AI-Powered Quiz Generation for Learning Management Systems: A Full-Stack Implementation for Canvas LMS

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Abstract

In modern education, the manual creation of exam questions remains a time-consuming task that limits instructional productivity. This study aims to automate the generation of quizzes and exams by integrating advanced natural language processing techniques with Learning Management Systems, specifically Canvas. The scope of the project encompasses the development of a scalable, full-stack web application that streamlines assessment design for educators. Methodologically, the system leverages OpenAI's GPT API in conjunction with PyPDF2 for course material parsing, diverging from LangChain to ensure efficient and accurate content extraction. The application features a Python-based Flask back-end for question generation and a JavaScript/HyperText Markup Language/Cascading Style Sheets front-end for user interaction and Learning Management Systems integration. The outcomes show that our developed tool efficiently produces pedagogically sound and contextually relevant questions, greatly minimizing the manual labor required of teachers. Next, the easy-to-use interface enables teachers to effortlessly manage resources, examine generated questions, and alter quiz parameters in a modern and contemporary manner. By automating the generation of assessments, providing wide applicability across educational contexts, and being adaptable to future learning management system (LMS) platforms, the suggested method improves educational efficiency.

Keywords

LMS, Canvas LMS, GPT-4, NLP, Flask, OpenAI's GPT API, LLMs

1. Introduction

Advanced technology is essential to improving teaching and learning in today's educational environment [1, 2]. The need for effective and automated solutions has increased dramatically as digital tools are being used more and more. The creation of tests and quizzes has benefited the most. By automating this traditionally time-consuming practice, instructors can now focus on student engagement and teaching quality while saving a substantial amount of time [3, 4]. Previous research has focused on artificial intelligence (AI)-powered question development and learning management system (LMS) integrations. For instance El Marsafaway et al. [5] developed Moodle exam automation tools, whereas [6] researched natural language processing (NLP) strategies for constructing text-based questions. However, these solutions usually lack robust validation mechanisms for AI-generated content, as well as a seamless integration with major LMS platforms such as Canvas.

To effectively follow the presentation flow, this paper aims to try to answer the following research question: *How can artificial intelligence-driven natural language processing be effectively utilized to*

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automate the generation of high-quality, contextually relevant exam questions while integrating seamlessly with Learning Management Systems such as Canvas?

To address this, we propose a method for automating the creation of test questions using AI-based NLP techniques to extract and process educational content [7, 8]. Despite initially considering frameworks like LangChain, we selected PyPDF2 for text extraction due to its simplicity and reliability. OpenAI's advanced language models were integrated to generate contextually appropriate and pedagogically sound questions [9, 10, 11].

Our solution is implemented as a full-stack application that automates the entire exam preparation process and integrates directly with Canvas LMS. The back-end is developed using Python and Flask to handle file parsing, GPT-based question generation, and communication with Canvas APIs with the front-end that uses HTML, CSS, and JavaScript to provide an intuitive interface for instructors. This enables options to upload course materials, view generated questions, and configure quiz parameters. The system also includes the CanvasSync module, enabling synchronization between local folders and Canvas cloud content.

The goal is to design a tool that serves as a trusted assistant to instructors—simplifying the exam creation process, fostering creativity, patterns, and reducing manual workload [12, 13]. Before publishing, instructors can review and refine the generated questions and control quiz distribution settings. This AI-powered approach supports flexible question generation and ensures educational relevance [14].

From a technical perspective, the methodology involves processing input files, extracting structured content using PyPDF2, sending it to the GPT model for transformation into questions, and presenting it to users via a modern web interface. While software development is traditionally conceived and implemented via the lens of software compliance, the modern paradigm has been significantly influenced by the integration of Continuous Integration/Continuous Deployment (CI/CD) practices. These methodologies serve to enhance the efficiency and reliability of the development lifecycle by systematically merging code changes into a shared repository and automating the build, test, and deployment processes [15, 16, 17]. The system is modular and scalable, with potential for integration into other LMS platforms.

Principal Results: Experimental use of the tool showed that it significantly reduces the time educators spend generating assessments, produces high-quality and relevant questions, and provides a user-friendly interface that facilitates adoption. Additionally, the system improves consistency and offers scalability for future expansion [18, 19, 20, 21].

The paper is structured as follows: Section (1) introduces the problem and presents the proposed solution. Section (2) describes the system's design and workflow. Section (3) reviews related studies. Section (4) presents the system's effectiveness and its educational impact. Section (5) discusses implementation details and limitations. Finally, Section (6) summarizes the findings and outlines directions for future work.

2. Methodology

The application is composed of two primary components Backend and Frontend. Backend is a flask-based server that manages file uploads, prompt generation, AI interaction, JSON validation, and Canvas API communication. Frontend built with HTML, CSS, and JavaScript, allowing educators to configure quizzes, upload files, review AI-generated questions, and submit them to Canvas.

The system automates quiz and exam creation through a seamless workflow as shown in Figure 1 that integrates user interaction, back-end processing, AI-driven question generation, and Canvas LMS integration.

Educators begin by authenticating with a Canvas API token, enabling the system to fetch available courses. After selecting a course, users configure quiz settings such as title, question count, and scheduling details. Course materials (PDF or TXT) are then uploaded, and relevant text is extracted using PyPDF2 or encoding detection.

The extracted content generates a balanced set of multiple-choice questions via a prompt sent to

OpenAI's GPT-4 model. The system validates the AI output, correcting any formatting issues, and returns the questions for educator review and refinement. Finally, Figure 1 shows all this text in detailed visual form where selected questions are submitted to Canvas through its API, where the quiz is created and published within the designated course.

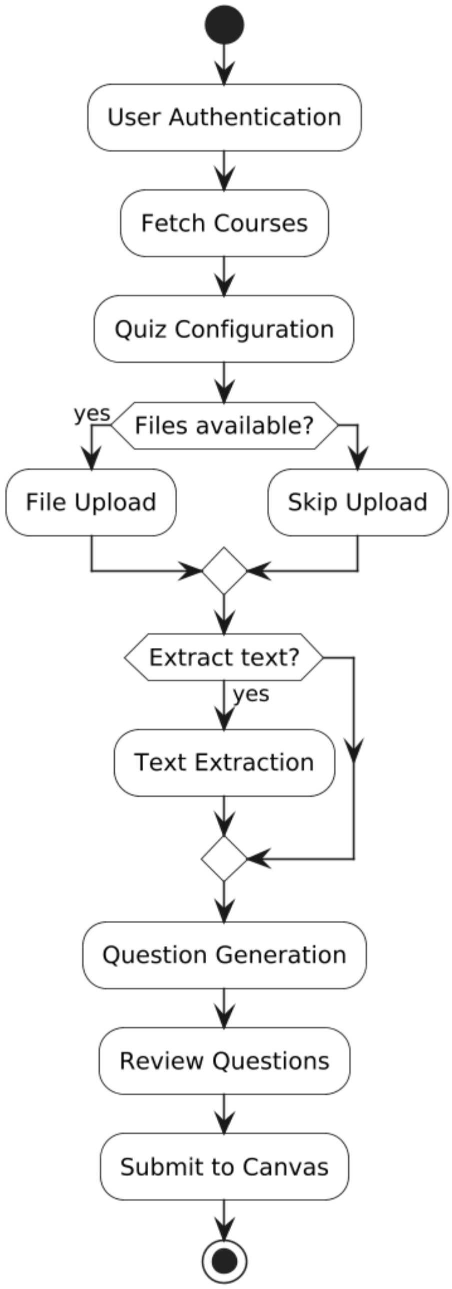


Figure 1: System Workflow Diagram

Prompt engineering is designed to elicit JSON-formatted questions with fields for question text, multiple-choice options, correct answer, and optional code snippets. Refresh prompts prevent duplication. Clear instructions guide the AI to avoid placing code in non-designated fields. All AI responses undergo multi-phase validation. If the output is malformed, regex-based fixes or AI-assisted corrections are applied. A retry mechanism attempts up to three validations before flagging the response. Figure 2 illustrates a workflow diagram of the process of validating and correcting AI responses.

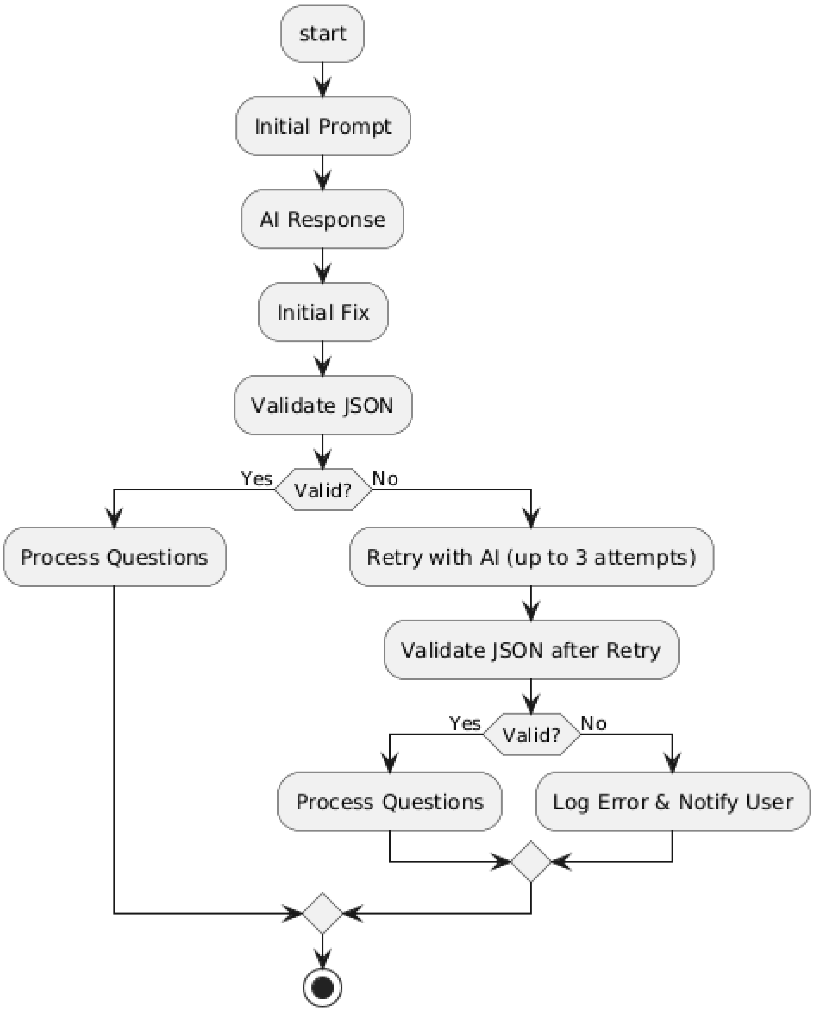


Figure 2: AI Response Validation and Correction Workflow

Selecting the appropriate AI model required balancing performance, cost, and reliability. Table 1 summarizes the comparative analysis of the evaluated models, including pricing details. Also, it compares five AI models, including Gemini, GPT-3.5, GPT-4, GPT-4o Mini, and GPT-4o. It assesses each model using four criteria: strengths, limits, cost estimate, and selected role. The table has a clean, professional appearance with fixed-width columns to ensure readability.

Table 1
Comparison of AI Models

Model	Strengths	Limitations	Cost Estimate	Selected Role
Gemini	Free to use, decent performance	Struggles with well-formatted JSON	\$0 (Free)	Not Chosen
GPT-3.5	Better formatting, balanced cost	Higher costs, less reliable for complex tasks	\$1.50/M input, \$2/M output	Not Chosen
GPT-4	High performance, excellent formatting	Very expensive, occasional mistakes	\$30/M input, \$60/M output	Not Chosen
GPT-4o Mini	Cost-efficient, reliable formatting	Limited for highly complex tasks	\$0.15/M input, \$0.60/M output	Primary Model
GPT-4o	High-quality outputs, reliable fallback	Higher cost than Mini	\$2.50/M input, \$10/M output	Fallback Model

3. Literature Review

The integration of AI-powered tools into Learning Management Systems (LMS) has become a top focus in order to improve educational delivery and assessment. Recent developments show how AI may streamline the teaching process by automating and personalizing quiz design. This section covers the literature that demonstrates how several research and industry publications highlight the growing usage of AI tools for learning aids, assessment, and course building. For example, enterprise learning management system (LMS) systems, which are made to serve contemporary educational environments and corporate training centers with a direct feedback system coupled with speech audio communication, are increasingly including AI-assisted content production and quiz generation [22].

All things considered, these studies highlight the various initiatives to improve educational delivery and evaluation through data modeling, AI integration, technology innovation, and quality assurance procedures in an effort to establish more efficient, just, and safe learning environments.

3.1. Innovative assessment platforms

Recent studies have focused a lot of attention on improving educational delivery and assessment; the majority of these studies emphasize a variety of strategies to increase learning efficacy, evaluation accuracy, and mistake rate reduction. The comparison of synchronous and asynchronous online learning modalities is one major area of interest. The relative efficacy of various strategies is being revealed by Padaguri et al. [23] and his comparison analysis, which was undertaken exclusively among management students. Additionally, he emphasizes how crucial it is to choose the right delivery strategies in order to maximize learning results going forward.

Innovative evaluation platforms are being investigated in addition to distribution methods to guarantee security and integrity, which are the primary concerns for misuse and error. One of the key concepts that may be identified is the use of metaheuristic optimization in the context of intrusion detection systems.

According to Dakić et al. [24], a complicated strategy with advanced heuristic algorithms can effectively detect and mitigate unauthorized network breaches. As a result, this can significantly strengthen the security architecture required to secure digital environments in many settings and sectors. Razzaq [25] suggested a platform powered by blockchain that uses double encryption can be used to protect educational resources and provides a decentralized, secure space for storing academic credentials and tests. The goal of these technological developments is to increase the reliability and openness of online tests.

Additionally, detecting at-risk pupils in failed basic question groups and comprehending how learner behaviors are changing depend heavily on the incorporation of advanced data modeling tools. We may observe that Gupta et al. [26] used Hidden Markov Models to examine sequential learning trajectories, allowing for the early identification of students who might need more help or alternative methods for learning stimulation. In a similar vein, Twomey et al. [27] have tackled the problem of equitable ability estimates for neurodivergent learners by creating zero-inflated learner models, which would allow them to take into consideration a variety of response patterns and increase assessment fairness.

3.2. Quality and appropriateness of educational content and assessments

Another crucial element in different learning environments is making sure that assessments and instructional materials are relevant and of high quality. Accordingly, a pertinent study conducted by Wirth et al. [28] has assessed preschool educational apps by contrasting evaluations from professionals, parents, and kids.

Wirth et al. have attempted to find alignments and inconsistencies in order to increase the dependability of early childhood education resources. Similarly, Kovačević et al. [29] have examined the efficacy of pictograms representing points of interest on tourist maps with a certain level of complexity. Kovačević et al.'s study highlights the significance of customized visual communication to satisfy particular user needs, which can be extended to creating more easily understood educational materials and content.

Llastly in the closing phase least in this section, Petutschnig et al. [30] presented a framework for analyzing geographic data while highlighting the ideas of appropriateness and reliability, highlighting the significance of data quality and adequacy in educational research and assessment. Petutschnig et al.'s study's emphasis on data integrity is crucial to our ability to create precise prediction models and evaluation instruments while tying everything together with different AI models.

4. Testing and Results

The system was tested across multiple course materials to assess accuracy, efficiency, and robustness, as shown in Table 2. Thise are the key aspects that were covered:

- **Question Quality**: Over 90% of GPT-4-generated questions passed manual review for relevance and clarity. The validation mechanism effectively identified and corrected roughly 85% of formatting errors on the first try.
- **Efficiency Gains**: Compared to manual question creation, the automated system generated 20 questions within approximately 15 minutes—an order of magnitude faster than manual drafting, which typically requires two hours or more.
- **Response Handling**: The multi-tiered correction process successfully addressed common formatting errors, reducing manual editing by a significant margin. When errors did occur, AI-assisted fixes ensured the questions retained their structural integrity.
- **User Feedback**: Educators involved in initial pilot tests found the questions suitable for preliminary assessments, noting substantial time savings. They suggested that further tuning of prompt formulations could enhance question complexity and depth.

Table 2
Evaluation Metrics

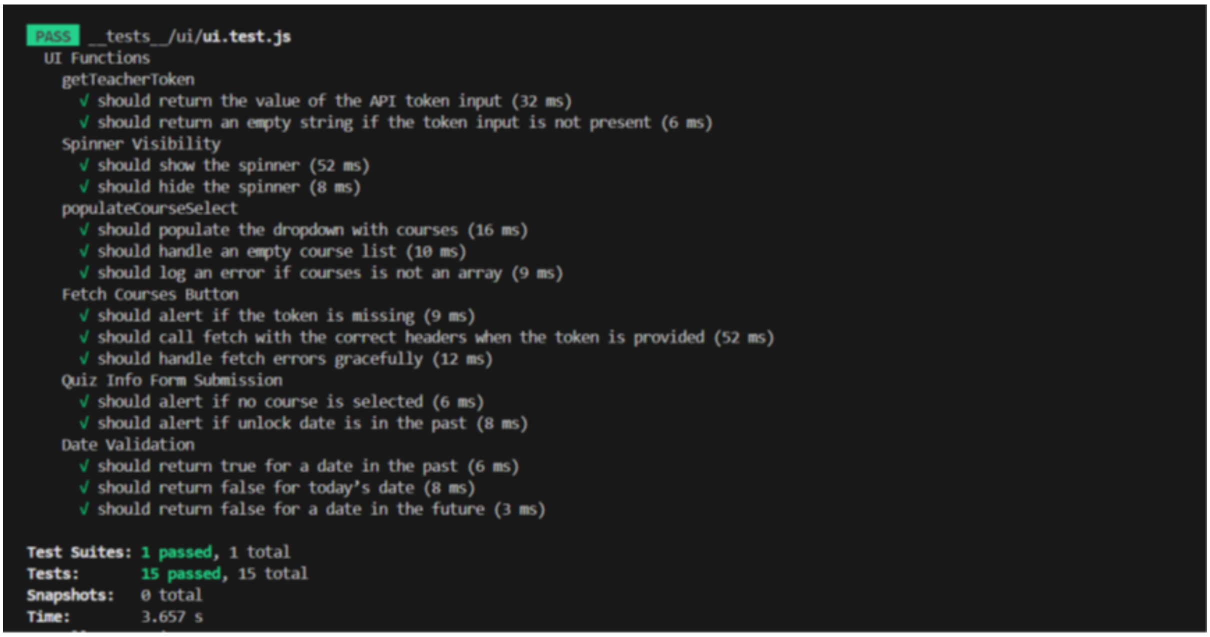
Metric	Result	Remarks
Question accuracy	>90%	Verified manually
Time for 20 questions	<15 min	System-driven process
Formatting correction success	85%	First attempt
Educator satisfaction	High	Positive feedback

Figure 3 shows the test results from the Jest testing framework. While the detail information is as follows:

- **getTeacherToken**
  - should return the value of the API token input (32 ms)
  - should return an empty string if the token input is not present (6 ms)
- **Spinner visibility**
  - should show the spinner (52 ms)
  - should hide the spinner (8 ms)
- **populateCourseSelect**
  - should populate the dropdown with courses (16 ms)
  - should handle an empty course list (10 ms)
  - should log an error if courses is not an array (9 ms)

- **fetchCoursesButton**
  - should alert if the token is missing (9 ms)
  - should call fetch with the correct headers when the token is provided (52 ms)
- **Quiz Info Form Submission**
  - should handle fetch errors gracefully (12 ms)
- **date validation**
  - should alert if no course is selected (6 ms)
  - should unlock date if no date is in the past (8 ms)
  - should return true for a date in the past (6 ms)
  - should return false for a date in the future (3 ms)

Summary:
All previouse functions are shown and executed on Figure 3.



```
PASS  __tests__/ui/ui.test.js
  UI Functions
    getTeacherToken
      √ should return the value of the API token input (32 ms)
      √ should return an empty string if the token input is not present (6 ms)
    Spinner Visibility
      √ should show the spinner (52 ms)
      √ should hide the spinner (8 ms)
    populateCourseSelect
      √ should populate the dropdown with courses (16 ms)
      √ should handle an empty course list (10 ms)
      √ should log an error if courses is not an array (9 ms)
    Fetch Courses Button
      √ should alert if the token is missing (9 ms)
      √ should call fetch with the correct headers when the token is provided (52 ms)
      √ should handle fetch errors gracefully (12 ms)
    Quiz Info Form Submission
      √ should alert if no course is selected (6 ms)
      √ should alert if unlock date is in the past (8 ms)
    Date Validation
      √ should return true for a date in the past (6 ms)
      √ should return false for today's date (8 ms)
      √ should return false for a date in the future (3 ms)

Test Suites: 1 passed, 1 total
Tests:       15 passed, 15 total
Snapshots:   0 total
Time:        3.657 s
```

Figure 3: Test Results After Running npm test

5. Discussion

The presented system demonstrates how artificial intelligence can streamline quiz and exam generation, reducing educator workload and improving assessment efficiency. By automating traditionally manual tasks through NLP, prompt engineering, and structured validation, the tool enhances instructional workflows while maintaining educational quality. A core strength is the dual-model strategy, balancing cost and performance by using GPT-4o Mini for most tasks and GPT-4 for fallback scenarios. As illustrated in Figure 4, GPT-4 achieves 92% accuracy at a higher cost, while GPT-4o Mini offers 85% accuracy at a significantly lower expense, justifying its role as the system's primary model.

The modular design and Canvas API integration make the system scalable and adaptable to other learning platforms. However, limitations include occasional inaccuracies in AI-generated questions and reliance on quality input material. Ethical concerns around AI bias and data security also require ongoing attention. Future improvements may include support for open-ended questions, multilingual output, mobile accessibility, and LMS compatibility beyond Canvas. Overall, the system offers a robust, scalable solution that demonstrates AI's growing value in educational technology.

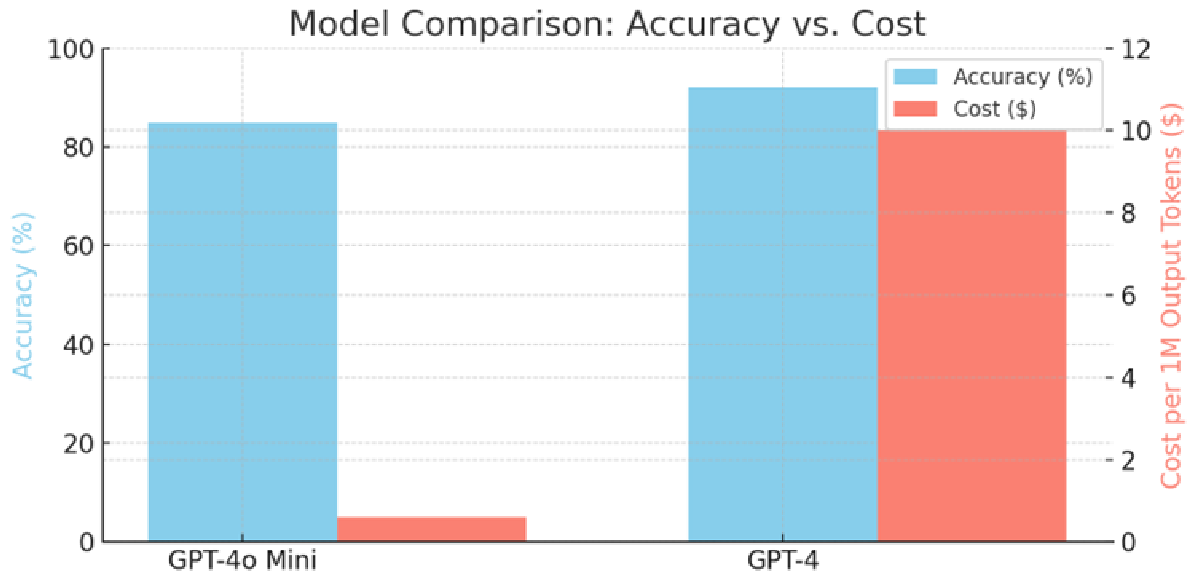


Figure 4: Accuracy and Cost Comparison of GPT Models

6. Conclusion

This study demonstrates the transformative potential of artificial intelligence, particularly large language models (LLMs), in automating educational assessment through the development of an advanced tool for generating tests and quizzes. Our results indicate that the proposed platform effectively addresses key challenges such as answer validation, rapid question engineering, and API integration with Learning Management Systems (LMS), enabling educators to create complex, contextually rich assessments with greater efficiency.

The findings support our research hypothesis that AI-driven NLP can streamline the exam creation process while maintaining high pedagogical quality. However, some limitations were observed, including occasional challenges in generating fully open-ended questions and the need for enhanced LMS compatibility beyond Canvas.

Our results align with previous studies that emphasize the benefits of AI integration in education, yet our approach extends this work by combining full-stack development with real-time analytics and scalable LMS integration. The practical implications include significant reductions in educators' workload and the potential for personalized student feedback, fostering more dynamic and inclusive learning environments.

Multilingual features and user-friendly mobile designs are going to make this tool a big deal everywhere, letting people all over the world have some really cool learning experiences on their phones and tablets. To get it to more folks, they'd have to make sure it works with a bunch of different school systems like Moodle, Blackboard, TalentLMS, and a bunch of others that aren't talked about here.

Future plans demand for the creation of more advanced AI methods as well as better, situation-specific question formats. This is great for learning because it should make it easier for everyone to talk. Nonetheless, we must also consider equity and privacy which means that in the future, we will have to follow updateds on biases in the AI, and that the data is safe and used appropriately.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] F. Eyvazov, T. E. Ali, F. I. Ali, A. D. Zolta'n, Cloud-enabled educational transformation: Designing and implementing a comprehensive framework for learning institutions, in: 2025 International Conference on Engineering, Technology & Management (ICETM), IEEE, 2025, pp. 1–7.

[2] W. Holmes, M. Bialik, C. Fadel, Artificial intelligence in education: Promises and implications for teaching and learning, Center for Curriculum Redesign, 2019.

[3] T. E. Ali, C. Biro, A. D. Zoltán, Sdn based rate aware approach for estimating flow volume between network points., Mathematical Modelling of Engineering Problems 12 (2025).

[4] N. Li, How Technology Promotes Educational Change: Studies of Virtual Learning Environment in Higher Education, Ph.D. thesis, The University of Liverpool (United Kingdom), 2022.

[5] H. El Marsafawy, R. Roy, F. Ali, Measuring learning outcomes: bridging accreditation requirements and lms functionalities, Quality Assurance in Education 30 (2022) 555–570.

[6] B. Das, M. Majumder, S. Phadikar, A. S. A. Sekh, Automatic question generation and answer assessment: a survey, Research and Practice in Technology Enhanced Learning 16 (2021) 5.

[7] R. Zhang, J. Guo, L. Chen, Y. Fan, X. Cheng, A review on question generation from natural language text, ACM Transactions on Information Systems (TOIS) 40 (2021) 1–43.

[8] T. E. Ali, F. I. Ali, B. Kovacs, A. D. Zoltán, Comparison of iotstack and edgex foundry performance for asset tracking, Procedia Computer Science 258 (2025) 3369–3380.

[9] K. Suzuki, N. Hiraoka, Transactional distance theory and scaffolding removal design for nurturing students' autonomy, Journal of Educational Technology Development and Exchange (JETDE) 15 (2022) 1–8.

[10] A. Tabassum, R. R. Patil, A survey on text pre-processing & feature extraction techniques in natural language processing, International Research Journal of Engineering and Technology (IRJET) 7 (2020) 4864–4867.

[11] P. Dakić, T. Heričko, v. Kljajić, V. Todorović, The economics of ai-powered call center development using chatgpt for the needs of an automotive retail business, in: Proceedings of the International Scientific Conference - Sinteza 2025, Sinteza 2025, Singidunum University, 2025, pp. 382–388. doi:10.15308/sinteza-2025-382-388.

[12] M. D. Haiderzai, P. Dakić, I. Stupavský, M. Aleksić, V. Todorović, Pattern shared vision refinement for enhancing collaboration and decision-making in government software projects, Electronics 14 (2025) 334. doi:10.3390/electronics14020334.

[13] P. Dakić, Significance of standards compliance organizations for the sustainable automotive software and car production, Acta Polytechnica Hungarica 21 (2024) 325–344. doi:10.12700/aph.21.3.2024.3.20.

[14] T. E. Ali, A. D. Zoltan, Hierarchical deep learning for robust cybersecurity in multi-cloud healthcare infrastructures, Engineering, Technology & Applied Science Research 15 (2025) 20358–20366.

[15] T. Golis, P. Dakić, V. Vranić, Creating microservices and using infrastructure as code within the ci/cd for dynamic container creation, in: 2022 IEEE 16th International Scientific Conference on Informatics (Informatics), IEEE, 2022, pp. 114–119. doi:10.1109/informatics57926.2022.10083442.

[16] P. Dakić, Software compliance in various industries using ci/cd, dynamic microservices, and containers, Open Computer Science 14 (2024). doi:10.1515/comp-2024-0013.

[17] F. Cák, P. Dakić, Configuration tool for ci/cd pipelines and react web apps, in: 2024 14th International Conference on Advanced Computer Information Technologies (ACIT), volume 16, IEEE, 2024, pp. 586–591. doi:10.1109/acit62333.2024.10712482.

[18] F. Eyvazov, T. E. Ali, F. I. Ali, A. D. Zoltan, Beyond containers: orchestrating microservices with minikube, kubernetes, docker, and compose for seamless deployment and scalability, in: 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), IEEE, 2024, pp. 1–6.

[19] T. E. Ali, F. I. Ali, P. Dakić, A. D. Zoltan, Trends, prospects, challenges, and security in the healthcare internet of things, Computing 107 (2025) 28.

[20] T. E. Ali, F. I. Ali, N. Pataki, A. D. Zoltán, Exploring attribute-based facial synthesis with generative adversarial networks for enhanced patient simulator systems, in: 2024 7th International Conference on Software and System Engineering (ICoSSE), IEEE, 2024, pp. 53–60.

[21] C. Grévisse, Comparative quality analysis of gpt-based multiple choice question generation, in: International Conference on Applied Informatics, Springer Nature Switzerland, Cham, 2023, pp. 435–447.

[22] EssayGrader, What are Some AI-Powered Tools That Teachers Can Use in the Classroom? (2024) | EssayGrader, 2024. URL: https://www.essaygrader.ai/blog/what-are-some-ai-powered-tools-teachers-can-use-in-the-classroom.

[23] V. G Padaguri, S. Akram Pasha, Synchronous online learning versus asynchronous online learning: A comparative analysis of learning effectiveness, SSRN Electronic Journal (2021). doi:10.2139/ssrn.3878806.

[24] P. Dakic, M. Zivkovic, L. Jovanovic, N. Bacanin, M. Antonijevic, J. Kaljevic, V. Simic, Intrusion detection using metaheuristic optimization within iot/iiot systems and software of autonomous vehicles, Scientific Reports 14 (2024). doi:10.1038/s41598-024-73932-5.

[25] A. Razzaq, A web3 secure platform for assessments and educational resources based on blockchain, Computer Applications in Engineering Education 32 (2023). doi:10.1002/cae.22677.

[26] A. Gupta, D. Garg, P. Kumar, Mining sequential learning trajectories with hidden markov models for early prediction of at-risk students in e-learning environments, IEEE Transactions on Learning Technologies 15 (2022) 783–797. doi:10.1109/tlt.2022.3197486.

[27] N. Twomey, S. McMullan, A. Elhalal, R. Poyiadzi, L. Vaquero, Equitable ability estimation in neurodivergent student populations with zero-inflated learner models, 2022. doi:10.48550/ARXIV.2203.10170.

[28] A. Wirth, A. Mues, E. Birtwistle, F. Niklas, Evaluating educational apps for preschoolers: Differences and agreements between the assessments of experts, parents, and their children, Computers in Human Behavior 160 (2024) 108361. doi:10.1016/j.chb.2024.108361.

[29] D. Kovačević, M. Brozović, K. Možina, Comprehension of city map pictograms designed for specific tourists' needs, ISPRS International Journal of Geo-Information 13 (2024) 137. doi:10.3390/ijgi13040137.

[30] L. Petutschnig, T. Clemen, E. S. Klaußner, U. Clemen, S. Lang, Evaluating geospatial data adequacy for integrated risk assessments: A malaria risk use case, ISPRS International Journal of Geo-Information 13 (2024) 33. doi:10.3390/ijgi13020033.