

AlgoQuest: An Agentic AI-Powered DSA Revision System

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Abstract

In the current landscape of technical recruitment, proficiency in Data Structures and Algorithms (DSA) has become a critical requirement for aspiring software engineers. Despite the availability of numerous online coding platforms, learners often face challenges in mastering DSA due to the lack of personalized guidance, adaptive learning paths, and real-time feedback mechanisms. Traditional systems largely rely on static problem sets and binary evaluation methods, which fail to address individual learning gaps and cognitive differences.

This research introduces AlgoQuest, an Agentic AI-powered gamified DSA revision system that aims to transform the learning experience by integrating multi-agent artificial intelligence with adaptive learning strategies. The proposed system employs a collaborative agent-based architecture, where specialized AI agents analyze user-submitted code, identify

logical errors, and provide scaffolded hints instead of complete solutions. This approach encourages critical thinking and enhances conceptual understanding.

Furthermore, AlgoQuest incorporates gamification elements such as reward systems, level progression, and performance tracking to improve user engagement and motivation. The system dynamically adjusts problem difficulty based on user performance metrics, ensuring an optimal learning curve. Experimental evaluation demonstrates that AlgoQuest significantly reduces dropout rates, improves problem-solving efficiency, and enhances user satisfaction.

The proposed system represents a paradigm shift from traditional static coding platforms to intelligent, personalized tutoring systems, offering a scalable and effective solution for DSA learning.

Keywords: Agentic AI, DSA, Gamification, Personalized Learning, Adaptive Systems, LLM, Intelligent Tutoring Systems.

1. Introduction

The rapid growth of the software industry has intensified the importance of algorithmic problem-solving skills. Data Structures and Algorithms (DSA) form the backbone of technical interviews, and proficiency in these areas is often a decisive factor in securing employment in top technology companies. However, despite the abundance of learning resources, a significant number of students struggle to effectively revise and apply DSA concepts.

As highlighted in your synopsis, current learning platforms exhibit several limitations:

- Lack of personalized feedback mechanisms
- Absence of adaptive difficulty adjustment
- Over-reliance on static problem repositories
- Limited support for conceptual understanding

Most platforms evaluate user solutions using predefined test cases, providing only binary feedback (correct/incorrect). This approach does not offer insights into the reasoning process or highlight specific logical errors, leading to inefficient learning.

Another major issue is the “difficulty cliff” phenomenon, where students experience a sudden increase in problem complexity. Without incremental guidance, many learners become overwhelmed and abandon their preparation.

To overcome these challenges, there is a need for a system that mimics the behavior of a human tutor—one that understands the learner’s thought process, provides step-by-

step guidance, and adapts to individual learning needs.

AlgoQuest addresses this need by introducing an Agentic AI-based tutoring system that combines:

- Multi-agent reasoning
- Real-time feedback
- Gamified learning environment

The system transforms DSA revision into an interactive and engaging experience, enabling learners to develop deeper conceptual understanding and problem-solving skills.

2. Literature Review

2.1 Traditional Coding Platforms and Their Limitations

Over the past decade, online coding platforms such as LeetCode, HackerRank, and GeeksforGeeks have become the primary resources for learning and practicing Data Structures and Algorithms (DSA). These platforms offer extensive repositories of problems categorized by difficulty levels, enabling learners to practice a wide range of algorithmic challenges. While these platforms have significantly contributed to improving coding skills, they are inherently limited in their pedagogical design.

Most traditional platforms operate on a static evaluation model, where user-submitted solutions are assessed based on predefined test cases. The feedback provided is typically binary in nature, indicating whether the solution is correct or incorrect. This approach fails to capture the underlying reasoning process of the learner and does not provide actionable insights into logical errors or misconceptions. As a result,

learners often struggle to understand why their solutions fail, leading to repeated mistakes and inefficient learning cycles.

Furthermore, these platforms lack adaptive learning capabilities. All users are presented with the same set of problems, irrespective of their skill level, prior knowledge, or learning pace. This "one-size-fits-all" approach creates significant challenges, particularly for beginners who may find advanced problems overwhelming, and for advanced learners who may find simpler problems unchallenging.

Another critical limitation is the absence of guided learning mechanisms. When learners encounter difficulties, they are often left with two extreme options: either view the complete solution or abandon the problem altogether. This binary choice disrupts the learning process, as viewing full solutions can hinder independent thinking, while abandoning problems reduces confidence and motivation.

2.2 Artificial Intelligence in Education and Personalized Learning

The integration of Artificial Intelligence (AI) in education has opened new possibilities for personalized and adaptive learning systems. AI-driven educational platforms leverage machine learning algorithms to analyze user behavior, identify learning patterns, and provide customized content tailored to individual needs.

As demonstrated in your Minor 1 research, AI can effectively process complex user data to generate personalized recommendations. In the context of education, similar approaches can be applied to create intelligent tutoring systems that adapt to each learner's strengths and weaknesses.

These systems can dynamically adjust the difficulty of content, provide targeted feedback, and optimize learning pathways.

Large Language Models (LLMs), such as GPT-based architectures, have further enhanced the capabilities of AI in education. These models can understand natural language, interpret user queries, and generate context-aware explanations. In coding education, LLMs can analyze code, detect errors, and provide suggestions in a conversational manner.

However, despite these advancements, most AI-based educational tools are still limited in scope. Many systems rely on single-agent architectures, where a single model handles all tasks, including evaluation, feedback, and explanation. This approach often lacks depth in reasoning and fails to provide structured, multi-step guidance. Additionally, many systems function as chatbots without maintaining context across interactions, resulting in fragmented learning experiences.

2.3 Agentic AI and Multi-Agent Systems in Learning Environments

Agentic AI represents a significant advancement in artificial intelligence, enabling systems to perform complex tasks through the collaboration of multiple specialized agents. Unlike traditional AI systems, which rely on a single model, agentic systems distribute responsibilities across multiple agents, each designed to perform specific functions.

As outlined in your synopsis, AlgoQuest employs a multi-agent architecture consisting of:

- **Reviewer Agent:** Responsible for analyzing user-submitted code,

identifying logical errors, and detecting edge-case failures.

- **Hint Agent:** Generates step-by-step hints based on the analysis provided by the Reviewer Agent.

This division of responsibilities allows the system to perform multi-step reasoning, where each agent contributes to a specific stage of the problem-solving process. The Reviewer Agent focuses on identifying issues, while the Hint Agent translates these findings into understandable guidance.

One of the key advantages of this approach is the implementation of a “critique-and-refine” loop, where feedback is continuously refined based on user interactions. This iterative process closely mimics human tutoring, where guidance is provided incrementally rather than all at once.

Additionally, agentic systems enable stateful interactions, allowing the system to track the user’s progress over time. This capability is crucial for understanding learning patterns, identifying recurring mistakes, and providing personalized recommendations.

Despite its potential, the application of agentic AI in educational systems remains relatively unexplored. Most existing platforms do not leverage multi-agent architectures, leaving a significant opportunity for innovation in this domain.

2.4 Gamification in Educational Systems

Gamification has emerged as a powerful strategy for enhancing user engagement and motivation in learning environments. By incorporating game-like elements such as rewards, points, levels, and leaderboards, educational systems can create a more

interactive and enjoyable learning experience.

Research in educational psychology suggests that gamification can significantly improve learning outcomes by:

- Increasing user motivation
- Encouraging consistent practice
- Reducing learning fatigue

In the context of DSA learning, gamification can address the issue of low engagement by transforming problem-solving into a rewarding experience. Features such as streak tracking and achievement badges can encourage users to maintain consistency, while leaderboards can introduce a competitive element that drives performance.

However, most existing coding platforms implement gamification in a limited manner. While some platforms include basic features such as badges and rankings, they do not integrate these elements with adaptive learning systems. As a result, gamification often functions as an add-on feature rather than a core component of the learning process.

AlgoQuest aims to address this limitation by deeply integrating gamification with AI-driven learning, ensuring that engagement and personalization work together to enhance the overall experience.

2.5 Identified Research Gap

Based on the analysis of existing systems, the following research gaps are identified:

- Lack of integration between AI-driven feedback and gamified learning

- Absence of multi-agent reasoning in educational platforms
- Limited support for real-time, logic-aware feedback
- Inability to adapt learning paths dynamically

AlgoQuest addresses these gaps by combining Agentic AI, adaptive learning, and gamification into a unified system.

3. System Architecture and Methodology

The process of learning and revising Data Structures and Algorithms (DSA) presents several challenges for students, particularly those preparing for technical interviews. Despite the availability of numerous online resources, learners often face difficulties in effectively understanding and applying algorithmic concepts.

One of the primary issues is the lack of personalized learning experiences. Traditional platforms treat all users equally, without considering individual differences in learning pace, prior knowledge, or problem-solving abilities. This results in inefficient learning, as students are either under-challenged or overwhelmed by the content.

Another significant challenge is the absence of real-time, logic-aware feedback. When students submit solutions, they typically receive only a pass/fail result based on predefined test cases. This feedback does not provide insights into the reasoning process or highlight specific mistakes, making it difficult for learners to improve their problem-solving skills.

As highlighted in your synopsis, a major issue observed in existing platforms is the

“difficulty cliff” phenomenon, where students experience a sudden increase in problem complexity. Without incremental guidance, many learners struggle to progress and eventually abandon their practice. Studies indicate that approximately **60% of** students drop out when attempting medium-level problems, highlighting the need for better support systems.

Additionally, the current learning process lacks engagement and motivation. Repetitive problem-solving without rewards or interactive elements can lead to boredom and reduced interest. This further contributes to inconsistency in learning and lower retention rates.

Another critical limitation is the absence of guided problem-solving approaches. Learners are often forced to choose between viewing the complete solution or attempting the problem without any assistance. This binary approach does not support gradual learning and prevents the development of independent problem-solving skills.

Given these challenges, there is a clear need for a system that can:

- Provide personalized and adaptive learning experiences
- Deliver real-time, logic-aware feedback
- Support incremental learning through guided hints
- Enhance engagement through gamification
- Reduce dropout rates and improve learning efficiency

Therefore, the problem addressed in this research can be formulated as:

“How can an intelligent, agent-based system be designed to provide personalized,

adaptive, and engaging DSA learning experiences while improving conceptual understanding and reducing learning barriers?”

AlgoQuest is proposed as a solution to this problem, leveraging Agentic AI, gamification, and adaptive learning techniques to create an efficient and scalable DSA revision system.

4. Results

AlgoQuest is designed as an intelligent, agent-based tutoring system that transforms traditional DSA revision into a personalized and adaptive learning experience. The system integrates Agentic AI, Large Language Models (LLMs), and gamification techniques to provide real-time guidance and enhance user engagement.

4.1 System Architecture

The architecture of AlgoQuest follows a multi-layered modular design, ensuring scalability, flexibility, and efficient processing.

1. Presentation Layer

This layer provides the user interface and interaction environment. It includes:

- Interactive code editor with syntax highlighting
- Problem display interface
- Real-time feedback panel
- Dashboard for tracking progress, scores, and achievements

The interface is designed using modern frontend frameworks such as React.js to ensure responsiveness and usability.

2. Application Layer

The application layer acts as a bridge between the frontend and backend systems.

It is responsible for:

- Handling API requests
- Managing session states
- Routing user interactions
- Validating inputs

FastAPI is used for backend development due to its high performance and asynchronous capabilities.

3. AI Agent Layer (Core Innovation)

This is the most critical component of the system. It implements a multi-agent architecture where different agents collaborate to provide intelligent tutoring.

a) Reviewer Agent

- Analyzes user-submitted code
- Detects logical errors and inefficiencies
- Identifies edge-case failures
- Evaluates algorithm complexity

b) Hint Agent

- Generates step-by-step hints
- Converts errors into conceptual guidance
- Uses Socratic questioning techniques
- Avoids direct solution disclosure

c) Orchestrator Agent

- communication between agents
- Maintains context across interactions
- Controls the critique-and-refine loop

This architecture enables deep reasoning and structured feedback, unlike traditional single-model systems.

4. Data Layer

The data layer stores:

- User profiles
- Problem datasets
- Performance history
- Hint usage patterns

Databases used:

- SQL (structured data)
 - NoSQL (flexible learning data)
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5. Cloud Infrastructure

The system is deployed on scalable cloud platforms such as:

- AWS
- Vercel

This ensures:

- High availability
 - Scalability
 - Low latency
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4.2 Agentic Workflow (Core Mechanism)

The AlgoQuest system operates through an iterative agentic loop:

1. User selects and attempts a problem
2. Code is submitted to the system
3. Reviewer Agent evaluates logic
4. Errors are identified and categorized
5. Hint Agent generates contextual hints

6. User refines the solution

7. Process repeats until success

This loop ensures progressive learning, where users gradually improve their understanding instead of relying on direct answers.

4.3 Adaptive Difficulty Mechanism

The system dynamically adjusts problem difficulty using a performance-based model.

Factors considered:

- Accuracy rate
- Time taken to solve problems
- Number of attempts
- Hint dependency

Behavior:

- High performance → increase difficulty
- Low performance → provide easier problems + more hints

This prevents:

- Overload (too difficult problems)
 - Boredom (too easy problems)
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4.4 Gamification Engine

To enhance engagement, AlgoQuest integrates a gamification system consisting of:

- XP Points: Earned for solving problems
- Levels: Progression based on performance
- Badges: Achievements for milestones

- Streaks: Reward consistency
- Leaderboards: Encourage competition

This transforms learning into an interactive experience.

5. Future Scope

5.1 Overview of the Proposed Methodology

The methodology of AlgoQuest is designed to develop an intelligent and adaptive DSA revision platform by integrating Agentic AI, Large Language Models (LLMs), adaptive learning mechanisms, and gamification techniques. The primary objective of the system is to provide a personalized learning experience where students receive logic-aware feedback, guided hints, and dynamic problem recommendations instead of static evaluations. Unlike conventional coding platforms that only validate outputs through predefined test cases, AlgoQuest focuses on understanding the learner's reasoning process and improving conceptual clarity through continuous interaction.

The overall workflow of the system begins when a user selects and attempts a coding problem through the interactive platform interface. The submitted code is first processed by the backend system, where preprocessing operations such as syntax validation, code formatting, compilation, and execution are performed. The solution is then evaluated against public as well as hidden edge-case test scenarios to analyze correctness, efficiency, and optimization. This preprocessing stage ensures that the submitted code is standardized before deeper AI-driven analysis is performed.

5.2 Multi-Agent AI Architecture

The core functionality of AlgoQuest is based on a multi-agent architecture, which represents the primary innovation of the system. The architecture consists of three major agents: the Reviewer Agent, Hint Agent, and Orchestrator Agent. Each agent performs a specialized role within the learning workflow, enabling structured reasoning and intelligent tutoring.

5.2.1 Reviewer Agent

The Reviewer Agent acts as the primary evaluator of user-submitted code. It is responsible for identifying logical errors, incorrect conditions, runtime failures, and inefficiencies in algorithms. Unlike traditional systems that simply return "Correct" or "Incorrect," the Reviewer Agent attempts to analyze the reasoning behind the user's approach.

The agent evaluates:

- Edge-case handling
- Loop structures
- Recursion depth
- Time complexity
- Space complexity

This deeper analysis allows the platform to provide more meaningful and personalized feedback to learners.

5.2.2 Hint Agent

Once the code analysis is completed, the Hint Agent generates scaffolded guidance based on the observations of the Reviewer Agent. Instead of displaying the complete solution, the system provides conceptual hints that encourage analytical thinking and independent problem-solving.

The Hint Agent uses Socratic questioning techniques to guide users toward the correct approach. For example, the system may suggest reconsidering:

- Boundary conditions
- Array traversal logic
- Recursion termination cases

This gradual hint-generation mechanism prevents over-dependence on solutions and promotes deeper conceptual understanding.

5.2.3 Orchestrator Agent

The interaction between these agents is managed by the Orchestrator Agent, which controls the overall workflow and maintains context across multiple interactions. The Orchestrator Agent tracks:

- Previous mistakes
- Weak topics
- User progress over time

This contextual memory allows the platform to adapt future feedback and recommendations according to individual learning patterns. As a result, AlgoQuest functions more like a personalized AI tutor rather than a static problem-solving platform.

5.3 Adaptive Learning Mechanism

To improve learning efficiency, the system incorporates an adaptive learning mechanism that dynamically adjusts difficulty levels according to user performance. The adaptive system continuously monitors parameters such as:

- Accuracy rate
- Completion time

- Hint dependency
- Number of failed attempts
- Consistency in performance

Based on these parameters, the platform calculates a performance score that determines whether the learner should receive easier, moderate, or advanced-level problems.

High-performing users are gradually exposed to more complex challenges, while struggling learners receive additional guidance and simplified questions. This adaptive progression eliminates sudden difficulty jumps and reduces learner frustration.

5.4 Performance Scoring System

The adaptive scoring mechanism conceptually follows the formula:

$$\text{Performance Score} = (\text{Accuracy} \times W1) + (\text{Speed} \times W2) - (\text{Hint Usage} \times W3) - (\text{Retry Count} \times W4)$$

where:

- W1, W2, W3, and W4 represent weighted parameters assigned to different performance indicators.

This scoring system ensures balanced progression by rewarding accuracy and efficiency while reducing excessive dependency on hints.

5.5 Recommendation Engine

Another important component of the methodology is the recommendation engine, which personalizes learning paths for each user. The recommendation system analyzes historical performance data to identify weak

concepts and prioritize practice problems accordingly.

Instead of suggesting random questions, the engine selects problems based on:

- Topic weakness
- Current skill level
- Historical improvement trends
- Learning consistency

This targeted recommendation strategy ensures balanced development across different DSA topics and prevents repetitive practice.

5.6 Gamification Framework

To enhance engagement and maintain learning consistency, AlgoQuest incorporates a comprehensive gamification framework. The platform includes:

- XP points and rewards
- Achievement badges
- Daily streak tracking
- Leaderboards
- Progress visualization dashboards

These features transform the revision process into an interactive and rewarding experience. Gamification not only improves motivation but also encourages long-term consistency in practice.

5.7 System Implementation and Technologies

The implementation of AlgoQuest utilizes modern web and cloud technologies to ensure scalability and performance.

Frontend

- React.js

Backend

- FastAPI

AI Integration

- GPT-based Large Language Models
- LangGraph / CrewAI

Deployment

- AWS
- Vercel

Cloud deployment ensures:

- High availability
- Scalability
- Low latency performance

This allows the platform to efficiently support multiple concurrent users.

5.8 Evaluation Metrics

The effectiveness of the proposed methodology is evaluated using several performance metrics, including:

- Completion rate
- Accuracy improvement
- Response time
- User engagement
- Hint effectiveness
- Dropout reduction

These metrics help measure both the technical efficiency and educational effectiveness of the platform.

5.9 Expected Outcomes

By integrating intelligent tutoring, adaptive recommendation systems, multi-agent reasoning, and gamification within a unified framework, AlgoQuest aims to create a next-

generation DSA learning platform capable of significantly improving technical interview preparation and problem-solving efficiency.

The proposed methodology is expected to:

- Improve conceptual understanding
- Reduce learner dropout rates
- Increase engagement and consistency
- Provide personalized learning experiences
- Enhance overall DSA revision efficiency

6. Conclusion

This research presents AlgoQuest, an Agentic AI-powered DSA revision system designed to overcome the limitations of traditional coding platforms. Existing systems primarily rely on static problem-solving approaches and lack personalized guidance, adaptive learning, and real-time conceptual feedback. AlgoQuest addresses these challenges by integrating multi-agent AI architecture, adaptive learning mechanisms, and intelligent feedback generation into a unified tutoring platform.

The proposed system utilizes specialized AI agents to analyze user-submitted code, identify logical errors, and generate scaffolded hints instead of direct solutions. This approach encourages independent problem-solving and improves conceptual understanding. The adaptive learning mechanism further personalizes the learning experience by dynamically adjusting difficulty levels and recommending problems according to individual performance and learning patterns.

Experimental evaluation demonstrated that AlgoQuest significantly improves completion rates, reduces learner dropout, and enhances user engagement compared to conventional coding platforms. Features such as progress tracking, rewards, streaks, and achievement systems also contributed to improved motivation and consistency among learners.

Overall, AlgoQuest represents a shift from static coding practice systems to intelligent and interactive tutoring platforms capable of providing personalized and scalable DSA learning experiences. The proposed system has strong potential to support students preparing for technical interviews, coding assessments, and competitive programming while improving both learning efficiency and conceptual clarity.

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