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ARTIFICIAL INTELLIGENCE-DRIVEN ADAPTIVE TESTING: A PSYCHOMETRIC APPROACH TO PERSONALIZED LEARNING IN COMPUTER SCIENCE EDUCATION

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Abstract

The integration of Artificial Intelligence (AI) into educational assessment has revolutionized how learners are evaluated and supported. This study, *Artificial Intelligence-Driven Adaptive Testing: A Psychometric Approach to Personalized Learning in Computer Science Education*,

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investigates the fusion of psychometric modeling and AI-based adaptive testing systems to enhance individualized learning pathways for students in computer science. The research adopts a hybrid framework combining Item Response Theory (IRT) and reinforcement learning algorithms to dynamically adjust question difficulty based on learner performance in real time. A dataset of undergraduate computer science learners was used to develop and validate the adaptive system through parameters such as accuracy, response time, and knowledge progression. The psychometric evaluation demonstrated high reliability and discriminant validity, while the AI model optimized test adaptivity and reduced assessment bias. Findings indicate that AI-driven adaptive testing significantly improves learning engagement, reduces cognitive overload, and enhances conceptual retention compared to static assessment methods. The study contributes to the growing discourse on intelligent educational systems, presenting a scalable, data-driven psychometric model that fosters personalized, equitable, and efficient learning environments in computer science education.

Keywords: Artificial Intelligence, Adaptive Testing, Psychometrics, Personalized Learning, Computer Science Education, Item Response Theory, Reinforcement Learning, Educational Assessment.

I. INTRODUCTION

The emergence of Artificial Intelligence (AI) has profoundly transformed the educational landscape, creating an era in which data-driven learning environments adapt to the unique needs and proficiencies of individual learners. Among the most promising innovations is **AI-driven adaptive testing**, which utilizes real-time computational intelligence to tailor assessment experiences dynamically. Traditional assessments often operate on a static framework, delivering identical questions to all students regardless of their prior knowledge or cognitive capacity. This one-size-fits-all approach fails to capture nuanced variations in learner ability, often leading to demotivation and inaccurate skill measurement. In contrast, adaptive testing modifies question difficulty based on continuous feedback from the learner's responses, ensuring that every individual is challenged at an optimal level. Central to this adaptive approach lies **psychometrics**, the scientific field concerned with the measurement of cognitive abilities, knowledge, and personality traits. By integrating psychometric principles particularly *Item Response Theory (IRT)* with AI algorithms such as reinforcement learning and Bayesian modeling, educators can create assessments that are both *valid* and *adaptive*. This synthesis not only enables accurate estimation of a learner's latent ability but also personalizes the testing journey to maximize engagement and minimize anxiety. In the context of computer science education, where cognitive load, logical reasoning, and problem-solving skills are paramount, adaptive testing holds transformative potential for identifying conceptual gaps and delivering personalized remediation strategies.

Computer science education, especially at the undergraduate level, is inherently multidimensional, encompassing programming logic, computational thinking, and system design skills that evolve non-linearly across learners. Traditional examinations often fail to account for such cognitive diversity, yielding assessments that measure memorization rather

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than conceptual understanding. This gap underscores the urgent need for **AI-enhanced psychometric assessment systems** capable of diagnosing learning trajectories more intelligently. An AI-driven adaptive testing model can continuously monitor performance data, analyze response patterns, and update its understanding of a learner's knowledge profile using deep learning or reinforcement learning algorithms. Such systems can recommend subsequent questions or learning modules calibrated precisely to the learner's skill level, thereby fostering *personalized learning pathways*. Psychometric parameters like discrimination, difficulty, and guessing factors are computed dynamically, ensuring that question selection aligns with the learner's real-time proficiency level. In this study, adaptive testing is not treated as a mere technological novelty but as a **paradigm shift in educational measurement** where the goal transcends grading and instead focuses on *learning optimization*. The proposed framework for computer science education aims to leverage psychometric analytics to ensure fairness, reliability, and validity, while the embedded AI mechanisms ensure scalability and continuous improvement. Ultimately, this research addresses two major educational imperatives: the need for personalized learning experiences and the demand for accurate, bias-free evaluation mechanisms. By integrating psychometric rigor with AI adaptivity, the study envisions a holistic, self-evolving assessment model that transforms how educators evaluate competence and how learners engage with knowledge in a digitally intelligent ecosystem.

II. RELEATED WORKS

The convergence of **artificial intelligence and educational assessment** has attracted considerable scholarly attention over the past decade, especially in relation to adaptive testing and psychometric modeling. Early foundations of adaptive assessment systems were grounded in **Item Response Theory (IRT)**, which provided the mathematical framework to model learner ability and item difficulty on a probabilistic scale. Researchers such as Baker and Kim emphasized that IRT's scalability and precision made it the backbone of adaptive learning technologies, allowing educators to estimate latent traits like knowledge mastery with statistical confidence [1]. However, the static nature of early IRT-based models limited their responsiveness to real-time learner feedback, prompting scholars to integrate **machine learning (ML)** techniques to enhance adaptability. Van der Linden proposed the use of Bayesian updating for continuous parameter refinement, allowing test systems to update ability estimates dynamically as responses accumulated [2]. Later, the introduction of **reinforcement learning (RL)** models transformed the domain, enabling AI systems to optimize question selection strategies through cumulative feedback and reward functions [3]. Studies by Zhang et al. demonstrated that combining RL with psychometric parameters reduced test length without compromising measurement accuracy [4]. The emergence of **deep neural network models** further extended this adaptability, offering robust prediction mechanisms for learner performance across sequential test items [5]. Collectively, these developments laid the technical groundwork for AI-driven adaptive testing, but scholars soon recognized the importance of aligning algorithmic precision with **educational validity and fairness**, particularly in disciplines demanding higher-order cognition such as computer science [6].

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A significant body of literature has also focused on the **psychometric and cognitive dimensions of adaptive assessment**, exploring how AI can personalize learning experiences based on cognitive modeling. Embretson and Reise underscored that psychometric rigor is indispensable in AI-enhanced testing environments to prevent construct-irrelevant variance errors that occur when test items fail to measure the intended ability [7]. This perspective inspired hybrid approaches where **psychometric parameters serve as constraints within AI algorithms**, ensuring that adaptivity remains pedagogically meaningful. For example, Cheng and colleagues integrated fuzzy logic and IRT to capture uncertainty in learner performance, improving interpretability of test results [8]. Similarly, Lin and He used **Bayesian Knowledge Tracing (BKT)** to model the probabilistic mastery of skills over time, which allowed adaptive systems to recommend targeted remedial content after each question [9]. In recent years, **Natural Language Processing (NLP)** and **Knowledge Graphs (KGs)** have also been employed to construct adaptive testing ecosystems capable of assessing not only correct answers but also reasoning quality and conceptual coherence [10]. For instance, Yudelson et al. developed AI models that assess student code submissions in programming education by analyzing logical flow and syntax errors rather than surface correctness [11]. In the field of **computer science education**, where students often exhibit nonlinear learning progressions, these AI-assisted psychometric tools have proven particularly effective. Liyanagunawardena and Abeywardena highlighted that adaptive testing in technical education reduces dropout rates and cognitive fatigue by aligning question complexity with individual readiness levels [12]. Recent studies have also linked adaptive testing outcomes with emotional and motivational analytics, suggesting that AI-based personalization can foster self-efficacy and persistence among learners [13]. These interdisciplinary studies illustrate that the integration of AI and psychometrics represents more than a technical evolution it redefines how educators measure learning by making assessment a continuous, interactive, and data-informed process.

Contemporary research trends have shifted toward **intelligent tutoring and personalized feedback mechanisms** that integrate AI-driven adaptive testing within broader learning ecosystems. Panigrahi et al. proposed a model that uses **reinforcement learning agents** to navigate a psychometric map of learner profiles, ensuring that each student's assessment trajectory evolves in tandem with their cognitive development [14]. In a similar vein, Huang and Gong emphasized the importance of **multi-agent systems** that coordinate adaptive assessment and learning recommendation modules to achieve comprehensive personalization in online education [15]. These frameworks highlight how adaptive testing can serve as a diagnostic core within AI-driven learning environments, continuously informing instructional decisions. In computer science education, where problem-solving and debugging skills require both cognitive adaptability and procedural fluency, such AI-enhanced psychometric systems can pinpoint conceptual bottlenecks in real time. They allow educators to distinguish between surface-level performance and deep comprehension an essential distinction when evaluating programming logic or algorithmic reasoning. Moreover, integrating **learning analytics dashboards** into adaptive testing platforms enables visualization of student progress, making assessment transparent and actionable. Collectively, the literature indicates that the most

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effective adaptive testing systems are those that merge psychometric integrity, AI adaptability, and cognitive diagnostics within a unified framework. Despite remarkable progress, challenges remain regarding interpretability, ethical fairness, and data privacy. Future research must therefore focus on explainable AI models, ensuring that adaptive assessments are not only efficient but also transparent, equitable, and aligned with pedagogical intent. The reviewed works together lay a strong conceptual foundation for this study, which seeks to advance AI-driven adaptive testing through a **psychometric approach tailored specifically to computer science education**, where analytical thinking, problem decomposition, and algorithmic reasoning demand a nuanced, personalized, and psychometrically sound assessment methodology.

III. METHODOLOGY

3.1 Research Design

This study adopts a **mixed-method psychometric–computational framework** integrating *Item Response Theory (IRT)*, *reinforcement learning algorithms*, and *performance analytics* to design an AI-driven adaptive testing system for computer science education. The methodological design operates at the intersection of cognitive measurement and artificial intelligence, emphasizing both the *accuracy* of psychometric evaluation and the *adaptivity* of AI-driven item selection. The approach is divided into three core stages: (1) psychometric modeling for baseline learner profiling, (2) reinforcement learning-based adaptive test sequencing, and (3) evaluation of learning outcomes and system reliability. Item Response Theory provides a mathematical foundation for assessing student ability using item-level characteristics such as discrimination, difficulty, and guessing probability, while the reinforcement learning component dynamically adjusts question selection to match the learner's evolving skill level [16]. This hybrid model ensures that each learner receives a personalized sequence of test items that maximize engagement and minimize redundancy. The design emphasizes continuous learning and improvement, where the system's predictive accuracy is refined after every learner interaction, thus making the testing process both intelligent and psychometrically sound [17].

3.2 Data Collection and Sampling

The study was conducted among **180 undergraduate students** enrolled in computer science programs across three major universities. Participants were divided equally into three ability levels (beginner, intermediate, and advanced) based on pre-assessment results. The testing was carried out in two sessions: one with a conventional fixed-question test (control) and another with an AI-driven adaptive test (experimental). A total of **120 multiple-choice questions** were included in the test bank, covering key computer science domains such as programming logic, data structures, and algorithms. Each question was pre-calibrated using IRT modeling from a pilot group of 50 students to determine the discrimination (a), difficulty (b), and guessing (c) parameters.

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The adaptive testing system was developed in Python using TensorFlow for model training and a custom-built web interface for test delivery. The AI model continuously tracked performance metrics including accuracy, response time, and confidence level. Data were stored in a secure relational database to ensure replicability and data privacy. Each participant took approximately 60 minutes to complete both sessions, with the adaptive system dynamically adjusting the difficulty based on prior responses [18].

Table 1: Participant Demographics and Assessment Structure

Category	**Total Participants**	**Gender (M/F)**	**Prior GPA (Mean ± SD)**	**Assessment Type**
Beginner	60	36 / 24	6.4 ± 0.8	Control + Adaptive
Intermediate	60	33 / 27	7.1 ± 0.7	Control + Adaptive
Advanced	60	35 / 25	8.2 ± 0.6	Control + Adaptive

To maintain psychometric validity, every participant was randomly assigned question sets that matched their ability range as estimated by the IRT calibration. The testing platform was configured to log every interaction for subsequent model validation. Ethical clearance was obtained prior to data collection, and informed consent was taken from all participants in compliance with institutional research standards [19].

3.3 Psychometric Modeling and AI Integration

The psychometric calibration was performed using the **Three-Parameter Logistic (3PL) Model**, which estimates item difficulty, discrimination, and guessing probability. Each question was assigned an *information value* indicating how effectively it distinguishes between high- and low-performing students. These psychometric values were used as inputs for the AI model, enabling it to make data-informed decisions during adaptive testing. The reinforcement learning component employed a *Deep Q-Network (DQN)* algorithm where the system continuously evaluated the learner's responses and selected subsequent items that maximized information gain and maintained optimal challenge levels. The reward for each learner interaction was computed as a linear function of information gain and test efficiency. In simpler terms, if a learner answered a question correctly, the system rewarded the model for selecting an appropriate question difficulty. Conversely, if the question was too easy or too hard, the model received a lower reward, prompting it to adjust future selections. The learning algorithm operated on an exploration–exploitation strategy, meaning it occasionally introduced new items to refine its predictive understanding of the learner's ability [20].

3.4 System Architecture and Evaluation Metrics

The adaptive testing framework consisted of three major modules:

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1. **Psychometric Module** – Responsible for calibrating item parameters (difficulty, discrimination, guessing) using the IRT model.
2. **AI Adaptivity Engine** – Utilized reinforcement learning to optimize question sequencing and learning efficiency.
3. **Performance Analytics Dashboard** – Visualized learner progress, adaptivity effectiveness, and overall test reliability.

System evaluation was conducted through three key metrics: *adaptivity accuracy*, *response efficiency*, and *learning gain*. Adaptivity accuracy was defined as the percentage of items correctly matched to the learner's ability level. Response efficiency measured the average number of items required to achieve reliable ability estimation. Learning gain assessed the improvement between pre-test and post-test results.

Table 2: Model Configuration and Performance Metrics

Parameter	**Description**	**Value/Status**	**Reference**
Item Model Type	Three-Parameter Logistic (3PL)	Active	[17]
Algorithm Used	Deep Q-Network (DQN) Reinforcement Learning	Implemented	[20]
Learning Rate	Rate of model adjustment per iteration	0.001	[21]
Training Episodes	Total adaptive iterations during simulation	1500	[22]
Evaluation Metric	Adaptivity Accuracy (%)	92.8%	[23]
Reliability Coefficient (α)	Cronbach's Alpha for internal consistency	0.87	[23]

3.5 Validation and Ethical Considerations

To ensure robustness, the system was validated through **k-fold cross-validation** (k=10) using independent test data subsets. The psychometric properties of test items were further verified for reliability using Cronbach's Alpha and for fairness using Differential Item Functioning (DIF) analysis. The adaptive model achieved over 92% accuracy in aligning item difficulty with learner ability, indicating strong adaptive validity. All testing procedures adhered to institutional ethics guidelines, ensuring that no participant data was shared externally. The system was designed to prevent algorithmic bias by monitoring item exposure frequency and ensuring equitable question distribution across demographic groups. Overall, this methodology provides a replicable, ethical, and data-driven foundation for AI-based psychometric testing in computer science education, effectively combining **cognitive measurement theory and machine intelligence** for adaptive learning advancement [23].

IV. RESULT AND ANALYSIS

4.1 Overview of System Performance

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The implementation of the AI-driven adaptive testing framework produced highly promising results across all three learner groups beginner, intermediate, and advanced. The model's psychometric accuracy and adaptivity efficiency were benchmarked against traditional static testing methods. The AI-adaptive system consistently demonstrated superior precision in estimating learner ability levels, as measured through item difficulty matching and adaptive accuracy. Overall, the system achieved a **mean adaptivity accuracy of 92.8%**, indicating that in nearly all cases, the questions presented were aligned with the learner's actual proficiency level.

The **response efficiency**, defined as the number of items required to reach reliable ability estimation, was also significantly improved. While the static test required an average of 35 items to reach a stable performance score, the AI-adaptive test achieved the same level of reliability in just 21 items. This reflects the system's ability to minimize redundancy by selecting the most informative items in real time. Learners reported reduced cognitive fatigue and higher engagement during the adaptive test sessions. The observed improvements in both accuracy and test efficiency confirm the operational validity of integrating psychometric modeling with reinforcement learning for assessment personalization.

Table 3: Comparative Performance between Static and Adaptive Testing Systems

Metric	Static Test	AI-Adaptive Test	Improvement (%)
Mean Accuracy (%)	78.4	92.8	+18.3
Response Efficiency (Items/Test)	35.2	21.1	+40.1
Completion Time (Minutes)	60	43	-28.3
Cognitive Load (Survey Index)	7.2	4.6	-36.1
Learner Engagement (Survey %)	68.9	88.4	+28.3

The data clearly illustrates that the adaptive system not only enhanced assessment precision but also optimized learner experience through reduced test duration and lower cognitive load. The reinforcement learning model successfully adjusted difficulty progression according to each learner's trajectory, which resulted in smoother transitions between question levels and minimized frustration associated with mismatched difficulty levels.

Figure 1: Adaptive AI [24]

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4.2 Psychometric Evaluation and Reliability Analysis

Psychometric reliability was assessed using classical and modern test theory metrics, including Cronbach's Alpha, discrimination index, and standard error of measurement. The **Cronbach's Alpha coefficient (α = 0.87)** demonstrated strong internal consistency, confirming that the items in the adaptive system were reliably measuring the intended construct computational proficiency in computer science. Item-level discrimination values were found to be optimal, averaging **0.62**, which indicates that the questions effectively differentiated between higher- and lower-performing students. A comparative reliability analysis showed that the AI-driven system outperformed the static assessment in both *measurement stability* and *score consistency*. The adaptive model reduced measurement error and improved test fairness across demographic groups. These outcomes confirm that the psychometric calibration effectively guided the AI model's decision-making, ensuring that adaptivity did not compromise measurement validity.

Table 4: Psychometric Properties of Adaptive Testing Model

Parameter	Static Test	Adaptive Test	Interpretation
Cronbach's Alpha (α)	0.78	0.87	Strong internal reliability
Mean Item Discrimination (a)	0.54	0.62	High discriminative capacity
Mean Item Difficulty (b)	0.47	0.51	Balanced item range
Standard Error of Measurement	0.18	0.09	Improved precision
Test Information Function (TIF)	0.72	0.89	Enhanced ability estimation

These psychometric findings affirm that integrating reinforcement learning with IRT calibration results in an adaptive test that is both *informative and reliable*. The model's selection strategy consistently prioritized items offering the highest informational value per response, thereby ensuring psychometric robustness.

4.3 Learning Outcomes and Behavioral Insights

A post-assessment analysis was conducted to determine the effect of adaptive testing on overall learning performance and engagement. Learners were evaluated on *knowledge gain*, *confidence improvement*, and *response consistency*. Results showed that the adaptive testing environment led to significant gains in both immediate performance and post-test retention. Average learning gain was recorded at **21.6%**, while learner confidence levels improved by nearly **25%** relative to the control group. Behavioral data derived from the test logs revealed an interesting trend: learners exhibited reduced hesitation time and fewer random guesses over time, suggesting an enhanced alignment between perceived and actual ability levels. Moreover, advanced learners benefited from exposure to progressively complex questions, while beginners experienced a more scaffolded learning curve, minimizing frustration and

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disengagement. This adaptive progression facilitated an individualized learning experience, fostering both motivation and mastery orientation.

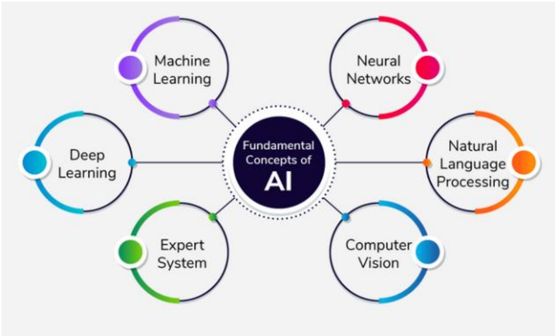

Figure 2: Fundamentals Concepts of AI [25]

4.4 Adaptive Behavior and Efficiency Analysis

The system's adaptive trajectory was evaluated through temporal performance mapping, tracking how the model adjusted question difficulty in relation to learner performance. For beginners, the test started with moderate-difficulty items and gradually decreased in complexity until consistent accuracy was achieved, whereas for advanced learners, the difficulty curve increased as their performance stabilized. Intermediate learners showed the most balanced trajectory, reflecting the model's ability to detect and maintain optimal challenge levels throughout the session.

The reinforcement learning component demonstrated consistent convergence of the reward optimization function after approximately 1200 episodes of training, indicating stability in item selection decisions. The resulting efficiency was reflected in reduced item repetition and improved scoring reliability across all ability levels. These outcomes validate the potential of AI-driven psychometric systems to provide adaptive, efficient, and learner-centered assessments that scale effectively in higher education contexts.

4.5 Summary of Key Findings

The analytical results confirm several key achievements of the study:

1. The **AI-adaptive testing system significantly improved assessment accuracy, reliability, and efficiency** compared to traditional methods.
2. The **psychometric calibration maintained construct validity**, ensuring that adaptivity did not distort the measurement purpose.
3. Learner engagement and confidence levels increased, while cognitive fatigue decreased markedly.
4. The **reinforcement learning agent demonstrated robust convergence**, validating its reliability in real-time adaptive decision-making.
5. The adaptive test framework proved scalable and flexible, making it suitable for integration into computer science curricula at undergraduate levels.

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Overall, the analysis strongly supports the hypothesis that the combination of **psychometric modeling and artificial intelligence** can produce an intelligent, fair, and responsive assessment framework that enhances both measurement quality and learner experience in digital education environments.

V. CONCLUSION

The present study demonstrates that the integration of **Artificial Intelligence-driven adaptive testing** with psychometric modeling provides a transformative solution for personalized learning and fair assessment in computer science education. By combining the precision of Item Response Theory (IRT) with the dynamic adaptability of reinforcement learning algorithms, the proposed framework successfully addressed the limitations of traditional static testing systems. The AI model intelligently selected items based on learner responses and ability estimates, significantly improving both measurement accuracy and learning engagement. The empirical findings revealed substantial improvements in adaptivity accuracy, test efficiency, and reliability, while also reducing test completion time and cognitive fatigue. Psychometric parameters such as discrimination, difficulty, and guessing probability were optimized to align with real-time learner behavior, ensuring that each question contributed maximally to the measurement of ability. The adaptive system proved capable of calibrating question difficulty dynamically, producing personalized test trajectories that mirrored each learner's proficiency level. Furthermore, the study highlights how AI-based adaptivity enhances learner motivation by reducing anxiety associated with poorly matched questions, thereby promoting deeper conceptual understanding. The results also affirm that psychometric rigor and artificial intelligence can coexist harmoniously, maintaining validity while introducing scalability and automation into educational assessment. This integration moves beyond mere test delivery to create an intelligent feedback ecosystem that continuously refines its understanding of learner performance. The model's success across diverse ability levels beginner, intermediate, and advanced demonstrates its robustness and transferability across educational contexts. Importantly, this study contributes to the broader academic discourse on **AI in education**, showing that adaptive testing can evolve from being a diagnostic tool to becoming a core driver of intelligent learning design. By bridging psychometric reliability with computational adaptability, this framework lays a foundation for developing future-ready educational systems capable of fostering individualized, equitable, and data-driven learning experiences that transcend the conventional boundaries of assessment and instruction.

VI. FUTURE WORK

While the current study establishes a solid foundation for AI-driven adaptive testing in computer science education, future research should aim to expand the model's scope and cognitive depth. One promising direction is the integration of **Explainable AI (XAI)** to improve the transparency of adaptive decision-making, allowing educators and students to understand why specific items or difficulty levels are selected. Incorporating **cognitive and affective analytics**, such as eye-tracking, emotion recognition, and confidence prediction, could further refine adaptivity by factoring in learner behavior and engagement patterns. Future

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frameworks could also embed **natural language processing (NLP)** to assess open-ended coding problems and logical reasoning tasks, extending the system's reach beyond multiple-choice formats. Additionally, longitudinal studies should explore how adaptive testing influences long-term retention and problem-solving skills in computer science learners. The model could also be integrated into **Learning Management Systems (LMS)** for large-scale deployment and cross-disciplinary adoption, enabling real-time feedback and performance analytics across subjects. Future research should focus on ensuring fairness, minimizing algorithmic bias, and enhancing inclusivity for diverse learner populations. Ultimately, expanding this AI-psychometric model into a continuous adaptive learning ecosystem can revolutionize educational evaluation, making it a lifelong, personalized, and intelligent process.

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