DOI: https://doi.org/10.4038/sljas.v27i1.8235

Sri Lankan Journal of Applied Statistics, Vol (27-1)

Exploring Adaptive Learning Design Through R shiny: An IRT-Based Approach for Mathematics Education in Sri Lanka

R. A. D. C. Didulan* and A. W. L. P. Thilan

Department of Mathematics, Faculty of Science, University of Ruhuna, Sri Lanka

*Corresponding author:didulanc@gmail.com

Received: 12th October, 2025/ Revised: 24th January, 2026/ Accepted: 27th January, 2026/ Published: 31st March, 2026

ABSTRACT

Mathematics consistently records the lowest pass rates at the G.C.E Ordinary Level (O/L) examinations in Sri Lanka, underscoring the urgent need for innovative approaches to address the wide variation in student ability. Globally, adaptive learning has been advanced through intelligent tutoring systems, Bayesian frameworks, and rule-based models: however, its adoption in Sri Lanka secondary education remains minimal. This study presents the design of an adaptive learning framework developed as a proof of concept rather than a fully operational system implemented using R-shiny. The framework employs Item Response Theory (IRT), specially the three-parameter logistic (3PL) model, which incorporates item difficulty, discrimination, and guessing, thereby offering a robust representation of student performance. Student ability estimates are uploaded recursively after each response, while subsequent items are selected using maximum information criteria to enhance both efficiency and measurement precision. Simulation results demonstrate that the proposed IRT-based design can efficiently distinguish among students at different ability levels and generate reliable estimates of performance. These findings highlight the potential of prototype-level adaptive learning designs to provide a statistically rigorous and scalable foundation for advancing mathematics education in Sri Lanka, while also establishing a pathway toward future system development and classroom integration.

Keywords: Item Response Theory (IRT), Three-parameter logistic (3PL) model, Personalized Education, R shiny, Education Statistics, G.C.E O/L Examination.

1 Introduction

Mathematics underpins critical thinking, problem solving, and learning, yet poor mathematical performance is strongly linked to weak educational outcomes worldwide. In Sri Lanka, the G.C.E. Ordinary Level (O/L) mathematics examination serves as a key benchmark, consistently reflecting challenges in student achievement. Despite reforms and teacher training, student records show persistent underperformance: in 2019, only 67% of students achieved satisfactory grades, with marked disparities across schools and regions (Ministry of Education, 2019; Damayanthi, 2018). These findings highlight ongoing inequities and difficulties in ensuring effective mathematics learning opportunities (Crowley, 2018; Jayasuriya et al., 2014).

Although conventional lectures are commonplace, they rarely account for variations in students' skills, rates of learning, and different learning preferences (Karjanto and Acelajado, 2022). As a result, students may develop incomplete or shallow understandings of key concepts, which can build up into major learning gaps. Additionally, the lack of individualized feedback and progression in the traditional classroom environment can easily lead to disengagement and weak long-term retention (Nguyen and Le, 2020). Therefore, it is necessary to think about pedagogical innovations that provide personalized support to the learner (Silva and Banneheka, 2019).

Adaptive learning technologies offer a promising solution to these challenges by continuously estimating a learner's ability and dynamically adjusting difficulty, order, and content of instructional materials (Crowley, 2018). This approach can improve student engagement and enable targeted interventions in individual points of weakness (Damayanthi, 2018; Hwang, 2022). International platforms such as ALEKS, Carnegie Learning, and Khan Academy demonstrate the effectiveness of adaptive systems in mathematics education (Nguyen and Le, 2020; Lu et al., 2024). Such adaptive design principles are also employed in other domains to track latent states under nonlinear and disturbed conditions (Thilan et al., 2022, 2023). However, methodologically robust models such as Item Response Theory (IRT) have not yet been applied in adaptive systems tailored to Sri Lankan O/L mathematics curriculum.

IRT offers a robust statistical structure for adaptive learning, modeling the probability of a correct answer as a function of learning ability (θ) and item characteristics: difficulty, discrimination, and guessing (Gyamfi and Acquaye, 2023; Ogunsakin and Shogbesan, 2018). Unlike classical test theory, which yields aggregate measures of performance, IRT incorporates the interplay between learner ability and item characteristics to more precisely estimate ability and select questions (Ariyadi, 2025). In particular, the three-parameter logistic (3PL) model provides increased flexibility, utilizing random guessing, and is therefore ideally suited for multiple-choice assessments (Ariyadi, 2025).

Despite the widespread international adoption of adaptive learning (Lu et al., 2024), IRT-based systems remain largely unexploited in Sri Lankan secondary education. This study introduces a novel web-based platform developed using R Shiny and MySQL, which estimates student ability in real time via the three-parameter logistic (3PL) model and delivers personalized learning in Algebra, Geometry, and Trigonometry. The primary aim is to investigate whether such an adaptive system can enhance student engagement and achievement in O/L mathematics through individualized learning paths. By integrating adaptive assessment with an interactive interface, this research addresses a critical gap in the local education context and demonstrates the potential of data-driven personalization to improve learning outcomes (Hwang, 2022; Crowley, 2018). The study highlights the feasibility of implementing statistically rigorous, real-time adaptive learning design in Sri Lanka, laying the groundwork for future expansion and classroom integration (Karjanto and Acelajado, 2022).

2 Methodology

In Sri Lanka, traditional assessment practices, such as the G.C.E O/L examination, are typically analyzed using Classical Test Theory (CTT). While CTT provides straightforward measures, including overall test scores and item difficulty, it relies on strong assumptions that limit its broader applicability. In particular, CTT assumes a constant level of measurement error across ability levels and is dependent on the sample. These limitations make CTT less suitable for adaptive learning or which require precise, individualized assessment to guide educational decisions for diverse student populations.

Item Response Theory (IRT) effectively addresses these limitations in several ways. IRT models a student's response to an item as a probability based on the combination of student ability (θ) and the characteristics of the item. Unlike CTT, IRT provides item-level information that is invariant across populations, making it well suited for adaptive assessment systems. Second, IRT offers multiple models to account for different aspects of item performance: the one-parameter logistic (1PL) model assumes equal discrimination across items; the two-parameter logistic (2PL) model incorporates item discrimination; and the three-parameter logistic (3PL) model further accounts for guessing. This study implemented the 3PL model of IRT to guide adaptive learning.

2.1 Three-Parameter Logistic (3PL) Model

In this study, the three-parameter logistic (3PL) model of IRT was employed to model student responses. The model calculates the probability of a student answering an item correctly using the following equation:

$$P(\theta) = c + \frac{1-c}{1+e^{-a(\theta-b)}} \tag{1}$$

where [1]θ represents student ability, a is item discrimination and b is the item difficulty and c is the Guessing parameter. Discrimination parameter (a) describes how well an item differentiates students with Higher values producing steeper item characteristic curves (Figure 1). Values of a are assigned based on expert judgment, response data, and pilot testing. typically, in the range from 0.5 to 2.0. The difficulty parameter (b) denotes the ability level with a 50% chance from correct response, with lower values indicating easier items and higher values more challenging ones, determined using syllabus, teacher judgment, or previous performance data. The Guessing parameter (c) accounts for correct response by chance, preventing the curve from approaching zero at very low ability levels, and is set at 0.1 or 0.3, depending on the number of plausible answer options (Gyamfi and Acquaye, 2023).

Figure 1 presents item characteristic curves (ICCs) illustrating the probability of a correct response as a function of student ability (θ) under the three-parameter IRT model. Questions 1, 2, and 3 correspond to difficulty levels 1, 2, and 3, respectively. The red curve, representing the lowest difficulty item, shows the highest probability of correct responses across all ability levels, while the blue and green curves demonstrate decreasing probabilities as difficulty increases. The x-axis represents standardized student ability (θ) with mean 0 and SD 1, where negative values indicate below-average ability and positive values indicate above-average ability. The y-axis represents the probability of a correct response. Each curve is determined by the item's difficulty (b), discrimination (a), and guessing (c) parameters, with higher difficulty shifting the curve to the right and the guessing parameter ensuring non-zero probabilities at very low ability levels.

In this study, the three-parameter logistic (3PL) model was chosen over simpler IRT models (1PL and 2PL) for assessing student ability in GCE OL mathematics. The 3PL model considers item difficulty and assumes equal discrimination across items, which can underestimate true performance. The 2PL model adds item discrimination to adjust for item characteristics across response situations but still assumes no 'guessing' effect. 3PL model further includes a guessing parameter (c), allowing for a more accurate estimation of true mastery, particularly for multiple choice or numerical-response items. Overall, the 3PL model provides the most complete and precise measure of student ability for this study

[1]θ is estimated using a simple step-size approach for illustrative purposes. Future versions may include Maximum likelihood Estimation (MLE) or Bayesian method.

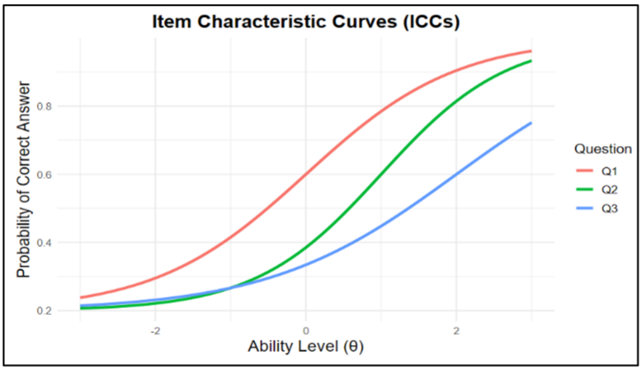

Fig. 1: Item characteristic curves (ICCs) showing the probability of a correct response as a function of student ability (θ) for three items of varying difficulty levels. The x-axis represents standardized ability (mean=0, SD=1), and the Y axis represents the probability of a correct response. Curves are determined by the item's difficulty(b), discrimination(a), and guessing (c) parameters.

2.2 Assumptions and Initialization of Model Ability

The three-parameter logistic (3PL) model employed in this research is based on standard Item Response Theory assumptions of unidimensionality, local independence and monotonicity. The assumption of unidimensionality states that a student's ability to respond to an item is primarily based on one underlying factor, i.e., their mathematical ability. The structured nature of the question bank supported this assumption, as the items within a given topic (Algebra, Geometry, Trigonometry) were aligned to an overarching skill set and reviewed for quality by subject matter experts. The assumption of local independence indicates that the responses to items are independent of one another given a student's ability. This assumption was met in this research by designing the questions to be independent of one another and to not overlap content. The monotonicity assumption indicates that as the ability of a student increases, the likelihood of correctly answering an item will also increase. The logistic form of the 3PL model meets the assumption of monotonicity by producing a logistic curve, which can be seen via a graphical representation of Item Characteristic Curves (Figure 1).

For a first-time user, the initial ability estimate (θ) was assigned to be $\theta = 0$, which corresponds to the mean ability level on the standard normal ability scale that is typically used in IRT. Therefore, the reason for this initial ability estimation was to provide a neutral starting point in the absence of pre-existing data on the user's performance. The ability value can take a range from approximately -3 to 3, which corresponds to low to high proficiency levels. The IRT model through the course of the analysis will continue to refine the user's estimated ability based on their responses to items.

2.3 System Overview and Adaptive Workflow

The adaptive learning system was developed using the R Shiny framework, which enables the creation of interactive web-based applications that combine statistical modeling, real-time computation, and dynamic visualization. Shiny was chosen for its ability to integrate complex algorithms with a user-friendly interface, allowing both students and instructors to interact with the system seamlessly. The platform was designed around an item response theory (IRT) model, where item parameters were calibrated through expert review, pilot testing, and analysis of student response data. This design ensures that the system can adaptively select questions, update ability estimates, and provide feedback in real time, making it both practical and effective for personalized learning.

Building on this development, the following workflow describes how the system operates in practice. Students log in to the system using their unique authentication credentials to initiate the platform. First, we determine or retrieve an initial estimate of the student's ability (θ), and we default to a value of zero for the first session. Using this estimate of ability and the parameters of items in the question bank, a question is selected using best fit for the student. Once the student gives an answer to this question, the student's ability (θ) is updated recursively based on the accuracy of the answer, and immediate feedback is given. The system will then assess if the student has achieved mastery. If the student has not achieved mastery, the system will go into another iteration and select the next question, which will incorporate the new ability estimate. The system will continue to evaluate the student's ability until the student achieves mastery and the session ends, and a summary report will then be generated. This adaptive workflow in Figure 2 provides a continuous opportunity for the learning experience to be personalized, such that the student receives focused practice and feedback unique to their present ability.

2.4 System Architecture and Technical Implementation

The proposed adaptive learning platform integrates an interactive R Shiny user interface with a MySQL backend for data management, supported by a suite of R packages for statistical computation and visualization. The R Shiny front end provides a web-based interface with consistent design and client-server communication, while MySQL stores the question bank and student performance data, with DBI and pool packages ensuring secure, efficient, and scalable database connections. Analytical computations and visualizations are enabled by key R packages: the *mirt* package estimates item parameters and generates Item Characteristic Curves (ICCs), *ggplot2* visualizes ICCs and student progress, and *stringr* and glue facilitate dynamic query construction. This modular architecture allows efficient data handling, flexible scaling, and easy

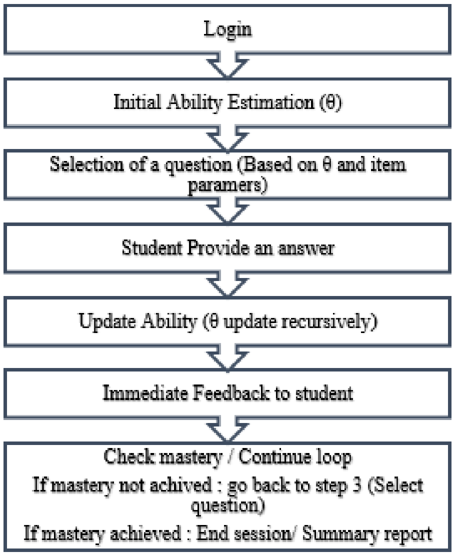

Fig. 2: Adaptive workflow of proposed learning system.

expansion of content, supporting a fully interactive and adaptive learning experience.

2.5 Data Collection and Question Bank

At the core of the system is a well-structured question bank organized into different domains.

2.5.1 Question Bank Content

A total of 60 questions were developed for the proof-of-concept system, with 20 questions per topic (Algebra, Geometry, and Trigonometry). Each question includes four options, hints, and solutions, where each question is also associated with item parameters: difficulty (b), discrimination (a), and guessing (c), which are stored in the MySQL database. Initial parameter values were assigned using Classical Test Theory and later refined based on preliminary responses in a sampled student group. This process ensures that each question is effectively integrated into the adaptive learning workflow. An example of the question is bank table structure provided in Figure 3.

2.5.2 Student Data

A separate table in the MySQL database is dedicated to storing student data

←T→	id	difficulty	question_text	solution	hint	image_path
Edit Copy Delete	1	1	Solve: x + 5 = 12	7	Subtract 5 from both sides	NULL
Edit Copy Delete	2	1	Find x: 3x = 15	5	Divide both sides by 3	NULL
Edit Copy Delete	3	1	Solve for x: x - 8 = 2	10	Add 8 to both sides	NULL
Edit Copy Delete	4	1	x / 4 = 3. Find x.	12	Multiply both sides by 4	NULL
Edit Copy Delete	5	1	x + 3 = 9. What is x?	6	Subtract 3 from both sides	NULL
Edit Copy Delete	6	2	Factor: x^2 - 9	-3,3	Difference of squares: (x+3)(x−3)	NULL
Edit Copy Delete	7	2	Solve: x^2 + 7x + 10 = 0	-2,-5	Factor the quadratic	NULL

Fig. 3: Question bank table, that illustrates the adaptive learning workflow, showing the sequence of steps involved in the platform. The chart outlines how the system updates student ability estimates in real time, delivers immediate feedback to the learner, checks for mastery, and either continues the loop with additional questions or concludes the session with a summary report structure (Algebra).

while ensuring privacy. Each record contains an anonymous Student_ID, username, password, name, and email. The system also logs student responses, timestamps, and performance metrics. This information allows monitoring of individual learning paths and performing item analysis and summary reports. This data is instrumental in continuous improvement of the learning experience and allows evaluation of the system's effectiveness. An example of the student table structure is Figure 4.

←T→	Student_Id	username	password	name	email
Edit Copy Delete	1	dradc2020	8cc9be43871639e20bfbef7a20b3c091	Chavi Didulan	didulanc@gmail.com

Check all *With selected:* Edit Copy Delete Export

Fig. 4: Student table structure, that presents the structure of the student table in the MySQL database. Each record includes anonymous student identifiers, login credentials, and contact details, alongside fields for timestamped activity and performance metrics. This structure enables secure tracking of individual student progress and supports item analysis, reporting, and overall evaluation of learning outcomes.

2.6 Adaptive Workflow and User Interaction Details

In Figure 5, the adaptive loop ensures a seamless and personalized experience for students; Questions are dynamically retrieved from the MySQL database based on the difficulty parameter (b) closest to the student's current ability (θ). Students submit answers via the Shiny interface, and responses are verified and logged along with timestamps and student ID. After each response, θ is updated: it is raised when correct answers increase by 0.2, and incorrect answers decrease by 0.2 allowing the system to adaptively select subsequent questions. Immediate feedback is provided, and an individualized student path is created. All responses, ability estimates, topic performance, question attempts, and mastery reports are tracked to monitor progress and evaluate learning outcomes.

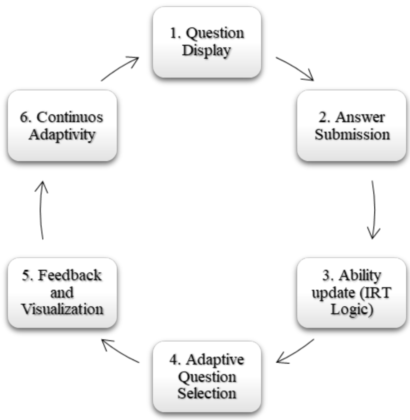

Fig. 5: Adaptive Workflow.

2.7 Evaluation Plan

A mixed-methods approach will be used to evaluate the adaptive learning platform with secondary students.

2.7.1 Quantitative Evaluation

Pre-test/Post-test Analysis: Students complete pre- and post-tests in Algebra, Geometry, and Trigonometry. Learning gains are calculated as the difference in scores to assess platform impact.

Trajectory Analytics: Individual θ trajectories are examined to document how the system adapts to each student's ability over time.

Time-to-Mastery Metrics: The system records attempts, and time spent on each topic until mastery, measuring adaptive learning efficiency.

2.7.2 Qualitative Evaluation

Student Feedback: Students provide feedback via questionnaires and brief interviews on usability, clarity, and engagement.

Expert Review: Teachers and subject matter experts assess the adaptive workflow and content alignment with the O/L syllabus.

This evaluation framework enables identification of improvements, assessment of personalized learning effectiveness, and evaluation of the platform's potential for scale-up.

3 Results

This section presents the outcomes of simulation-based analyses comparing adaptive and non-adaptive learning approaches across three student profiles: High-Ability Starter, Low-Ability Starter, and Mixed-Performance Student. Student ability (θ) was tracked over four to five practice stages using the three-parameter logistic (3PL) model, which incorporates item discrimination (a), difficulty (b), guessing (c), and the probability of a correct response (P(θ)). These analyses were conducted using the proof-of-concept system developed with a limited question bank to demonstrate the adaptive workflow. Key patterns are highlighted to illustrate differences in learning progression and the effectiveness of adaptive versus non-adaptive strategies.

3.1 Adaptive learner's Profile

Tables 1–3 summarize learner performance under the adaptive workflow, where item difficulty is dynamically adjusted based on the learner's current ability. These tables were formulated using an Item Response Theory (IRT)-based approach: each learner was assigned an initial ability (θ before) representing High, Low, or Middle performance. Items were selected from the pool based on their IRT parameters and the learner's current ability. For each stage, learner responses (correct / incorrect) were either observed or simulated based on the probability of a correct response, P(θ). After each response, the learner's ability (θ after) was updated using IRT estimation, and the next item's difficulty (b) and discrimination (a) were adjusted to keep the learner within an optimal challenge zone. For the High-Ability Starter (Table 1), items progressively increased in difficulty (b: 1.3 → 1.8; b: 0.8 → 1.6) as the learner answered correctly, resulting in continuous growth of ability (θ after: 1.00 → 1.80). This shows that the system maintained the learner in a challenging zone, where each correct response not only increased θ but also prompted a higher-difficulty item, supporting steady skill development. The Low-Ability Starter (Table 2) began with easier items (b after:0.5 → 0.2). When incorrect responses occurred, the system adjusted subsequent item difficulty downward or to a level appropriate for the learner's current ability, allowing gradual recovery and improvement (θ after: –0.70 → 0.10). This demonstrates how the adaptive workflow prevents stagnation by moderating challenges and enabling incremental gains in ability. The Middle-Performance student (Table 3) received items at intermediate difficulty, with adjustments reflecting both correct and incorrect responses. This approach resulted in moderate but steady improvement (θ after 0.00 → 0.40), as correct responses increased and item difficulty while incorrect responses moderated the c.

Table 1: Adaptive Learner—High-Ability Starter

Stage	a	b	c	θ Before	$P(\theta)$	Response	θ After
1	1.3	0.8	0.20	0.80	0.68	Correct	1.00
2	1.5	1.0	0.25	1.00	0.68	Correct	1.20
3	1.6	1.2	0.25	1.20	0.69	Correct	1.40
4	1.7	1.4	0.25	1.40	0.70	Correct	1.60
5	1.8	1.6	0.25	1.60	0.71	Correct	1.80

Table 2: Adaptive Learner—Low-Ability Starter

Stage	a	b	c	θ Before	$P(\theta)$	Response	θ After
1	1.0	-0.3	0.20	-0.50	0.44	Incorrect	-0.70
2	0.9	-0.5	0.15	-0.70	0.44	Correct	-0.50
3	1.0	-0.2	0.20	-0.50	0.46	Correct	-0.30
4	1.1	0.0	0.20	-0.30	0.48	Correct	-0.10
5	1.2	0.2	0.20	-0.10	0.50	Correct	0.10

Table 3: Adaptive Learner—Middle-Performance Student

Stage	a	b	c	θ Before	$P(\theta)$	Response	θ After
1	1.1	0.2	0.20	0.00	0.54	Correct	0.20
2	1.2	0.5	0.20	0.20	0.54	Incorrect	0.00
3	1.0	0.1	0.15	0.00	0.53	Correct	0.20
4	1.3	0.4	0.20	0.20	0.55	Correct	0.40
5	1.5	0.7	0.25	0.40	0.56	Incorrect	0.20

Figure 6 shows the development of student ability (θ), across sequential stages of learning for three sample learners. The trajectories demonstrate variations in change, with the High-Ability Starter exhibiting stable gains at each of the learning stages, the Low-Ability Starter exhibiting gains after initial declines, and the Mixed-Performance Student exhibiting a middle path with instability between the measured stages representing improved ability mixed with bad days. The figure presents a clear visual of how adaptive learning approaches can allow struggling learners to recover and continue to develop, while successful learners can continue to advance their abilities, through the modifications made to the difficulty of practice, all resulting in varied trajectories of growth for each learner profile.

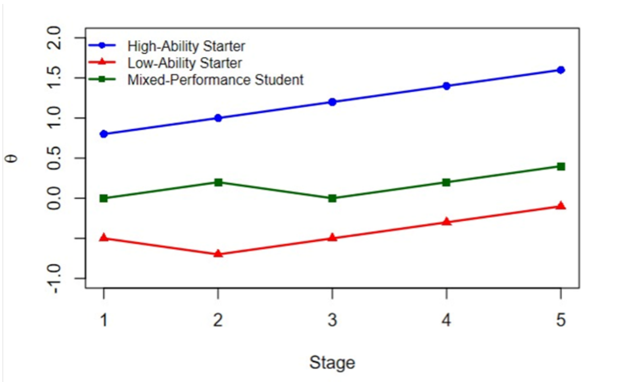

Fig. 6: Trajectories of student ability (θ) across learning stages for three learner profiles, highlighting stability, recovering, and fluctuating growth patterns under adaptive learning.

3.2 Non-Adaptive Learner Profile

Table 4 presents the evaluation results of learner performance under a non-adaptive workflow, where all students were given the same fixed sequence of items without adjustment to their ability level. Learner ability (θ) was estimated at each stage using an IRT -based evaluation of responses. In this non-adaptive workflow, the item difficulty parameter (b) remained fixed across learners, highlighting the absence of adaptation in task selection, while a and c were kept constant in the sequence. High-Ability learners demonstrate a gradual improvement in θ (0.80 → 1.30), though the fixed difficulty limited their rate of growth compared to the adaptive approach, which tailors item difficulty to maintain challenge. Low-Ability learners showed inconsistent performance, with θ fluctuating and only a slight net gain (–0.50 → –0.40). Middle-Performance learners achieved minimal improvement (0.00 → 0.20), reflecting how the fixed difficulty failed to provide adequate reinforcement or scaffolding. This evaluation highlights that without adaptive modifications, learning trajectories become constrained: high performers do not progress optimally, and struggling learners are not provided with sufficient support to recover, leading to disengagement and stagnation

Table 4: Non-Adaptive Learner—All Profiles (Fixed Item Sequence)

Stage	a	b	c	High-Ability θ	Low-Ability θ	Middle-Performance θ
1	1.3	0.8	0.20	0.80	-0.50	0.00
2	1.3	0.9	0.20	1.00	-0.60	0.10
3	1.3	1.0	0.20	1.10	-0.65	0.00
4	1.3	1.1	0.20	1.20	-0.50	0.10
5	1.3	1.2	0.20	1.30	-0.40	0.20

3.3 Comparison of Adaptive and Non-Adaptive Results

Adaptive learning systems are more effective than non-adaptive systems because they provide personalized learning paths, allowing all learners to achieve greater and faster improvements in ability. For high-ability students, dynamic adjustments in task difficulty accelerate learning, resulting in steeper learning curves and faster gains (θ increased from 0.80 to 1.60; P(θ) 0.68 → 0.70, Table 1). For low-ability learners, adaptive systems facilitate recovery after incorrect responses by presenting easier items, supporting gradual progression (θ recovered from –0.70 to –0.10; P(θ) 0.44 → 0.48, Table 2). Students with mixed performance, who fluctuate between low and high ability levels, remain engaged through continuous adjustments to item difficulty and discrimination. Although their ability values are less stable, they show an overall upward trend, reflecting incremental improvement (Table 3).

On the other hand, non-adaptive item ordering uses the same order for every learners regardless of their performance, providing very limited opportunity for growth for students at the low-ability and middle-performance levels (θ stagnates at about -0.40 for Low-Ability and at 0.20 for Middle-Performance; Table 4), but did show growth, albeit slow, for high-ability students (θ increased from about 0.80 to 1.30). These flat-to-variable learning rates signify a lack of personalization, which is a significant disadvantage in driving and maintaining learner motivation and growth.

Figure 7 displays the development of learner ability across six stages under different instructional conditions: Adaptive High-Ability, Adaptive Middle-Performance, Adaptive Low-Ability, Non-Adaptive High-Ability, Non-Adaptive Middle-Performance, and Non-Adaptive Low-Ability. The Y-axis represents ability estimates (θ, approximately –1.0 to 2.0), and the X-axis shows distinct learning stages (1–5). The adaptive groups (solid lines) show consistent upward trajectories. The Adaptive High-Ability group (solid blue) exhibits

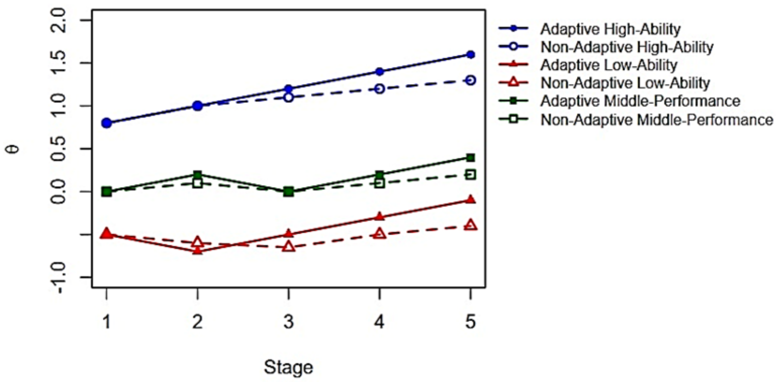

Fig. 7: Trajectories of learner ability across five stages under adaptive and non-adaptive instructional conditions, showing that adaptive learning yields higher and more consistent gains for all ability levels, whereas non-adaptive sequences produce slower or minimal improvements.

steady, straight-line improvement across all stages. The Adaptive Middle-Performance group (solid green) shows a moderate, positive trend, reflecting gradual gains. The Adaptive Low-Ability group (solid red) starts at a lower ability level but demonstrates noticeable improvement after the first stage, with a steadily increasing trajectory, though at a smaller rate. In contrast, the non-adaptive groups (dashed lines) display less pronounced gains. The Non-Adaptive High-Ability group (dashed blue) progresses slowly after an initially high ability, while the Non-Adaptive Middle-Performance group (dashed green) remains largely unchanged. The Non-Adaptive Low-Ability group (dashed red) shows minimal or no improvement. Overall, the figure highlights that adaptive learning promotes higher and more regular gains in ability across all starting levels, whereas non-adaptive conditions lead to slower or negligible improvements. This visual emphasizes how personalized, adaptive approaches can reduce learning gaps and enhance overall progression compared to fixed, non-adaptive sequences.

Figure 8 illustrates the layout of the adaptive GCE O/L Math Practice platform, which features three main tabs Algebra, Trigonometry, and Geometry located at the top of the exercise panel. Each tab provides a focused practice area, allowing students to select topics seamlessly while the platform delivers adaptive sequencing of questions tailored to their ability. As learners toggle between tabs, the application updates the question panel, user metrics, and previous attempt history, providing a fluid experience with personalized feedback. This design supports continuity and engagement across multiple mathematical domains, enabling students to track growth within each subject while benefiting from adaptive guidance.

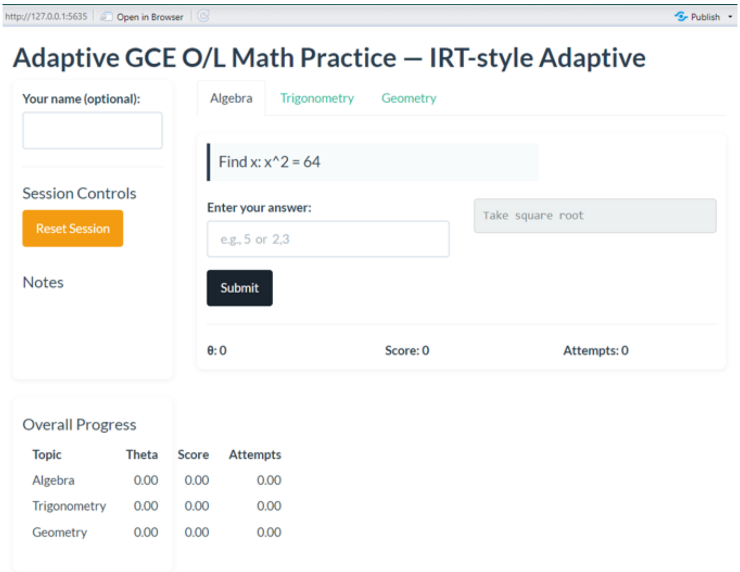

Fig. 8: Layout of the adaptive GCE O/L Math Practice platform, showing tabs for Algebra, Trigonometry, and Geometry, with adaptive question sequencing, user metrics, and feedback to support personalized learning across multiple mathematical domains.

4 Discussion

This concept paper demonstrates the feasibility of developing an adaptive learning platform for Sri Lankan secondary education grounded in Item Response Theory (IRT), implemented using R Shiny and supported by a MySQL database. Although the pilot study was limited in scale, the findings provide initial evidence that adaptive learning approaches can support improvements in student engagement, learning progression, and motivation in mathematics education.

The adaptive learning model employed in this study utilized the three-parameter logistic (3PL) IRT framework to dynamically align item difficulty with each learner's estimated ability level. This mechanism enabled differentiated learning pathways that respond to individual performance in real time. High-ability students were progressively challenged with more difficult items, contributing to steady growth in their ability estimates (θ). In contrast, low-ability students were presented with appropriately adjusted items following incorrect responses, allowing for gradual improvement rather than disengagement. This adaptive adjustment contrasts with fixed-sequence instructional models, where learners are often exposed to content that does not match their current level of understanding.

Qualitative feedback further supports these findings, indicating that immediate feedback, relevant item sequencing, and visual indicators of progress enhanced learners' sense of control and persistence. These features align with the principles of mastery learning, in which progression is based on demonstrated understanding rather than a fixed instructional pace. This approach is particularly relevant in the Sri Lankan secondary education context, where classrooms typically include students with wide variations in prior knowledge and ability. By accommodating this heterogeneity, adaptive learning systems may help reduce frustration among struggling learners while maintaining appropriate challenges for advanced students.

The observed learning trajectories in this study are consistent with findings reported in prior IRT-based and adaptive learning research, which highlight the advantages of dynamically adjusting item difficulty to match learner ability. Like previous studies, high-ability learners benefited from increased challenge through progressively more difficult items, while low-ability learners were supported through adaptive reductions in difficulty following incorrect responses. In contrast to non-adaptive systems commonly reported in the literature, which often lead to stagnation or disengagement among struggling learners, the proposed system demonstrated recovery and gradual improvement in ability for low- and mixed-performance learners. The integration of the 3PL model within a real-time R Shiny environment further distinguishes this work by enabling immediate feedback, continuous ability updating, and transparent learner trajectories, demonstrating the practical potential of IRT-driven adaptive learning for G.C.E. O/L mathematics education.

The outcomes observed in this study are consistent with findings reported in international research on adaptive and IRT-based learning systems, which show that tailoring content to learner ability and providing timely feedback can improve mathematics achievement. In line with this literature, the present study demonstrates that dynamic item selection and continuous ability updating can support differentiated learning trajectories. Empirical evidence further supports these observations. For example, (Crowley, 2018) reported that adaptive supplemental instruction significantly improved elementary students' mathematics achievement, while (Hwang, 2022) found that adaptive learning technologies enhanced cognitive abilities in mathematics education. Together, these findings underscore the potential of adaptive learning systems to improve educational outcomes across diverse contexts and provide external validation for the patterns observed in this pilot study.

Despite these promising observations, several limitations must be acknowledged. The small sample size restricts the generalizability of the findings, and item parameters were initially assigned based on expert judgment rather than empirical calibration, which may affect the precision of ability estimates. In addition, reliance on stable internet connectivity may limit deployment in rural or resource-constrained settings. The absence of automated item classification and advanced data security mechanisms also raises concerns regarding scalability and long-term implementation.

Nevertheless, the modular design of the prototype provides a strong foundation for future development. Expanding the item bank, empirically calibrating item parameters using established IRT tools, and increasing the participant base would allow for more robust evaluation and subgroup analysis. Further enhancements could include the integration of machine learning techniques to refine ability estimation and automate item selection, as well as extending the adaptive framework to subjects beyond mathematics.

This study illustrates that adaptive learning, when grounded in the 3PL IRT framework, offers a viable and effective alternative to traditional instructional methods in Sri Lankan secondary education. While the current prototype is limited in scope, the positive preliminary findings suggest that adaptive learning systems have the potential to enhance learning outcomes by providing personalized, responsive, and efficient instruction. With further development and empirical validation, such systems could play a pivotal role in transforming education in Sri Lanka and similar contexts.

5 Conclusion

This pilot study demonstrates that integrating Item Response Theory (IRT) into an R Shiny–based adaptive learning environment can provide personalized mathematics instruction for secondary school students in Sri Lanka. The system enhanced student engagement, incremental learning, and mastery by tailoring content and feedback to each learner's ability, enabling high-achieving students to progress efficiently, lower-achieving students to build confidence through appropriately adjusted tasks, and mixed-ability learners to maintain steady learning trajectories. The use of R Shiny proved effective for mathematics instruction by supporting interactive problem-solving, real-time computation, and immediate feedback, thereby fostering active learner engagement. Although the study was limited by its scale and the use of fixed-step ability updates, the findings provide preliminary evidence supporting the potential of adaptive learning systems to improve learning outcomes and learner motivation. With future work involving empirically calibrated item parameters, refined ability estimation methods, and platform-level scaling, the proposed system could achieve broader educational impact. Overall, this study highlights the promise of IRT-based adaptive learning systems in enabling more equitable, effective, and engaging mathematics education in resource-constrained contexts.

6 Acknowledgement of AI Assistance

This manuscript benefited from the use of artificial intelligence tools. OpenAI's ChatGPT was employed to assist with language refinement, enhance clarity, and rephrase certain passages. All final content was reviewed and approved by the authors.

7 References

Agresti, A. (1992). Analysis of ordinal paired comparison data. *Journal of the Royal Statistical Society*, 41(2), 287–297.

Ariyadi, D. J. (2025). Application of three-parameter logistic (3PL) item response theory in learning management system (LMS) for post-test analysis. *Journal of Informatics Development*, 3(2), 33–46. DOI: 10.30741/jid.v3i2.1554.

Crowley, K. (2018). The impact of adaptive learning on mathematics achievement. *Doctoral dissertation, ProQuest Dissertations & Theses Global*.

Damayanthi, B. W. R. (2018). Academic performance of students: The effect of classroom level factors and private tutoring. *American Journal of Educational Research*, 6(3), 262–269. DOI: 10.12691/education-6-3-13.

Fahrmeir, L. and Tutz, G. (1994). Multivariate statistical modeling based on generalized linear models. *Springer-Verlag*, New York.

Gyamfi, A. and Acquaye, R. (2023). Parameters and models of item response theory (IRT): A review of literature. *Acta Educationis Generalis*, 13(3), 68–78. DOI: 10.2478/atd-2023-0022.

Hwang, S. (2022). Examining the effects of artificial intelligence on elementary students' mathematics achievement: A meta-analysis. *Sustainability*, 14(20), 13185. DOI: 10.3390/su142013185.

Jayasuriya, J. E., Mampitiya, U. and Lecture, M. (2014). Twenty fourth mathematics education – past, present and future. *Department of Education, University of Colombo*.

Kannisto, V., Lauritsen, J., Thatcher, A. R. and Vaupel, J. W. (1994). Reductions in mortality at advanced ages: Several decades of evidence from 27 countries. *Population and Development Review*, 20, 793–809.

Karjanto, N. and Acelajado, M. J. (2022). Sustainable learning, cognitive gains, and improved attitudes in college algebra flipped classrooms. *arXiv preprint*, arXiv:2210.15979.

Lu, Y., Supriya, K., Shaked, S., Simmons, E. H. and Kusenko, A. (2024). Incentivizing supplemental math assignments and using AI-generated hints improve exam performance, especially for racially minoritized students. *arXiv preprint*, arXiv:2412.19961.

Ministry of Education (2019). Annual performance report – 2019. *Ministry of Education*, Sri Lanka.

Nguyen, T. C. and Le, C. T. (2020). A case study by using Khan Academy, an open-source environment. *Vietnam Journal of Education*, 4(4), 22–27. DOI: 10.52296/vje.2020.76.

Ogunsakin, I. B. and Shogbesan, Y. (2018). Item response theory (IRT): A modern statistical theory for solving measurement problems in the 21st century. *International Journal of Scientific Research in Education*.

Silva, H. P. T. N. and Banneheka, B. M. S. G. (2019). Factors associated with mathematics results at G.C.E. (O/L) examination. *Vidyodaya Journal of Humanities and Social Sciences*, 3, Article v03i00.4068. DOI: 10.31357/fhss/vjhss.v03i00.4068.

Thilan, A. W. L. P., Fisher, R., Thompson, H., Menendez, P., Gilmour, J. and McGree, J. M. (2022). Adaptive monitoring of coral health at Scott Reef where data exhibit nonlinear and disturbed trends over time. *Ecology and Evolution*, 12(9), e9233. DOI: 10.1002/ece3.9233.

Thilan, A. W. L. P., Menéndez, P. and McGree, J. M. (2023). Assessing the ability of adaptive designs to capture trends in hard coral cover. *Environmetrics*, 34(6), e2802. DOI: 10.1002/env.2802.