Issues in Information Systems
Volume 26, Issue 4, pp. 45-55, 2025

DOI: https://doi.org/10.48009/4_iis_2025_105

The evolution of mastery learning: Challenges, technologies, and the AI journey leading to the intelligent tutoring system DARTS

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Abstract

Bloom's theory of Mastery Learning (1968) and his "2 Sigma Problem" study (1984) revealed that one-on-one tutoring can produce learning outcomes two standard deviations above conventional instruction (Bloom, 1968, 1984). Despite its proven effectiveness, this model remains difficult to scale due to the cost and complexity of delivering personalized instruction (Guskey, 2007). The emergence of artificial intelligence offers the potential to replicate adaptive, responsive feedback traditionally delivered by human tutors (VanLehn, 2011; Ma, Adesope, Nesbit, & Liu, 2014). Concurrently, the ubiquity of mobile phones strengthens their potential to facilitate scalable AI-driven learning beyond fixed classroom settings (Traxler, 2007; Kukulska-Hulme, 2009). This paper investigates whether DARTS, an AI-driven Intelligent Tutoring System (ITS) delivered via mobile phones, can effectively replicate the learning benefits of one-on-one tutoring outlined in Bloom's 2 Sigma effect. It further explores DARTS' integration of real-time classroom interaction and out-of-class personalized tutoring, assessing its potential as a scalable solution for diverse and resource-constrained educational environments. Developed by the author, DARTS (Dynamic Academic Response and Tutoring System) addresses this challenge by combining AI, mobile interactivity, and SMS-based architecture to bridge Bloom's theoretical promise with real-world educational practice. While initial results are promising, limitations include dependency on consistent student-generated data and institutional readiness for AI adoption in education (Caldwell, 2007; Donker, Plomp, & Kuiper, 2009). Future research will focus on advancing DARTS into a long-term, personalized academic companion that supports learners throughout their educational journey, enhancing both retention and performance. This paper is the first in a three-part series. It focuses on the theoretical foundation and pedagogical rationale behind DARTS, while future installments address its system design and classroom implementation.

Keywords: AI in education, mastery learning, intelligent tutoring systems, 2 sigma problem

Introduction

Bloom's foundational work on Mastery Learning and the "2 Sigma Problem" highlighted the extraordinary potential of one-on-one tutoring, which consistently enabled students to perform two standard deviations better than peers in conventional classroom settings. However, Bloom also recognized the critical challenge: such individualized instruction was too costly and logistically impractical to scale (Bloom, 1984). This fundamental limitation, namely, how to deliver the benefits of individualized instruction at scale, has remained unresolved for over four decades (Guskey, 2007). This enduring challenge has directly informed the conceptualization and development of DARTS, an AI-driven ITS delivered through students' mobile phones.

This long-standing gap—between what is pedagogically ideal and what is operationally feasible, continues to drive the search for innovative, scalable solutions like DARTS. This study examines whether DARTS can effectively replicate the benefits of one-on-one tutoring—central to Bloom's 2 Sigma findings—through scalable, mobile AI-powered instruction. To guide this investigation, the study focuses on two central research questions.

1. *Can DARTS function effectively as a mobile-based Student Response System (SRS) to provide real-time input to an Intelligent Tutoring System?*

2. *Can DARTS deliver personalized instruction—via mobile phones—that is comparable to one-on-one tutoring, achieving learning gains comparable to Bloom's 2 Sigma effect?*

These questions aim to evaluate the dual role of DARTS as both an in-class student response tool and a mobile, out-of-class personalized learning platform, addressing the long-standing challenge of scaling individualized instruction in a cost-effective and accessible manner. Given the prevalence of mobile phones in students' lives, DARTS' SMS-based design, which uses a webhook-driven backend to obtain data from a cloud database, eliminates the need for internet infrastructure, app installations, or user training, making it a particularly economical and readily available choice. This raises a critical question: Can DARTS achieve rapid and effortless adoption among students, regardless of variations in their technological resources or academic preparedness?

As part of a pilot implementation, DARTS was deployed with 90 undergraduate students across Business and Computer Science programs during a semester. The study generated 71 survey responses, 52 in-class quizzes, 18 at-home tutorials, and 13 semi-structured interviews, totaling over 1,200 SMS interactions. Notably, 96% of students agreed that mobile phones enabled learning "anywhere, anytime," 88% stated phones supported their learning, and 83% expressed a preference to use phones in class. Qualitative feedback highlighted improved concentration and comfort, with students describing experiences like "a wave of peace being in my own home" and calling the system "very effective." These insights led to several design improvements. A full-scale, controlled evaluation will be presented in the third paper of this series.

Future research will explore DARTS' potential to serve as a continuous academic companion that adapts to students' changing needs, maintains contextual awareness, and delivers timely, personalized feedback throughout their academic journey, promoting sustained engagement and reducing dropout risk.The remainder of this paper is organized as follows: Section 2 traces the theoretical foundations of Mastery Learning and highlights the persistent challenges in delivering scalable, personalized instruction. It also explores historical efforts to replicate one-on-one tutoring through technology, analyzing why these approaches often failed to scale effectively. Section 3 introduces the conceptual evolution and design rationale behind DARTS as a response to these limitations. Section 4 concludes the paper by summarizing the key contributions and outlining future directions for research and classroom implementation.

From the 2 Sigma Problem to Scalable Solutions

Bloom's 2 Sigma effect is achieved only when Mastery Learning is delivered through one-to-one tutoring (1:1) which requires constant assessment, instructional continuity, and just-in-time feedback-and-evaluation cycle tailored to each student's individual progress and learning needs. The figure below visually reinforces the profound effect of individualized instruction, showing how one-on-one tutoring outperforms both conventional instruction and mastery learning in terms of student achievement, as originally demonstrated by Bloom (1984).

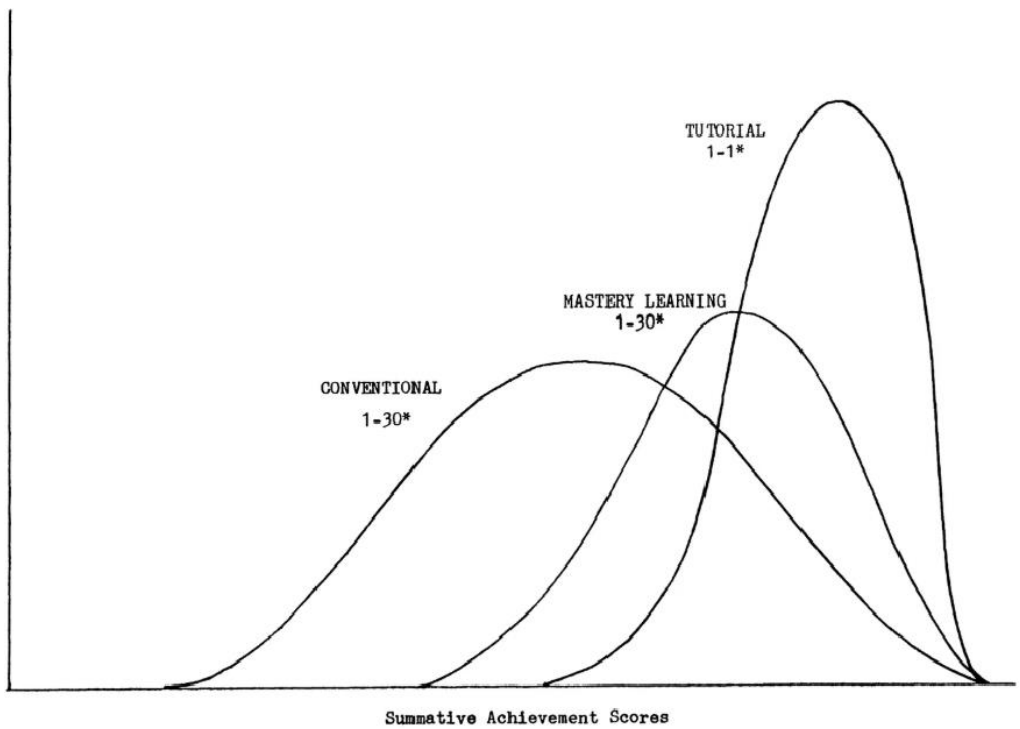

Figure 1. Bloom's 2 Sigma Problem

While remarkably effective, Bloom directly acknowledged, "it is too costly for most societies to provide one tutor per student." His entire 1984 article, "The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring", is a call to action to find a workaround. In reply to Bloom's request, many ways of teaching came about. Some of these were group tutoring, cooperative learning, programmed guidance, and computer-assisted learning methods that got smarter over time. Each approach had some success, but none of them were able to deliver consistent, personalized instructions on a large scale, especially in places with limited resources.To understand why Bloom's call for scalable tutoring has remained unfulfilled, it is essential to examine the historical barriers that have hindered the widespread adoption of mastery learning

Challenges in Scaling Mastery Learning: A Historical Review

The early implementation of mastery learning was constrained by the rigid structure of traditional classrooms. Standardized lessons and tight pacing plans make it hard to respond to students who are learning at different rates, which creates a lack of the flexibility needed for real mastery-based growth (Slavin, 1987; Anderson, 1994).

Lack of Real-Time Feedback and Adaptive Tools in Traditional Models

A significant deficiency was the absence of real-time feedback. In the past, exams usually happened after lessons, which made it harder to fix problems promptly or give specific help (Kulik et al., 1990). As a result, many students kept having problems without getting help right away. The tools used for instruction were another problem. In the beginning stages of mastery learning, most of the tools used were static and not interactive. This made it hard to tailor lessons to each student's needs (Briggs & Aronson, 1975). Teachers had trouble keeping track of their students' growth because of practical issues. Keeping notes and doing diagnostic tests was labor-intensive that took away a lot of time from teaching (Klausmeier, 1975).

Group-Based Learning: Promise and Pitfalls

Strategies based on group dynamics that attempted to simulate personalized learning also faced significant challenges. Glaser and Rosner (1975) noted that organizing and managing small groups with varying learning objectives introduced logistical complexities that often hindered instructional effectiveness. Moreover, these early approaches were constrained by the technological limitations of the time. Educational tools lacked the flexibility required for real-time adaptation and decision-making (Edling, 1971).

Challenges in Peer and Institutional Models

Peer tutoring and cooperative learning supported Mastery Learning but suffered from inconsistent tracking and a lack of standardization, making outcomes unreliable (Allen, 1976). Institutional constraints—such as age-based progression and rigid pacing schedules—further limited personalized instruction (Bloom, 1984). Additionally, manual methods lacked data and analytics, reducing the ability to adapt teaching based on student needs (Guskey, 2007). In summary, early efforts to implement mastery learning faced numerous challenges. Table 1 summarizes the most influential strategies, highlighting their core features, limitations, and supporting research. This progression of ideas directly informs the design rationale behind DARTS.

Table 1. Gaps in Classroom Implementation of Mastery Learning

Approach	Description	Effectiveness / Limitations	Supporting Research
Mastery Learning	Structured instruction with formative assessments and corrective feedback	Improves performance by ~1σ; time-intensive and requires teacher's capacity	Bloom (1968); Guskey (2007)
Peer Tutoring / Cooperative Learning	Students tutor or assist each other in small groups	Enhances learning outcomes; quality depends on training and group dynamics	Topping (2005); Fantuzzo et al. (1992)
Programmed Instruction / Scaffolding	Sequenced content delivery with structured support	Effective for procedural skills; less adaptive to individual misconceptions	Vygotsky (1978); Kulik & Kulik (1991)
Computer-Assisted Instruction (CAI)	Use of early educational software to provide drill and practice	Good for skill reinforcement; lacked real-time adaptation	Kulik & Kulik (1991); Suppes & Morningstar (1972)
Adaptive Learning Systems / ITS	AI-driven platforms that adjust to student input and pace	Effective for individual learning paths; often costly, requires high infrastructure	VanLehn (2011); Ma et al. (2014)
Clicker-Based Student Response Systems (SRS)	Wireless handheld devices to capture attendance and quick responses	Required hardware, logistical challenges, limited scalability	Caldwell (2007), Kay & LeSage (2009)
Mobile-Based Learning	Smartphones used for content access, quizzes, response systems	Widely accessible; enables real-time feedback; dependent on app and internet access	Traxler (2007); Kukulska-Hulme (2009)
SMS-based Learning Systems	AI-driven, Conversational text messaging used for attendance, quizzes, and instructional prompts	Low-cost and infrastructure-light; lacks rich multimedia but highly scalable	Donker et al. (2009); DARTS (Sarkar, 2022)

Note. *DARTS is an SMS-based Intelligent Tutoring System proposed and developed by the author in this study.*

Table 2 outlines the technological shortcomings that have historically hindered the full deployment of Mastery Learning in educational environments. The chart illustrates the differences between the instructional demands of mastery-based frameworks and current tools, emphasizing notable deficiencies in adaptive feedback, student engagement, data recording, and management of learning. These findings lay the groundwork for understanding the need for modern, AI-enhanced systems like DARTS to overcome these persistent limitations.

Table 2. Technological Evolution of Mastery Learning Criteria

Aspect	Technology Required or Suggested	Technological Gaps or Limitations Noted
Instructional	Print, mediated materials (e.g., filmstrips, cassettes), packaged instructional resources, and early mention of computers.	Lack of real-time, adaptive learning systems; no mobile or personalized tech integration for on-demand feedback.
Instructional Management	Learning contracts, task cards, computer managed instruction (CMI) hinted.	Manual or semi-manual tracking of student progress; minimal automation or analytics for learning paths.
Assessment	Use of pretests, posttests, and diagnostic tools.	No mention of AI-driven formative assessment or continuous feedback loops.
Instructional Grouping	Includes one-on-one tutoring, team problem solving, and peer discussions.	Coordination heavily reliant on teacher facilitation; lack of scalable platforms to manage varied grouping dynamically.
Instructional Materials	Adjunct (textbooks, films) and packaged materials (Learning Activity Packages – LAPs).	Static content lacking interactivity or real-time personalization.
Student Engagement	Encourages self-directed and independent study using contracts and study guides.	No digital tools or gamified elements to enhance motivation or track engagement levels.
Data and Record-Keeping	Emphasizes the need for forms to record learning progress.	No digital gradebooks, dashboards, or data-driven intervention systems.
Programming Model	Flowcharts and models for student progression based on performance on tests.	Lacks AI-based decision trees or mobile apps to guide students interactively.
Examples of Programs Referenced	IPI (Individually Prescribed Instruction), PLAN (uses learning guides), IGE (small group instruction) – early models of systematized learning.	All rely on static or pre-structured content, no real-time content generation or AI involvement.
Student-Led Instruction	Mentions peer tutoring and group problem-solving.	No platforms to track or scaffold peer teaching effectiveness.

Note. *Adapted from foundational literature on mastery learning, including Bloom (1968), Glaser & Resnick (1972), Kulik et al. (1990), and Guskey (2007). The comparative analysis and technological interpretation are original to this study*

To build on that analysis, Table 3 provides a chronological overview of the actual technologies employed in Mastery Learning implementations from the 1960s to the present. This timeline illustrates how evolving tools, from programmed instruction and Computer Aided Instruction (CAI) to adaptive AI-based tutors have incrementally addressed the gaps identified earlier. The table below highlights the shift from static, linear tools toward dynamic, interactive systems capable of supporting real-time feedback, learner analytics, and personalized instruction essential for effective mastery learning.

Table 3. Technology Used in Mastery Learning Over the Years

Years	Technologies Used	Description
1960s	Programmed Instruction (books, slides)	Benjamin Bloom introduced Mastery Learning; content delivered via printed booklets, teaching machines (Skinner-style).
1970s	Teaching Machines, Filmstrips	Linear progression through tasks; used in military and some K-12 settings. Early computer-assisted instruction in research labs.
1980s	Computer-Assisted Instruction (CAI)	Software like PLATO, LOGO; drill-and-practice systems began adapting to student pace.
1990s	CD-ROM Educational Software	Interactive tutorials with quizzes; limited tracking. Examples: Math Blaster, Reader Rabbit.
2000s	Learning Management Systems (LMS)	Blackboard, Moodle, and early adaptive testing; teachers began setting mastery thresholds in digital tools.
2010s	Adaptive Learning Platforms, MOOCs	Khan Academy, ALEKS, Coursera used data to adjust pace/content based on mastery.
2020s	AI-Powered Tutoring, Intelligent Tutoring Systems (ITS)	Tools like Carnegie Learning CTAT, Squirrel AI, and DARTS personalize learning paths and adapt in real-time.
2024+	Mobile AI platforms like DARTS use ChatGPT-style NLP via APIs and SMS to deliver conversational tutoring through mobile phones.	Enables AI-powered tutoring.in a mobile. App free, and infrastructure light format

Note. *Chronological progression of technology adoption in Mastery Learning compiled from educational technology literature and the author's analysis. The 2020s and 2024+ entries reflect the emergence of Intelligent Tutoring Systems and mobile-based AI tutoring platforms, including DARTS*

Bridging the Gaps—Design Rationale for DARTS

DARTS introduces an architecture in which pre-assessment becomes an in-class activity, conducted through active learning techniques such as quizzes, brainstorming, polling and short-answer questions. Recognizing that accurate pre-assessment depends on classroom attendance, the author strategically integrated attendance tracking as a core function within DARTS. Building on this foundation, the brainstorming feature for example, engages students immediately by allowing them to respond to discussion prompts via their mobile phones. This real-time interaction serves as a powerful diagnostic tool—capturing students' prior knowledge, misconceptions, and levels of engagement during open-ended, formative activities. Importantly, non-participation in brainstorming also becomes a critical data point, signaling disengagement, confusion, or technical barriers. These insights enable the system to identify students needing additional support and guide the delivery of personalized instruction.

However, in a typical classroom, students possess varying levels of aptitude, prior knowledge, and learning speed. As shown in Figure 2 illustrates how the time required for mastery learning often exceeds classroom duration, highlighting the need for personalized support beyond scheduled instruction. For example, when a teacher introduces, say, Instructional Unit 1 to the entire class, it is unrealistic to expect all students to grasp the concept simultaneously. In this scenario, a few students may quickly achieve mastery (Student A) and proceed to enrichment activities, then move on to Instructional Unit 2. Others, (Student B), may show partial understanding. According to Mastery Learning theory, these students (Student B) require corrective instruction followed by a second assessment or more to close their learning gaps before

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advancing. The variation in time required to achieve mastery is schematically presented in Figure 2. In conventional classrooms, such personalized interventions are often unavailable due to time and resource constraints. As a result, these gaps persist, leading to cumulative deficiencies and poor performance in final assessment

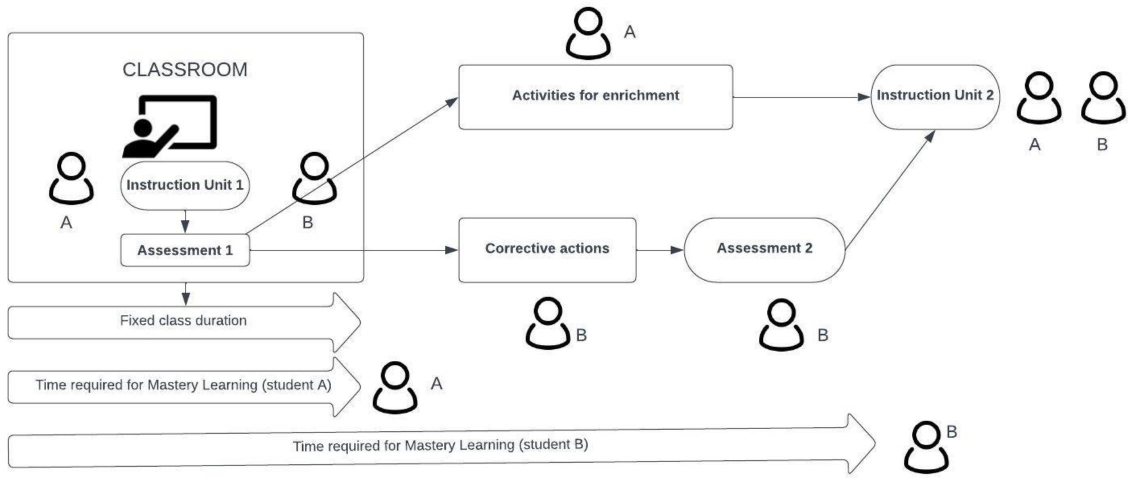

Figure 2. Time Required for Mastery Learning

To ensure all students reach mastery, we need a system that can assess understanding immediately after instruction and continue supporting learning outside the classroom—at the student's own pace, in their own time, and in any setting—while maintaining a seamless track of progress. DARTS applies these foundational learning principles through a reimagined ITS architecture. A typical ITS consists of four core components (Figure 3): the domain model, which holds subject knowledge and expert strategies; the student model, which tracks learner progress and misconceptions to build a personalized profile; the tutoring (pedagogical) model, which selects instructional strategies and feedback; and the user interface model, which manages interaction between the student and the system. Figure 3 below illustrates the structure and interconnection of these components in a conventional ITS.

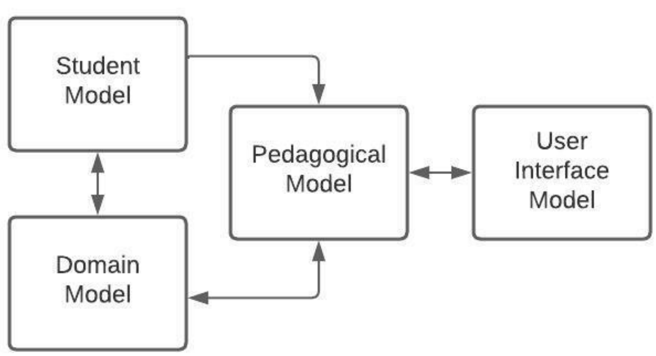

Figure 3. Models of a Conventional Intelligent Tutoring System

In traditional ITS designs, these models often operated in relative isolation, each receiving input and producing output with limited cross-model integration in real-time. Unlike earlier ITS models, which were largely confined to desktop-based environments, DARTS ITS was conceived as a fully mobile, studentcentered system that operationalizes the complete cycle of Mastery Learning with the mobile phone functioning simultaneously as an input device, feedback channel, and personalized tutor, allowing students as much time as necessary to achieve mastery. Figure 4 illustrates how mobile phone interfaces extend the capabilities of conventional ITS models described earlier in Figure 3. This integration supports greater accessibility and flexibility, enabling DARTS to function as a location-independent intelligent tutoring system within the constraints of low-infrastructure environments.

In addition to the versatility of the mobile interface, the AI engine in DARTS serves two key functions: (1) it constructs a real-time student profile by analyzing individual learning behaviors—including prior knowledge, strengths, and weaknesses—which serve as input to the underlying student model; and (2) it delivers personalized learning content through conversational interactions powered by Natural Language Processing. The AI interfaces are shown schematically in Figure 4.

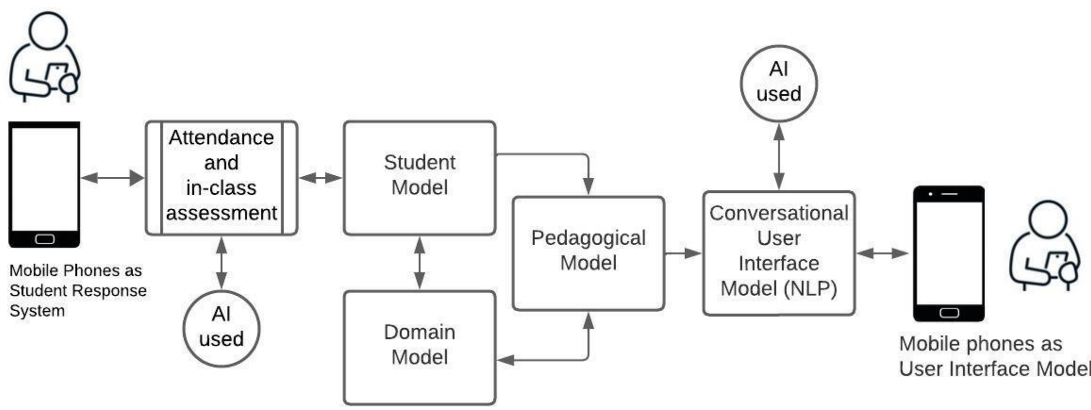

Figure 4. DARTS ITS Models with Mobile Interface and Use of AI

DARTS cycles of operation

The end-to-end process by which DARTS enables personalized, continuous learning, particularly for average learners, often left behind in traditional instruction (as shown in Figure 2), can now progress through a structured learning cycle.

This is illustrated in Figure 5, a schematic diagram of DARTS closed-loop learning model. When Instructional Unit 1 is introduced in the classroom, students' responses—such as quizzes, brainstorming inputs, and attendance via their mobile phones are stored in a cloud-based database, marking the "Classroom Input" phase. These inputs, serving as pre-assessments, trigger the domain and pedagogical models of the DARTS-ITS to generate personalized tutoring responses during the "Personalized Tutoring" phase (shown in the center block), which are then sent back to students via SMS. This automated instructional loop continuously monitors the student's progress and repeats as needed until a level of mastery is achieved.

At that point, the student is ready to be reintegrated into the classroom and proceed with Instructional Unit 2. By automatically guiding learners through targeted support and timely feedback—then reintegrating them only when prepared for the next instructional Unit 2, DARTS fully operationalizes the principles of Mastery Learning.

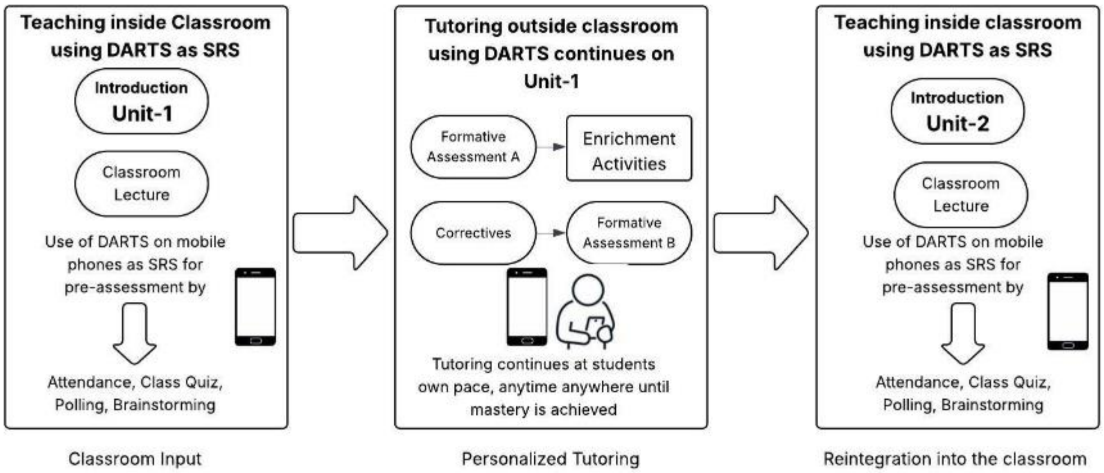

Figure 5. DARTS cycles of operation for implementing Mastery Learning

Comparison of DARTS with existing Systems

To fully appreciate DARTS' contribution to modern education, it is essential to examine how it compares to the tools currently in widespread use. Since products like Top Hat, Poll Everywhere, and iClicker focus primarily on in-class engagement, they were excluded from ITS comparison. Table 4 compares commonly used ITS platforms across key features such as learner modeling, feedback, and mobile accessibility.

Table 4. Comparison of DARTS with Other ITSs

Feature / System	AutoTutor	ALEKS	ASSISTments	Carnegie Tutor	DARTS
Learner Modeling	Yes	Yes	Yes	Yes	Yes
Personalized Feedback	Yes	Yes	Partial	Yes	Yes
Conversational AI	Yes	No	No	No	Yes
Mobile Support	Limited	Partial	Partial	Limited	Yes
Requires Internet/App	Yes	Yes	Yes	Yes	No
In-Class Integration	No	No	Limited	No	Yes
Instructor Interaction	No	Limited	Yes	Yes	Yes
Scalability	Medium	Medium	Medium	Medium	High
Cost per Student	High	Moderate	Moderate	High	Very Low
Best Suited For	Higher Ed	K–12	K–12	K–12, College	Higher Ed

As shown in Table 4, most ITSs require internet access and additional infrastructure, with limited classroom integration. DARTS stands out by using mobile phones and SMS—tools students already have—eliminating the need for apps or training, and providing scalable, seamless support aligned with Mastery Learning.

Conclusion

This article presents DARTS, an AI-powered Intelligent Tutoring System that delivers personalized Mastery Learning via mobile phones—making high-quality education accessible to all. DARTS offers a practical solution to the long-standing challenge of replicating the effectiveness of one-on-one tutoring for every student. DARTS, initially developed during the author's doctoral research, is protected by two pending U.S. patents (Application Nos. 18/521,928 and 18/433,800).

Future research will enhance DARTS as a student companion across disciplines and educational levels, aiming to provide scalable, individualized tutoring in a cost-effective way that addresses educational disparities and transforms learning. This paper lays the theoretical and architectural groundwork as the first in a three-part series, with forthcoming papers to address its system design and measurable learning outcomes. Despite rapid technological progress, today's education system remains schedule-bound, expensive, and inaccessible to many. Quality instruction is still largely confined within institutional walls. The author argues that AI and machine learning–based tutoring can fundamentally transform education by making high-quality learning universally accessible—delivered through personal mobile devices and secured with blockchain credentials.

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