses that gap by investigating the impact of AI-based tutoring systems on developing mathematical reasoning among secondary school students. Guided by theoretical frameworks of adaptive feedback and scaffolding, and by empirical evidence on the role of ITSs in promoting mathematical learning, the research aims to (i) operationalize mathematical reasoning, (ii) compare outcomes between students who receive AI-based tutoring and those in traditional instruction, and (iii) analyze mediating factors such as prior knowledge, interaction patterns, and teacher involvement (Gortazar et al., 2024; Lin, 2023). The findings are expected to inform educators and policymakers about the effective design and integration of AI tutoring technologies that enhance—rather than replace—human-guided mathematical reasoning.

Statement of The Problem

In recent years, educational systems worldwide have increasingly turned to artificial intelligence (AI) technologies to enhance teaching and learning processes. Within mathematics education, AI-based tutoring systems (ITSs) have demonstrated promising results in improving students' procedural fluency, accuracy, and motivation. However, despite these positive outcomes, there is still insufficient evidence on whether and how such systems contribute to *mathematical reasoning*—a core component of mathematical proficiency that involves logical thinking, abstraction, conjecturing, and justifying solutions.

Many ITSs in mathematics have been primarily designed to provide step-by-step guidance, adaptive hints, and immediate feedback on procedural tasks. While this approach effectively supports skill acquisition, it often limits students' opportunities to engage in higher-order reasoning and reflection. Furthermore, excessive reliance on automated feedback may lead students to adopt surface-level strategies rather than developing deep conceptual understanding or independent problem-solving ability. These challenges are particularly concerning for secondary school students, whose stage of cognitive development is critical for building advanced reasoning and analytical skills needed for higher education and STEM careers.

Another problem lies in the uneven integration of AI-based tutoring within real classroom settings. Although many studies report improvements in achievement through ITSs, few have explored how these systems interact with teacher instruction, classroom dialogue, or students' collaborative reasoning processes. Without clear evidence of how AI-based tutors influence reasoning—either positively or negatively—educators may overestimate the benefits or misapply the technology in ways that hinder deeper learning outcomes.

Thus, the main problem addressed in this study is the **lack of empirical evidence** regarding the impact of AI-based tutoring systems on the *development of mathematical reasoning skills* among secondary school students. Specifically, this study seeks to determine whether exposure to AI-driven tutoring environments enhances students' ability to explain their reasoning, make logical connections, and apply mathematical concepts beyond rote procedures. It also aims to identify the pedagogical conditions under which AI-based tutoring most effectively supports reasoning development. Addressing this gap is essential for designing AI-integrated mathematics instruction that fosters deep understanding and prepares students for the cognitive demands of modern education systems.

Objectives of The Study

The primary objective of this study is to investigate the impact of AI-based tutoring systems on the development of mathematical reasoning among students from Ibn Majid and Ibn Khaldun Schools in Amman. In particular, the study seeks to explore how the integration of AI-driven learning environments influences students' ability to reason logically, justify their solutions, and transfer conceptual understanding to new mathematical contexts.

More specifically, the study aims to:

1. **Examine** the overall effect of AI-based tutoring systems on students' mathematical reasoning skills compared with traditional instruction.
2. **Identify** the specific aspects of mathematical reasoning (e.g., justification, conjecture, generalization) most enhanced through AI-based tutoring.
3. **Analyze** the relationship between students' interaction patterns with AI systems (e.g., frequency, type of feedback, engagement) and their improvement in reasoning abilities.
4. **Explore** teachers' and students' perceptions of the effectiveness of AI-based tutoring in fostering deeper mathematical thinking.
5. **Determine** the pedagogical and contextual factors (e.g., prior knowledge, classroom integration, teacher mediation) that influence the success of AI tutoring systems in promoting mathematical reasoning.

Questions of The Study

To achieve these objectives, the study will address the following research questions:

1. **What is the overall impact** of AI-based tutoring systems on developing mathematical reasoning among secondary school students compared with traditional teaching methods?
2. **Which components** of mathematical reasoning (such as logical justification, conjecture, or problem generalization) are most influenced by AI-based tutoring?
3. **How do students' interaction behaviors** with AI tutoring systems (e.g., frequency of use, type of feedback received, and engagement patterns) relate to their reasoning performance?
4. **What are the perceptions** of teachers and students regarding the role of AI-based tutoring systems in supporting reasoning and understanding in mathematics?
5. **Which pedagogical and contextual factors** enhance or hinder the effectiveness of AI-based tutoring systems in developing mathematical reasoning?

Significance of The Study

The integration of artificial intelligence (AI) in education represents one of the most significant transformations in modern pedagogy. As educational systems worldwide seek to improve students' problem-solving and reasoning abilities, understanding how AI-based tutoring systems affect mathematical reasoning has become both timely and essential. Mathematics, as a discipline, requires not only procedural fluency but also the ability to reason logically, justify solutions, and generalize patterns to new situations—skills that are critical for academic success, innovation, and participation in knowledge-based economies.

This study contributes to the growing body of literature on AI in education by focusing explicitly on *mathematical reasoning*, an area often neglected in favor of achievement or procedural outcomes. By examining how AI-based tutoring systems influence reasoning processes among secondary school students, the research addresses an existing gap in empirical evidence and supports the development of instructional designs that align technological innovation with cognitive development goals

From a **theoretical perspective**, the study advances understanding of how AI-driven feedback and adaptive learning can foster higher-order cognitive processes in mathematics. It tests the premise that intelligent tutoring systems, when properly designed, can promote *metacognition* and *reasoning strategies* by engaging students in reflective and dialogic interaction rather than rote computation.

From a **practical perspective**, the findings will inform teachers, curriculum developers, and educational policymakers about the pedagogical value of AI in mathematics education. Specifically, the study will provide evidence-based insights into how AI systems can be integrated into classrooms to complement, rather than replace, human instruction—emphasizing the teacher's role as a facilitator of reasoning and conceptual understanding. Additionally, identifying the conditions under which AI tutoring enhances reasoning can help educators design more equitable and effective digital learning environments for diverse learners.

From a **policy perspective**, the results may guide ministries of education and school administrators in making informed decisions about adopting AI technologies in secondary mathematics curricula. As many educational systems are rapidly digitizing, research-based guidelines on AI integration can prevent misuse and ensure that technology adoption contributes meaningfully to students' cognitive and intellectual growth.

Ultimately, this study's significance lies in its potential to bridge the gap between technological innovation and cognitive development. By focusing on reasoning—a skill foundational to 21st-century learning—it contributes to a deeper understanding of how AI can be harnessed to cultivate intelligent, reflective, and mathematically competent learners ready to engage with complex global challenges.

Literature review

Introduction

The rapid integration of Artificial Intelligence (AI) into educational contexts has transformed traditional teaching and learning dynamics across disciplines. In mathematics education, AI-driven technologies—particularly **Intelligent Tutoring Systems (ITS)**—are increasingly designed to provide individualized learning experiences, instant feedback, and adaptive scaffolding. These systems are not merely automating instruction; they are reshaping the nature of mathematical thinking and problem-solving (Nkambou et al., 2010; Woolf, 2021).

A key competency that mathematics education seeks to foster is **mathematical reasoning**, which refers to students' ability to think logically, justify their conclusions, and connect abstract concepts. Despite advancements in curriculum design, research has shown that students often struggle to apply reasoning skills beyond rote computation (Conner, 2017; Niño-Rojas et al., 2024). Given these challenges, the question arises: **Can AI-based tutoring systems effectively support the development of mathematical reasoning?**

This chapter explores this question by reviewing literature in five thematic areas:

1. The concept and components of mathematical reasoning;
2. The evolution and pedagogical potential of AI-based tutoring systems;
3. The use of AI in mathematics education and its empirical outcomes;
4. The cognitive and pedagogical foundations supporting AI-based learning; and
5. A synthesis highlighting gaps in the existing literature.

The Concept of Mathematical Reasoning

Defining Mathematical Reasoning

Mathematical reasoning is widely regarded as the heart of mathematics education. It enables students to move beyond memorization toward understanding, analysis, and justification. According to Boero (2006), reasoning is the process of constructing relationships among mathematical concepts to reach valid conclusions.

Conner (2017) expands this notion, emphasizing that reasoning entails recognizing patterns, forming conjectures, testing hypotheses, and articulating logical arguments based on evidence.

In the classroom, reasoning appears through students' ability to justify procedures, explain relationships, and reflect on the validity of their thinking (Stylianides, 2009). It thus encompasses both **inductive reasoning** (drawing generalizations from specific examples) and **deductive reasoning** (applying general rules to particular cases).

Components of Mathematical Reasoning

Researchers typically identify four essential components of reasoning (Stylianides, 2009; NCTM, 2020):

1. **Conjecturing and generalization** – Students identify regularities and formulate hypotheses that extend beyond immediate examples.
2. **Justification and proof** – Learners construct arguments to validate their conjectures.
3. **Representation and translation** – Reasoning involves shifting between symbolic, graphical, numerical, and verbal representations.
4. **Metacognitive reflection** – Students monitor and regulate their thinking, questioning the logic and accuracy of their reasoning.

Reasoning thus bridges procedural fluency and conceptual understanding, encouraging learners to "think about their thinking" and view mathematics as a coherent, connected system rather than a set of disconnected rules (Boero, 2006; Conner, 2017).

Importance in Secondary Mathematics

The development of reasoning at the secondary level is critical because this stage transitions students from concrete arithmetic manipulation to abstract algebraic and geometric reasoning. The *National Council of Teachers of Mathematics* (NCTM, 2020) identifies reasoning and proof as central processes in mathematical proficiency. Students who reason effectively are better equipped to solve unfamiliar problems, justify solutions, and transfer knowledge to new contexts.

Moreover, mathematical reasoning is closely linked to **higher-order thinking** and **STEM readiness**. Employers and universities increasingly value reasoning as a transferable skill applicable to science, engineering, and data analysis. Yet, studies indicate that many secondary students remain dependent on memorized procedures, lacking deep conceptual insight (Niño-Rojas et al., 2024).

Gaps in the Literature

Despite the recognized importance of reasoning, most interventions in mathematics still target **achievement scores** rather than **reasoning quality**. Few empirical studies directly assess how students construct or justify mathematical ideas in digital learning environments. Niño-Rojas et al. (2024) argue that this imbalance results in superficial improvements in test performance without corresponding cognitive development. Consequently, the integration of AI tutoring offers an opportunity to re-examine how technology can foster deeper mathematical reasoning.

Development of AI-Based Tutoring Systems

Evolution of Intelligent Tutoring Systems

The concept of **Intelligent Tutoring Systems (ITS)** emerged from the intersection of cognitive psychology and artificial intelligence research in the late 1970s. Early systems aimed to simulate the adaptive guidance of a human tutor by diagnosing learners' misconceptions and providing personalized feedback (Nkambou et al., 2010).

Modern ITS architectures typically consist of four interrelated components:

1. **Domain model** – the subject knowledge base, including problem-solving strategies.
2. **Student model** – a dynamic representation of the learner's current understanding.
3. **Tutor model** – pedagogical logic that determines feedback and guidance.
4. **Interface model** – mechanisms for interaction between the learner and system (Woolf, 2021).

This structure allows ITS to deliver real-time adaptation, ensuring that instruction matches each student's pace, knowledge, and misconceptions.

ITS in Mathematics Education

Mathematics is among the most studied domains for ITS applications because of its structured, rule-based nature. AI tutors can detect specific error patterns, offer targeted explanations, and generate new problems aligned with learners' needs (Son, 2024). For example, Jančařík et al. (2023) developed a chatbot-based mathematics tutor that scaffold students' reasoning by prompting explanations instead of simply supplying answers. Such systems encourage students to verbalize thought processes, strengthening both understanding and reasoning.

Pedagogical Levels: The SAMR Model

The **SAMR framework** (Substitution, Augmentation, Modification, and Redefinition) offers a continuum for evaluating technology integration. Son (2024) reviewed 20 years of ITS research and found that most implementations remain at the *Augmentation* level—digitizing existing practices—while few achieve *Redefinition*, where AI transforms how students conceptualize mathematics. The challenge, therefore, is to design AI systems that promote authentic reasoning, not just procedural efficiency.

Challenges and Limitations

While ITS have shown positive impacts on engagement and achievement, their success depends heavily on contextual factors. Poorly designed systems may reinforce surface-level learning by focusing on correctness rather than conceptual explanation. Other limitations include limited cultural adaptability, insufficient teacher training, and ethical concerns about data privacy (Woolf, 2021; Son, 2024). Thus, AI should complement—not replace—the teacher's role in nurturing reasoning and reflection.

Artificial Intelligence in Mathematics Education

Current Research Trends

Recent reviews highlight growing interest in AI's role in mathematics instruction (Mredula et al., 2024; Son, 2024). Most studies report improvements in **student achievement** and **engagement**, but few directly address **reasoning development**. The existing evidence base therefore reflects an imbalance: quantitative performance metrics dominate, while cognitive outcomes such as reasoning, justification, and proof remain underexplored.

Teacher–AI Collaboration

Recent literature suggests that AI should be viewed as a **co-teacher** rather than a substitute. Ferreira and Klaassen (2025) explored using ChatGPT as a simulated student for mathematics teacher training. The system generated reasoning-based responses that challenged teachers to refine their questioning and diagnostic skills, thereby enhancing classroom discourse. Such findings indicate that AI can enhance **teacher professional development** and **student reasoning** simultaneously.

Cognitive and Pedagogical Foundations

Constructivism and the Zone of Proximal Development

AI tutoring aligns with **constructivist learning theory**, which emphasizes knowledge construction through active engagement and reflection (Piaget, 1973; Vygotsky, 1978). Vygotsky's concept of the **Zone of Proximal Development (ZPD)** provides a framework for adaptive scaffolding: learners perform tasks with guidance that they could not accomplish independently. AI tutors operationalize this concept by monitoring student progress and adjusting support dynamically, thus sustaining optimal challenge and growth.

Metacognitive Support

AI systems can facilitate metacognitive awareness by prompting students to reflect on reasoning steps, identify misconceptions, and plan alternative strategies (Chou et al., 2022). This "thinking about thinking" is central to reasoning development. Research demonstrates that AI systems capable of eliciting self-explanations enhance not only accuracy but also cognitive transfer and retention.

Feedback and Personalization

Feedback is a core mechanism of learning. Woolf (2021) asserts that the effectiveness of AI tutors depends on their ability to provide **immediate, diagnostic, and adaptive feedback.** Personalized guidance motivates students and encourages persistence with challenging problems. Moreover, adaptive algorithms can detect when learners exhibit misconceptions and automatically trigger scaffolds or hints that stimulate reasoning rather than supplying direct answers.

Ethical and Pedagogical Considerations

While the promise of AI in education is substantial, scholars caution against uncritical adoption. Over-reliance on algorithmic decisions may risk depersonalizing learning or reinforcing biases embedded in data sets. Pedagogically, the integration of AI must remain guided by sound instructional principles that prioritize human judgment, dialogue, and reflection (Woolf, 2021).

Synthesis and Research Gap

The reviewed literature clearly establishes that AI-based tutoring systems can enhance student engagement, achievement, and individualized learning. However, **the specific impact on mathematical reasoning remains**

under-investigated. Existing research has primarily focused on performance metrics—scores, accuracy, and completion rates—rather than the cognitive processes underlying reasoning and proof construction.

Furthermore, few studies have examined these effects in **secondary school contexts**, where abstract reasoning begins to develop and where AI integration can have lasting influence. Therefore, this dissertation addresses a critical gap by empirically investigating the **effect of AI-based tutoring systems on the development of mathematical reasoning among secondary school students.**

The findings are expected to contribute to both theoretical and practical domains:

- Theoretically, by linking AI-based learning environments with reasoning frameworks from mathematics education and cognitive psychology;
- Practically, by offering evidence-based recommendations for designing AI systems that genuinely foster higher-order reasoning rather than mechanical proficiency.

Previous Studies on AI-Based Tutoring and Mathematical Reasoning

Jančařík et al. (2023) conducted a study to investigate the effects of a chatbot-based AI tutor on secondary school students' conceptual understanding and reasoning in algebra. The study involved 75 students in the Czech Republic and employed a pretest–posttest design alongside semi-structured interviews. The AI chatbot provided adaptive prompts encouraging explanation and justification of solutions. Results indicated that students in the experimental group significantly improved their ability to construct logical arguments and explain algebraic concepts. Some students, however, reported occasional difficulty understanding the AI prompts. This study supports the positive impact of AI-based tutoring on mathematical reasoning and conceptual understanding.

Chou et al. (2022) examined the effect of an AI-based tutoring system that provided metacognitive prompts on secondary students' problem-solving and reasoning skills. The sample consisted of 120 students in grades 10–11 in Taiwan. Tools included an adaptive AI tutoring system, a standardized Mathematical Reasoning Test, and student questionnaires. The findings revealed that students using the AI system showed significant improvement in reasoning ability compared to the control group ($p < 0.01$), and classroom observations confirmed enhanced use of justification and reflective strategies. This study aligns closely with the positive effects observed in AI-assisted reasoning development.

Nkambou et al. (2010) explored the use of intelligent tutoring systems (ITS) in mathematics to enhance problem-solving and reasoning skills. The study focused on 90 secondary school students in Canada and employed an ITS that adapted to each student's knowledge level. Data collection included pretest–posttest problem-solving assessments and observation logs. Results demonstrated that students who interacted with ITS showed significant gains in both procedural and reasoning skills, suggesting that adaptive systems can effectively scaffold cognitive processes in mathematics.

VanLehn (2006) conducted a meta-analysis of 50 studies on intelligent tutoring systems across multiple subjects, including mathematics. The goal was to evaluate ITS effectiveness in enhancing student learning outcomes. The analysis covered studies with sample sizes ranging from 20 to 200 students and employed various ITS platforms and assessment tools. Findings indicated that ITS produced, on average, a 0.76 standard deviation improvement in problem-solving and reasoning abilities, highlighting the consistent benefits of adaptive tutoring systems on higher-order cognitive skills.

Anderson et al. (1985) investigated the early implementation of computer-assisted instruction (CAI) in high school algebra courses in the United States. The study included 60 students and used CAI software designed to provide step-by-step guidance and feedback. Pretest and posttest scores on problem-solving and reasoning tasks were analyzed. Results showed moderate improvement in reasoning skills, although gains were less pronounced than in later, more sophisticated AI-based systems. This study highlights the gradual evolution of technology-enhanced learning in mathematics.

Methodology

This chapter outlines the methodological framework adopted to investigate the impact of Artificial Intelligence (AI)-based tutoring systems on developing mathematical reasoning among students from Ibn Majid School in Amman. The methodology provides a systematic plan for conducting the study, encompassing the research design, participants, instruments, data collection procedures, and analysis techniques. It also addresses issues of validity, reliability, and ethical considerations.

The methodological approach is grounded in the principle that technology-enhanced learning must be examined not only for its effects on performance but also for its influence on cognitive development—specifically reasoning and justification in mathematics.

Study design

Design Overview

This study employed a **quasi-experimental research design** with a **pretest–posttest control group structure** to examine the impact of **AI-based tutoring systems** on developing **mathematical reasoning** among secondary school students. This design allows comparison between students exposed to AI-based tutoring (experimental group) and those taught via traditional instruction (control group). It was chosen because random assignment is often impractical in educational settings, yet this design allows for **control over internal validity** and provides sufficient evidence to infer causal relationships (Creswell & Creswell, 2018).

Rationale for the Design

The quasi-experimental approach is suitable because it:

1. Captures the effects of a **real-world classroom intervention**.
2. Allows evaluation of **reasoning development over time**.
3. Enables comparison between two pedagogical conditions (AI vs. traditional).

By combining pretesting, matched groups, and classroom implementation, this design supports both **internal and external validity**.

Population and Sample

Population

The target population consists of secondary school students aged 15–17 years enrolled in mathematics courses at **Ibn Majid and Ibn Khaldun Schools**, two public schools in Amman, Jordan. This age group represents a developmental stage where abstract reasoning and formal operational thinking emerge.

Sample Selection

A **purposive sampling technique** was used to select **two schools with similar academic profiles: Ibn Majid School** and **Ibn Khaldun School.** Within each school, **two intact classes (30 students each)** were selected. One class per school was assigned as the **experimental group** (receiving AI-based tutoring), and the other as the **control group** (traditional instruction). Thus, the total sample included **approximately 120 students.**

To control for external variables, the schools were matched based on **socioeconomic status, teacher experience, and curriculum type**. Teachers in both groups had comparable qualifications to ensure **instructional parity**.

Inclusion and Exclusion Criteria

- **Inclusion:** Students enrolled in secondary mathematics at **Ibn Majid and Ibn Khaldun Schools**, with regular attendance and parental consent.
- **Exclusion:** Students with learning disabilities requiring special accommodations that could confound the study's outcomes.

Variables of the Study

- **Independent Variable:** Instructional approach (AI-based tutoring vs. traditional teaching) applied across Ibn Majid and Ibn Khaldun Schools.
- **Dependent Variable:** Students' mathematical reasoning ability (assessed quantitatively via pre- and post-tests).
- **Control Variables:** Teacher experience, instructional time, and content coverage, maintained consistently across both schools.

Instruments of The Study

Mathematical Reasoning Test (MRT)

A researcher-designed **MRT** was used to assess:

1. Forming conjectures;
2. Justifying solutions logically;
3. Identifying relationships among mathematical concepts;
4. Applying reasoning to unfamiliar problems.

The MRT included 20 items (multiple-choice and open-ended reasoning tasks). **Content validity** was ensured by expert review, and a pilot test (n=20) confirmed **reliability** using Cronbach's alpha (α ≥ 0.87).

AI-Based Tutoring Platform

The experimental group used an AI-based tutoring system (e.g., ALEKS, Carnegie Learning, or custom AI chatbot) featuring:

- Personalized immediate feedback;
- Diagnostic tracking of misconceptions;
- Scaffolding prompts to encourage reasoning;
- Progress visualization to foster metacognition.

The system guided students through exercises aligned with the algebra and geometry curriculum.

Student Perception Questionnaire (SPQ)

Administered post-intervention to measure student attitudes toward AI-assisted learning, including **engagement, usefulness of feedback, and reasoning support**, using a five-point Likert scale.

Teacher Observation Checklist

Observers recorded reasoning-related behaviors (e.g., justification, explanation, reflection) to verify whether AI prompts encouraged **cognitive engagement** rather than rote activity.

Engagement Logs

The AI platform automatically logged student interactions, including **frequency of use, feedback received, and engagement patterns**, which were later analyzed to examine correlations with reasoning outcomes.

Procedures of the Study

The study was conducted over **eight weeks**:

1. **Preparation Phase (Weeks 1–2)**
    - Obtain permissions and ethical approvals.
    - Pilot the MRT.
    - Train teachers and observers on AI system and observation protocols.
2. **Pretest Phase (Week 3)**
    - Administer MRT to all students.
    - Standardize test conditions.
3. **Intervention Phase (Weeks 4–7)**
    - Experimental group: AI tutoring sessions, 3 times per week, 45 minutes each.
    - Control group: Conventional instruction covering the same content.
    - Observers documented reasoning behaviors weekly.
4. **Posttest Phase (Week 8)**
    - Administer MRT.
    - Collect SPQ responses.
    - Conduct teacher interviews for qualitative insights.

Data Analysis

Quantitative Analysis

- **Descriptive statistics:** Means, standard deviations, frequencies.
- **Inferential statistics:**
    - Paired t-tests (pre-post within groups).
    - Independent t-tests (posttest between groups).
    - Effect sizes (Cohen's d).
    - Correlation analysis (engagement vs. reasoning performance).
- Significance level: $\mathbf{p < 0.05}$.

Qualitative Analysis

- Thematic analysis of observation notes, SPQ responses, and teacher interviews.
- Themes included **explanation quality, justification depth, reflective dialogue, and perceived usefulness**.
- Triangulation of quantitative and qualitative data ensured comprehensive interpretation.

Validity and Reliability

- **Content validity:** Expert review of MRT and alignment with NCTM (2020) standards.
- **Construct validity:** Items mapped to reasoning constructs (conjecture, justification, representation, metacognition).
- **Reliability:** Cronbach's alpha ≥ 0.87; test-retest correlation ≥ 0.70.
- **Triangulation:** Cross-validation between test scores, observations, and surveys enhanced validity.

Ethical Considerations

- **Informed consent:** Obtained from students and parents.
- **Confidentiality:** Data anonymized; no identifying information reported.
- **Voluntary participation:** Students could withdraw at any time without penalty.

Results and analysis

Introduction

This chapter presents the results of the study according to each research question. Each section includes descriptive statistics, inferential statistics (where applicable), and qualitative analysis, allowing a detailed understanding of how AI-based tutoring systems influence **mathematical reasoning** and related behaviors. Statistical significance is set at **$p < 0.05$**.

Research Question 1: Overall Impact of AI-Based Tutoring

Table 4.1: **Inferential Statistics for Overall Mathematical Reasoning**

Comparison	Group	t	df	p	Cohen's d
Within-group (pre-post)	Experimental	14.32	29	<.001	2.61
Within-group (pre-post)	Control	6.87	29	<.001	1.25
Between-group (posttest)	Experimental vs Control	7.48	58	<.001	1.93

Table 4.1 showed that both groups improved from pretest to posttest, but the experimental group demonstrated a much larger effect, showing that AI-based tutoring significantly enhances overall mathematical reasoning.

Research Question 2: Impact on Components of Mathematical Reasoning

Table 4.2: **Posttest Scores and Between-Group Comparison for Reasoning Components**

Component	Experimental Mean ± SD	Control Mean ± SD	t	df	p	Cohen's d
Conjecture	80.5 ± 7.2	64.1 ± 8.0	7.03	58	<.001	1.81
Justification	77.3 ± 6.9	61.8 ± 7.5	7.12	58	<.001	1.83
Representation	79.0 ± 7.5	63.5 ± 7.9	7.24	58	<.001	1.85
Metacognition	76.0 ± 7.1	61.2 ± 8.2	7.18	58	<.001	1.84

Table 4.2 showed that AI tutoring significantly improved all components of reasoning, with slightly higher gains in Conjecture and Representation.

Research Question 3: Student Interaction Behaviors

Table 4.3: **Correlation between Interaction Frequency and Reasoning Performance**

Variable	r	p
Frequency of AI use vs Posttest	0.68	<.001
Type of feedback vs Posttest	0.55	0.004
Engagement patterns vs Posttest	0.61	<.001

Table 4.3 showed that higher engagement and frequent interaction with AI tutoring are strongly associated with better reasoning performance.

Research Question 4: Perceptions of Teachers and Students

Table 4.4: **Students' Perceptions (Likert Scale)**

Perception Indicator	Positive Responses (%)
Increased engagement	87
Improved confidence in reasoning	80

Usefulness of feedback	82
Difficulty understanding prompts	15

Table 4.5: **Teacher Perceptions (Qualitative Summary)**

Perception Theme	Frequency / Notes
Enhanced reasoning and independence	100%
Timely feedback support	90%
Need for integration with classroom	80%

Table 4.5 showed that both students and teachers perceive AI tutoring positively, particularly for engagement, feedback, and reasoning support, although some usability issues exist.

Research Question 5: Pedagogical and Contextual Factors

Table 4.6: **Factors Enhancing or Hindering AI Tutoring Effectiveness**

Factor Type	Enhancing Factors	Hindering Factors
Pedagogical	Teacher guidance, structured scaffolding	Lack of integration, unclear prompts
Contextual	Regular monitoring, supportive learning environment	Low digital literacy, limited access

Table 4.6 showed that AI tutoring effectiveness is maximized when combined with teacher guidance, scaffolding, and an enabling learning environment. Conversely, low digital literacy or unclear instructions can reduce effectiveness.

Summary of Results

1. **RQ1:** AI tutoring significantly improves overall mathematical reasoning.
2. **RQ2:** All reasoning components are enhanced, with Conjecture and Representation showing slightly higher gains.
3. **RQ3:** Higher student engagement and frequent interaction predict better reasoning outcomes.
4. **RQ4:** Students and teachers perceive AI tutoring positively for reasoning support.
5. **RQ5:** Pedagogical guidance, scaffolding, and proper context enhance AI effectiveness, while low digital literacy and unclear prompts hinder it.

Discussion

Introduction

This chapter discusses the findings of the study on the impact of AI-based tutoring systems on developing mathematical reasoning among secondary school students. Each research question is addressed individually, with a comparison to prior studies, highlighting areas of agreement or divergence, and providing interpretive insights for educational practice.

Research Question 1: Overall Impact of AI-Based Tutoring

Question: *What is the overall impact of AI-based tutoring systems on developing mathematical reasoning among secondary school students compared with traditional teaching methods?*

Discussion:

The results indicated that students in the AI-based tutoring group significantly outperformed the control group in overall mathematical reasoning ($t = 7.48$, $p < .001$, Cohen's $d = 1.93$). This finding is consistent with **Chou et al. (2022)**, who reported that AI tutoring with metacognitive prompts significantly improved reasoning skills among secondary students. Similarly, **Jančařík et al. (2023)** found that chatbot-based AI tutoring enhanced students' ability to explain and justify mathematical concepts.

By contrast, **Anderson et al. (1985)** observed only moderate gains in reasoning with early computer-assisted instruction (CAI), highlighting that modern AI systems—adaptive, interactive, and reflective—are more effective than early CAI technologies. **VanLehn (2006)** also emphasized that intelligent tutoring systems (ITS) improve reasoning when prompts are well-designed and tailored to learners' needs.

Interpretation: The strong overall improvement confirms that **AI-based tutoring can shift students from procedural understanding to higher-order reasoning**, emphasizing the value of adaptive and metacognitive scaffolds.

Research Question 2: Impact on Components of Mathematical Reasoning

Question: *Which components of mathematical reasoning (logical justification, conjecture, problem generalization, metacognition) are most influenced by AI-based tutoring?*

All reasoning components were significantly enhanced in the experimental group. Conjecture and representation showed slightly higher gains, consistent with **Jančařík et al. (2023)**, who reported improved hypothesis formulation and conceptual explanation. **Chou et al. (2022)** similarly found that metacognitive prompts encouraged students to justify and reflect on solutions, aligning with our findings in justification and metacognition.

However, **Nkambou et al. (2010)** noted that insufficiently contextualized prompts could hinder conjecture formation, which was observed occasionally in our study when students faced complex AI prompts. This highlights the **importance of carefully designed AI scaffolds** tailored to student readiness.

Interpretation: AI tutoring enhances all reasoning components, but **prompt clarity and adaptive support are critical** for maximizing gains.

Research Question 3: Student Interaction Behaviors

Question: *How do students' interaction behaviors with AI tutoring systems (frequency, type of feedback, engagement patterns) relate to reasoning performance?*

Correlation analyses revealed that higher frequency of interaction and immediate feedback strongly predicted better reasoning outcomes ($r = 0.68$ for frequency, $r = 0.55$ for feedback). Observations confirmed that students who actively engaged with the AI system explored multiple strategies and verbalized reasoning steps, while less engaged students relied on hints.

These results align with **Chou et al. (2022)** and **Jančařík et al. (2023)**, who emphasized the importance of active engagement with AI systems for reasoning development. Engagement facilitates **self-regulation, exploration, and reflection**, which are critical for higher-order mathematical thinking.

Interpretation: Student behavior and engagement are key mediators of AI effectiveness; the system alone is insufficient without active student participation.

Research Question 4: Perceptions of Teachers and Students

Question: *What are the perceptions of teachers and students regarding the role of AI-based tutoring systems in supporting reasoning and understanding in mathematics?*

Students overwhelmingly reported that AI tutoring enhanced engagement, confidence, and reasoning skills, with only minor difficulties in understanding prompts. Teachers highlighted that AI systems provide timely feedback and support reasoning but should complement, not replace, classroom instruction.

These perceptions are consistent with **Nkambou et al. (2010)** and **Chou et al. (2022)**, who emphasized that **positive attitudes towards AI tutoring correlate with better learning outcomes**. Teachers' support and integration into lessons are crucial for maximizing system effectiveness.

Interpretation: Both student and teacher perceptions confirm that **AI tutoring is beneficial**, but **pedagogical integration and guidance** are essential for success.

Research Question 5: Pedagogical and Contextual Factors

Question*: Which pedagogical and contextual factors enhance or hinder the effectiveness of AI-based tutoring systems in developing mathematical reasoning?*

Key enhancing factors included teacher guidance, structured scaffolding within the AI system, and a supportive learning environment. Hindering factors included low digital literacy, unclear prompts, and limited access to devices.

These findings resonate with **VanLehn (2006)**, who emphasized that ITS effectiveness depends on system design, learner characteristics, and contextual factors. Similarly, **Nkambou et al. (2010)** highlighted that adaptive feedback and scaffolding must align with learners' prior knowledge and classroom integration.

Interpretation: Effective AI tutoring requires **synergy between technology, pedagogy, and context**; without this alignment, even advanced AI systems may underperform.

Synthesis across Research Questions

- AI tutoring enhances **overall mathematical reasoning** and all its components.
- Student engagement, frequency of interaction, and feedback quality are crucial for realizing benefits.
- Positive perceptions from students and teachers support the integration of AI into classrooms.
- Pedagogical and contextual factors moderate the system's effectiveness, highlighting the need for **careful instructional design**.

Conclusion: The study confirms that **AI-based tutoring is a powerful tool for developing higher-order mathematical reasoning**, but its success depends on **system design, student engagement, and classroom integration**, consistent with prior research.

Conclusion and implications

Conclusion of the study

The findings of this study indicate that **AI-based tutoring systems significantly enhance mathematical reasoning** among secondary school students. Specifically:

1. **Overall reasoning:** Students using AI-based tutoring outperformed the control group in overall reasoning ability, confirming the value of adaptive, interactive, and metacognitive scaffolds (**Chou et al., 2022; Jančařík et al., 2023**).
2. **Components of reasoning:** Conjecture, justification, representation, and metacognition were all significantly improved, with conjecture and representation showing slightly higher gains, consistent with prior research on AI's role in developing higher-order thinking (**Nkambou et al., 2010**).
3. **Student interaction behaviors:** Higher engagement, frequency of use, and immediate feedback were strongly associated with better reasoning performance, highlighting the importance of active participation (**Chou et al., 2022**).
4. **Perceptions:** Both students and teachers reported positive perceptions, particularly regarding engagement, reasoning support, and feedback, confirming that favorable attitudes correlate with better outcomes.
5. **Pedagogical and contextual factors:** Teacher guidance, structured scaffolding, and a supportive learning environment enhanced AI effectiveness, while low digital literacy, unclear prompts, and limited access hindered it (**VanLehn, 2006; Nkambou et al., 2010**).

Overall Conclusion: AI tutoring is not only a technological tool but also a **pedagogical enhancer**. Its success depends on the synergy between system design, student engagement, teacher facilitation, and the learning environment.

Educational and Practical Implications

Based on the findings, the study provides several implications for educational practice:

1. **Integration into classrooms:** AI tutoring should complement traditional teaching, providing individualized scaffolds and immediate feedback while teachers guide conceptual understanding.
2. **Teacher training:** Educators should receive professional development to **effectively integrate AI tools**, interpret AI feedback, and support reasoning.
3. **Curriculum design:** Curricula should incorporate AI-based problem-solving activities that target all components of mathematical reasoning.
4. **Student engagement strategies:** Encourage frequent interaction with AI systems, use gamification or interactive challenges to maintain motivation, and provide guidance for effective self-regulated learning.
5. **System design recommendations:** AI prompts must be clear, adaptive, and aligned with students' prior knowledge to avoid cognitive overload.

Recommendations for Future Research

1. **Longitudinal studies:** Examine the sustained impact of AI tutoring on mathematical reasoning over multiple years.
2. **Diverse populations:** Expand research to include students from varied educational settings and cultural backgrounds.
3. **Comparative studies:** Compare different types of AI systems (chatbots, adaptive tutors, intelligent feedback systems) to identify the

most effective features for reasoning development.

4. **Integration with pedagogy:** Explore optimal strategies for teacher-AI collaboration and curriculum integration.
5. **Focus on engagement and motivation:** Investigate how gamification, adaptive challenges, and personalized feedback influence sustained engagement and reasoning outcomes.

Final Remarks

This study contributes to understanding how **AI-based tutoring systems can advance mathematical reasoning** in secondary education. It demonstrates that **technology, when integrated with pedagogy and contextual support**, can facilitate higher-order thinking, promote self-regulated learning, and enhance student engagement. Future research and practice should focus on **refining AI interventions, teacher preparation, and classroom integration** to maximize learning outcomes.

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