iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** II **Month of publication:** February 2026

DOI: https://doi.org/10.22214/ijraset.2026.77388

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

A Comprehensive Survey of AI-Driven Smart Campus Systems for Adaptive Learning and Assessment

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Abstract: Smart Campus project is a learning and management application that is meant to enhance learning experiences and operational efficiency in institutions. The system supports students, faculty, and administrators by means of academic AI, Retrieval-Augmented Generation (RAG), and data analytics. It provides adaptive learning tracks, dynamic course recommendations, and skills-based assessments, as well as productivity and engagement tools. The platform also has real-time analytics dashboard to monitor performance in academics, attendance, and resource utilization to aid the stakeholders in making effective decisions. Smart Campus responds to the deficiency of the traditional education system as it lacks individualized assistance, since the implementation of AI-based modules contributes to the academic guidance, administration, and monitoring of achievements. The outcomes of the experiments demonstrate increased efficiency and engagement, demonstrating the strengths of the platform in providing alterable data-driven sustainable campus conditions. Frequent changes according to the feedback of the users make the system relevant and approachable to the learners that have different needs and technological awareness. In education, we consider the use of technology, automated evaluation of answers and auto grading systems.

Keywords: RAG, LLM, OLLAMA, AI in Education, Digital Learning Efficiency, Learning Analytics, Artificial Intelligence.

I. INTRODUCTION

RAG pre-setting of LLM answers based on a given information or situation increases the likelihood of the model providing an accurate answer and reduces the number of hallucinations. Research indicates that RAG-based AI content generation increases relevance and factual truth in learning environments and it also enables us to create assessment that are more related to course material and student needs than fixed question banks did.

Another equally significant aspect of training this technology is the novel methods concerning the construction of huge question-answer databases in which record of student submissions and assessment outcomes is stored. The new document-based databases such as MongoDB allow creating, storing, and retrieving unlimited structure and unstructured data on a large scale, allowing you to audit and analyze the entire process of assessment in a matter of seconds.

Moreover, the advent of image recognition and other digitalized forms of submission implies that the real-life artifacts of the students can also be digitized. A teacher can snap a picture of a handwritten response, post it to an online service and receive the final grade back to the school system; all of this is automated.

Automated grading system (AGS) is an AI-based tool that is used to automatically grade a response typed or written down by a student by matching it to a stored reference answer semantically. This reduces the amount of work needed by the instructors, provides quicker feedback, offers standardized scoring, adjusts the difficulty of questions to match the individual level of the learner and offers scoring explanations, which are becoming a vital part of the present-day classroom.

As much as studies on AGS have produced promising findings, it is a matter of concern that there is a possibility of bias, absence of transparency, domain congruence problems, and little explanation on the outputs of the system.

This ongoing project is part of the Smart Campus Initiative based on the vision of creating a system that would help in completing these four functions by connecting AGS technologies into a unified system.

This will enable it to dynamically generate academic questions, store and manage said questions and answers in a high-performance, scalable database (such as MongoDB) and process handwritten submissions with images and use semantic evaluation with LLM models (such as Ollama) that can be deployed on either on-premises or cloud infrastructure, depending on the best fit.

In the end, the objective is an engine that acts in favor of Adaptive and Context sensitive Question Generation sensitive to topic, difficulty and student context.

A stable, robust system of data management will allow the analysis and monitoring of student performance by allowing complex analysis of data regarding a student.

One such use of an LLM-powered application would be an automated grading system based on a semantic approach to provide quick, consistent, and transparent scores, with a justification of each score, and continuous feedback. Such a system would ideally be able to scale up to a large number of subjects, curriculum boards and large amounts of students and dynamically change content with minimal manual input.

This will be one of the main aspects of explainability and equity, in particular, we must have a clear picture of how the questions are constructed, how the answers are rated, how the end score is counted, and how we can manage the issue of black-box AI as a grader.

The app will also propagate the Smart Campus trend that will foster a more dynamic, responsive and data-driven evaluation process by students, instructors and admins. We will receive timely feedback and more learning opportunities, and teachers will have more time to teach rather than enter grades, and institutions will get practical analytics to identify learning trends, determine the efficacy of their questions, and identify areas of performance deficit.

Natural Ultimately, the project is literally at the crossroads of the fields of the Language Processing, Computer Vision, Database Management and Educational Assessment Design. Smart Campus platform provides us with an opportunity to use the latest AI to enhance the old models of assessment with which we are familiar.

II. RELATED WORK

A. Assessment of AI-Improved Collaborative Learning Platforms

This paper literature review explores the literature on current AI-powered ed tech and research articles. It informs us that there is the necessity of a platform that incorporates AI suggestions and human interaction. Intelligent Tutoring and Assessment: the paper considers the system of creating modeling bots which assists beginners in Model-Driven-Engineering by the use of NLP and ML: the system called ModBud. It also analyzes conventional systems which categorize answers of the students by comparing them to anticipated answers.

AI-based content platforms: the review discusses the online platform, Unravel, which tries to make the education process easier in a teacher and a student. Unravel is an AI-based video editing application and Video to Text transcription service that was developed with ReactJS, NodeJS, and AWS.

Personalized and Collaborative Learning: the section presents a system by Sihem Amer-Yahia based on the application of ML to provide personalized teacher recommendations and encourage peer collaboration. It attracts such theories as the Zone of Proximal Development and Flow Theory.

Artificial Intelligence to Administrative Efficiency: the article presents the idea of Gupta et al. that suggests an AI-powered system that computerizes education and increases the efficiency of admins. It relies on statistics, including ANOVA, in order to determine the impact of AI on the performance of students. AI-based Mentorship: the journal article discusses the concept of MentorAI, proposed by Bagai and Mane, which is an attempt to offer professionals with scalable and customized and accessible mentorship experiences. Expansive AI in Education Research: the review has also referenced numerous studies that investigate AI in MOOCs, ML and AI in eLearning at KKU, and game-based tools to cover ML concepts in high school students

B. Explainable AI in Education: Current Trends, Challenges, and Opportunities

this article is supported by the background literature review that follows the history and definition of XAI in order to establish the context of its application to education. Recognizes a Research Gap: the authors mention that, on the one hand, the body of research on XAI in different fields is vast, whereas, on the other hand, a thorough investigation of XAI in education has not been carried out yet. History of XAI: the initial use of the term XAI was in a military training simulation in 2004. But explainability can be traced back to the 1970s by expert systems. This instance shows the explainable expert systems model of DARPA, an early ground-breaker in this field.

Reviews Different Definitions of XAI: to achieve an agreement, the article summarizes various definitions of XAI: a Data-Oriented Definition: “Determining the relevant knowledge in a machine learning model.” Human-Centric Definition -The ability to explain or clarify something to an individual in straightforward terms.

C. EduFlex: Adaptive E-learning Platform using RAG and Integrated APIs

During the course, we are informed that this article is indeed excavating deep into the existing academic literature about adaptive learning and the way EduFlex fits in that image. It is essentially a literature review which follows the recent research and the position of EduFlex in it.

This chapter mainly focuses on adaptive learning systems. The most important terms that are discovered are ITS (Intelligent Tutoring Systems) and AHS (Adaptive Hypermedia Systems). Another fact mentioned in the chapter is that machine-learning research is a boom- the increase of it is 230 percent between 2019 and 2022. Most available systems of adaptive learning, however, continue to use simple rule-of-thumb adjustments, instead of exploring advanced ML such as deep learning.

We have much evidence that adaptive learning tools are in fact effective. A number of researches indicate that these tools can increase performance by approximately 17.3 and student engagement by approximately 22.5 in academic institutions. A meta-analysis of 42 studies even found that systems with combination of cognitive and affective adaptivity produced a large positive effect, which included motivation and emotion on top of knowledge delivery.

Throughout the chapter, AI is a large point. The authors dissect different AI-enabled functions you will soon be using daily: AI-powered recommendations, which are based on surveys of learners, using NLP to personalize the recommendations based on student interaction with the content, predictive analytics, which must identify patterns of engagement and intelligent virtual assistants, which are personalized to each student.

According to the authors, learners using adaptive systems indicate a 27 percent increase in engagement. However, there is also a slight discrepancy indicated by the paper: 76 percent of platforms declare to provide adaptive learning, and only 34 percent truly use incorporated approaches to adapt to personal preferences.

D. CodeQA: Advanced Programming Question-Answering Using LLM Agent and RAG

We present a taxonomy of QA systems employed in programming in this section of the paper. Three simple types can be distinguished:

IRS uses responses to a canned, pre-populated knowledge base.

PythonQAS is an open-source closed-domain application that allows you to query Python using natural language, and then it converts your query into some query that queries a particular database. Since it relies on a set of knowledge it cannot give the answer to all questions that you put to it.

The task of APIBOT is to scrape API documentation and provide you with insights about what is behind the technology. It shares the known core NLP as SiriusQA with additional engineered capabilities.

There is also Python-Bot, a chatbot that is based on SnatchBot framework, developed to aid novice coders to learn Python basics and syntax.

Systems based on LLM Fine-Tuning This type of systems are those that have been trained by editing and fine-tuning a pre-trained language model on a particular QA dataset.

Bansal et al. constructed a strong neural QA system that combines encoder/decoder networks and is trained on 1,560,000 Java coding snippets and is capable of answering rudimentary questions, such as what each subroutine is doing.

Intelligent Question Answering Teaching Assistant (AI-TA) is a teacher-friendly tool that allows teachers to answer student questions in a fast manner. The reinforcement learning based on human feedback (RLHF) and dense policy optimization on LLaMA-2 models were used to train AI-TA. The authors state that RAG-only responses of the AI-TA outperform both the fine-tuned (SFT) and dense policy-optimized (DPO) pipelines on comparable queries using the LLaMA-2 series.

E. Exploring the Integration of Generative AI in Modern Education Systems: A Comprehensive Analysis

Literature reviews provide this paper with a summary of Generative AI and its application in education. The introduction defines what Generative AI is, or more precisely, a type of AI that is capable of generating original content, and mentions several of its most notable models, which include GPT, a text-generating model of OpenAI, DALL-, a description-generating image-generating model, and MusicLM and Codex, a music and code generation model respectively.

Historical Overview of Artificial Intelligence in Education: This part follows the history of the use of AI in education, beginning with early Computer Assisted Instruction (CAI) of the 1960s-70s to the emergence of Intelligent Tutoring Systems (ITSs) that operated on rule-based logic and were thus less flexible.

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The State of Recent Trends in Intelligent Learning Tools Development based on AI: In this case we address the current trend in the development of AI-based ITSs, where the current tools incorporate NLP, which gives them the ability to maintain a human-like dialog. Some of the existing adaptive learning systems are also featured in the paragraph, like Knewton.

III. PROPOSED SYSTEM FOR SMART CAMPUS

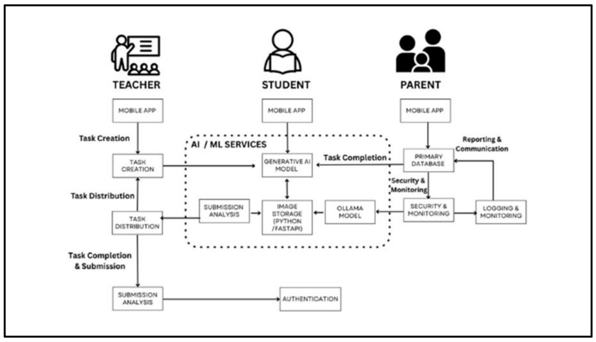

Fig 1. Workflow of Smart Campus

The Smart Campus Platform uses Generative AI and multimodal vision language models to improve communication and evaluation between teachers, students and parents. It is web or mobile based and it is an interactive academic management of operations.

A. *Architecture of the System*

Smart Campus has three primary user modules, namely, teacher, student, and parent modules, which are all linked to an AI/ML service layer. All the information required in reporting, analytics, and data storage is stored in the database.

1) The Teacher Module: Teachers can compose, administer and assign assignments, quizzes and tasks using their mobile devices. The Task Creation option allows them to select all the grade level up to the chapter level. Work is transferred to students through the Task Distribution Service. Once a student has posted a response, the AI services analyse and interpret it and provide the teacher with a detailed performance report.
2) Parent Module: With the help of the application, parents will be able to access performance dashboards and progress reports. The main database holds the data of students safely and facilitates real-time updates, which are used in reporting and communication of the student activities and achievements. The AI/ML layer supports the automation of the system, which ensures the protection of role-based logins, real-time monitoring, and data integrity.

LLAMA (through Ollama): The model is multimodal and it processes a text and a visual input so that it can correctly assess the handwritten or image-based submissions by the students without involving the use of traditional OCR software. It creates questions, personalizes quizzes, verifies answers, and provides feedback through such frameworks as LangChain and Hugging Face Transformers. It also incorporates results of the LLaVA model to provide auto-scoring and analysis and store the evaluation data, which is stored back in the primary database.

IV. CONCLUSION

The proposal to introduce Smart Campus is a sensible proposal to introduce AI in our classrooms in a somewhat scalable manner, uniting state-of-the-art LLM, Retrieval Augmented Generation, and multimodal vision models such as LLaVA through Ollama. In fact it puts the automation and real teaching in closer contact, allowing us to auto-create tasks, auto-assess and obtain real-time analytics on each workflow. Teachers, students, and parents find using it extremely easy due to the design allowing them to co-operate through the shared Python-FastAPI and React.js implementation. The secure database and multimodal understanding system substitutes simple OCR in such a way that the system can accurately read handwritten notes and other visual submissions and make the system scalable and adjustable to most academic environments. The findings of the experiments indicate that using Generative AI with LLaVA reduces feedback recognition errors, reduces hand-marking time, and enhances the motivation of students.

Further, the extensible, modular architecture allows us to add the future AI tools predictive analytics, adaptive learning, and explainable evaluation. Ultimately, Smart Campus prepares the foundation of next-generation, AI-powered ecosystems that provide educational efficiency, transparency and personalization on both the learning and assessment side.

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