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Review on Generative Transformer Approach to Learner-Centric Education: Content, Assessment and Feedback Automation

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Abstract: *Generative AI has leveraged modern Learning Management by getting the smart responses with flexibility and automation. This study shows a review of previous research, exploring and understanding the ideas behind a learning management system powered by GenAI. It shows that the main learning tasks such as study materials creation, evaluation based on quiz or test and personalized feedback for adaptive learning for learners.*

Exploiting the Large Language Models such as GPT-4 and LLaMA modles where, teachers can upload their video materials using suggested setup which converted into organized text summaries. The system further tests skills using quizzes or handson coding tasks. Additionally, the platform adaptively groups students into categories like fast,slow and moderate learner based on their interactions, engagement, and performance analytics.

This adaptive learning cycle gives personalized tailored lessons to each learner without adding extra load on teacher's workload. By integrating new recent AI advancements with the educational technology updates, this study helps to highlight the emerging new trends and foundational principles for building the next-generation modern learning environments where education springs with modern adaptive feedback.

Keywords: Generative Transformers, Adaptive Learning, Educational AI, Assessment Automation, Learner Profiling, LLM-based Tutoring

I. INTRODUCTION

The faster upgradation of Artificial intelligence (AI) mainly in the field of Generative AI has changed the way teachers teach throught online. As technology keeps getting better, online learning is becoming easier and more helpful for students.

In Traditional learning systems, teachers had to create lessons, quizzes, and feedback manually, which took a lot of time and was hard to manage for many students but this Generative AI-based LMS can automatically create study materials, quizzes, simulation and personalized feedback. Because of this automation, teachers can focus more on mentoring, and students get the learning help that fits their individual needs.

In Traditional learning systems, students often get feedback very late, so they cannot quickly fix their mistakes or improve on time. This slows down feedback generation making students less interested and takes away the chance to improve while they are still in the learning.

The proposed Generative AI-based Learning Management System solves this problem by giving smart with instant feedback using advanced AI models. These models check quiz answers on the spot and also understand how well the student is learning. Based on a student's learning speed, the system groups them as fast, average, or slow learners. This helps the platform adjust the lessons and study methods so that every student gets what they personally need to learn better . This study looks at the latest research and technologies used in AIbased learning platforms. It is mainly focuses on how these systems automate tasks and adjust to each student's learning style, and give personalized feedback based on learner. It also explains how advanced AI models can create study materials and design tests, while checking for any problems related to fairness.

It also examines how these systems can help to stay clear, fair, and flexible. Overall, this research shows how Generative AI can help to change the future of learning by creating automated tools and giving smart andtimely feedback that focuses on each learner student's needs.

One big problem in online education is to keep all the students equally engaged, especially when everyone learns at a different level and pace. Teachers are often don't have enough time to create different types of tasks or tests for each student based on their capability. With automated tools like this content generation, summarizing, and interactive features,The advanced AI models can create an personalized learning paths to each learner. These paths change accordingly based on how each student learns and how fast they progress.

This study not only explains the basic idea behind these AI based systems but also shows how they are can used in real life. It connects theory with practice by bringing different learning features together into one flexible system that grows and improves along with the students.

II. BACKGROUND AND RELATED WORK

The evolution of learner-centric education has been shaped by ongoing progress in flexible educational technologies. Early adaptive learning tools primarily relied on the statistical and parameter-based models in order to analyze student behavior and predict their learning outcomes. Bayesian Knowledge Tracing (BKT) and Performance Factor Analysis (PFA) are some examples, which studied how procedural knowledge is acquired through recorded student responses.

Although these approaches laid the foundation for personalized education, they lacked the capacity to process natural language that is spoken or written and were unable to interpret the underlying semantics of different learning materials such as video, code, or audio-based communication. Hence finding new approaches are important.

One such new approach to deal with this problem is the Transformer-based architectures, particularly Large Language Models (LLMs), which introduced a new dimension to AIdriven educational systems. Models like GPT4, LLaMA 3, and Claude are the best for contextual understanding, logical reasoning, and multi-step problem-solving. Unlike traditional computational learning models, Generative Transformers contains bidirectional contextual awareness, which allows them to summarize classroom discussions, generate assessments, and evaluate learner responses in real time and hence analysing their performance.

Recent studies have proven the use of LLMs in adaptive learning environments, their superior predictive and selfadjustive capabilities. For example, research by Zhang et al. examined how LLM-based models can forecast a student's reading comprehension by analysing the textual responses. Their findings shows that large language models achieved up to 18% higher prediction accuracy compared to traditional methods such as random forests or gradient boosting.

These findings tell us that LLMs models can capture linguistic patterns, behavioral clues, and contextual pattern that are not possible by basic statistical approaches thereby, making them well suitable for the adaptive, learner-focused educational frameworks.

Meyer *et al.* applied Large Language Models to generate the instructional guidance with researched supported on pedagogy practices, that shows how significant improvements in learning engagements can be done. Similarly, Huang et al. integrated LLM based reasoning mechanisms with traditional assessment frameworks to improve the equity, clarity, and flexibility in learner evaluation processes. These are the few ways through which LLMs were used.

Generative AI models not only contribute in the prediction and assessment by test but also serve as independent collaborators in the education field. These models can create the teaching materials, code simulation tasks, and interactive

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activities based on the individual learner's capacity and needs of the learner.This generation based capability enables automated management of the three essential components of online learning such as content creation, assessment design, and feedback automation.

The recent growth in Generative AI system not only present remarkable potential, but also introduced significant difficulties in many areas such as interpretability, biasing datasets, and ethical implementation.The previous research tells that the necessity of maintaining a balanced system required where human educators are actively involved to increase the standards of equality, transparency, and integrity within the learning process. The model proposed in this system tells that the study is based on these findings by exploring an integrated framework that leverages recent data and assesses alternative approaches. This approach extends prior to overall research through updated analytic methods including broader database, that finally contributes to the development of a Generative Transformer based system that aims at automating the learnercentric education through the adaptive materials, adaptive test and assessment mechanisms, and real-time personalized feedback based on learner.

III. SYSTEM OVERVIEW AND METHODOLOGY

Recent studies in Transformer-based architectures have enabled leading to the creation of flexible and modern Learning Management Systems that integrate automation, data-driven analysis, and personalized feedback mechanisms based on each learner. Various academic studies highlights that such tools will help to reduce learning barriers, optimize teacher teaching workloads enabling focusing on teaching only, and provide students with more engaging, adaptive, and interactive educational experiences.

This section explores the key components and methodologies commonly applied in Generative AI-driven LMS frameworks, focusing on three primary dimensions—content generation (text, simulations, Quiz Generation), learner adaptation, and feedback mechanisms.

A. Educator Workflow and Content Generation

Several studies highlight the use of Large Language Models (LLMs) to automate the generative transformation of instructions into many learning formats. Across the reviewed literature, a consistent pattern has been emerged in GenAIbased learning systems (Figure 1), where teachers provide instructional materials—such as recorded lectures such that other contents are generated such as written summaries and programming exercises—while the backend leverages integrated adaptive AI-driven processes. These processes typically include the following components:

Video-To-Audio Conversion: Conversion of video to audio can be done using the FFmpeg tool to extract the audio context in mp3 format and then process to next pipline of the architectural workflow

Audio-to-Text Transcription: Speech recognition models such as Whisper or DeepSpeech are employed to convert video lectures into well-structured written transcripts and summaries with no limitations of language as we can use multilingual models.

Summarization and Topic Segmentation: Transformer-based summarizers, including GPT-4 and LLaMA 3 helps to identify key educational objectives based on relevant terms and topics producing concise review notes that provide enhanced accessibility and comprehension.

Quiz Generation: Generative Transformer models are fine-tuned to create context-specific assessment items—both multiple-choice based on the topics and the content related to it.

Coding Simulation and Debugging: In programming based on education, LLMs models generate a sample code and examples with explanation, test cases, and guided exercises. These models also helps to provide feedback at realtime on code structure with code standards, logic, and execution flow. Some advanced frameworks employ reasoning based models which are capable of automatically identifying and helping to correct code errors while explaining the cause of the error with specific modifications.

B. Learner-Centric Adaptivity

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A defining characteristic of Generative AI-based Learning Management System frameworks lies in their ability in adapt to educational materials based on learner's group category preferences and performance data. Data such as test scores, task completion time, and interaction metrics is continuously analyzed to categorize students into flexible adaptive learning groups according to their performance levels.

Slow Learners: Receive reinforced explanations, shorter assessments, and more basic understanding with visual materials in order to strengthen the foundational understanding.

Moderate Learners: Progress through the standard moderate labeled content at a steady pace and maintaining a balanced level of learning.

Fast Learners: receive advanced quizzes, coding simulations challenges, and tasks which are designed to engage motivation and promote interactivity and engagement.

According to Zhang *et al.* [**?**], LLMs models shows better prediction accuracy up to 18% improvement when compared with traditional machine learning approaches—in identifying individual learning rates and change in behavioral patterns. Such dynamic grouping supports effective instructional balance, ensuring that content does not remain overly simple or complex, thereby maintaining consistent learner engagement.

C. Feedback and Instructor Dashboard

The examined systems consistently shows importance on feedback automation as a basic component of learner's interaction. Large Language Models are used to evaluate and assess student interactions, identify student capacity, and generate personalized textual feedback for each learner. Many studies

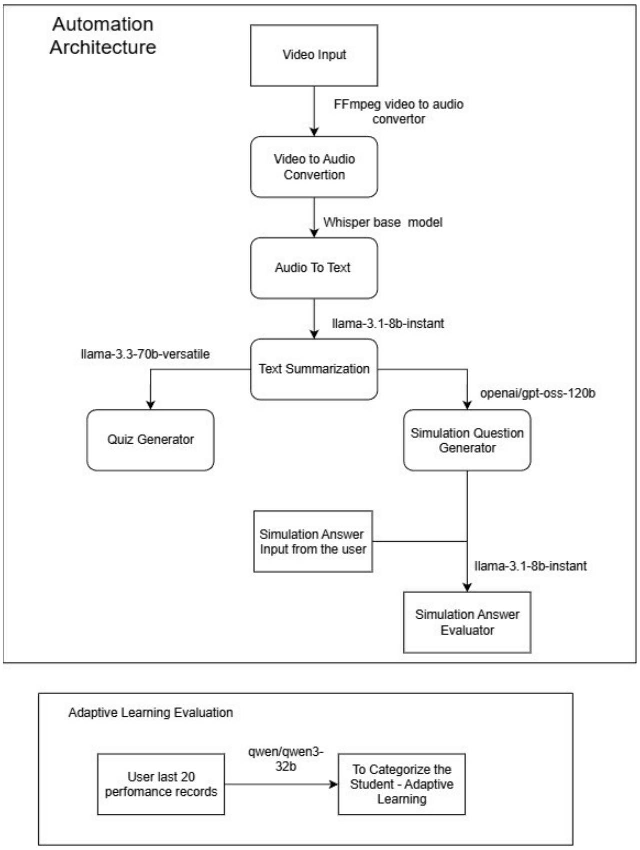

Fig. 1. Generalized workflow of GenAI-based LMS models: content video ingestion, automated content generation, learner analysis, and adaptive feedback loop.

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shows how to integrate visualization tools that display performance trends, engagement maps, and prediction indicators for students who may be struggling.

A continuous improvement across these research involves maintaining the human participation within the loop of allowing teachers to review,verify and evalute, or modify AIgenerated report. This balance of automation and educator helps in enhancing the system's reliability, transparency, and educational purpose, ensuring that AI-driven recommendation remain academically valid.

IV. EVALUATION METRICS AND BENCHMARKING

Across the literature, GenAI-based Learning Management Systems are evaluated using multiple constraints within a complete framework that helps to give educational methods and daily practices. In Total, these factors help assess how effectively transformer based systems can enhance performance, adaptability, scalability, and provide overall educational impact when compared to traditional Learning management system approach and machine learning models.

The following sections summarize the key assessment techniques and evaluation measures commonly applied in recent research on GenAI-enabled educational platforms

A. Learning Metrics

Learning-focused measures emphasize the educational outcomes that have been determined the effectiveness of AIbased learning systems. Numerous research efforts assess learning improvements through preand post-test analyses, where observed gains typically ranging from 25% to 45% compared to baseline methods [**?**].

Retention rate—defined as the proportion of students who complete a course or instructional unit — is frequently cited as a primary indicator of engagement system which often showing an increase of 10% to 25% compared to normal traditional and static LMS models.

Additionally, classification accuracy serves as a key performance metric in identifying learner's groups such as fast, average, or slow learners. Transformer-based models have shown prediction accuracies between 80% and 90%, highlighting their strong potential analyzing learning behaviors and predicting performance trends in more effectively than conventional older knowledge-tracking approaches.

B. Operational Metrics

Performance indicators shows the assess of how efficiently a system manages computational performance and adaptability—both of which are most crucial for real-world academic deployment. Research frequently evaluates *prediction latency*, which refers to the time taken to generate educational materials or produce other generative outputs and decisions.

Modern systems increasingly adopt iterative refinement rather than static design principles, where large neural networks are trained using adaptive learning signals instead of fixed set of rules . Models that used reduced precision techniques or stored data copies are able to have maintained response times of under 10 seconds across many operations.

Additional evaluation criteria include throughput (capacity handled per unit time) and resource utilization efficiency. Contemporary transformer-based implementations have demonstrated the ability to support thousands of many simultaneous learning activities while maintaining stable GPU and memory performance.

Such efficiency and scalability helps to underline the feasibility of deploying LLM-powered Learning Management Systems (LMS) within the large universities and digital education platforms.

C. User Experience Metrics

From the learner's point of view, user experience measures assess how closely AI-generated content aligns with human expectations and response patterns. Commonly used indicators include *Perceived Usefulness (PU)* and *Feedback Clarity*.

Survey-based research has consistently reports satisfaction scores above 4.2 out of 5 among both teachers and students, indicating that the automated educational resources and feedback mechanisms are considered as the highly useful and trustworthy.
Feedback clarity shows the easiness of understanding the practical value of AI-generated remarks, particularly within the evaluation contexts. Systems that add logic enhanced large language models and reasoning based on cues typically shows better performance in this education domain with instructional balance and transparencies.

D. Synthesis of Findings

When looking at all together, these evaluation measures have collectively highlighted that Generative AI powered Learning Management Systems givesimprovements in learner's engagement and personalization.
However, this system efficiency continues to be a central concern. Several studies have showed that further developments are needed, particularly making sure that there is equity and feedback clarity, while keeping less computational and processing costs which is an important issue for institutions with less resources.
hence, the rise of both instructional and functional metrics indicating that transformer based educational systems are slowly evolving towards more adaptive, scalable, and complete frameworks that are capable of supporting the diverse backgrounds of learner needs.

V. DISCUSSION

Advanced language models are built on transformer architectures such as LLaMA 3 and GPT-4 explains the advanced context based reasoning capability that directly improve the performance in the Learning Management system functions. These include setting up learners profile, adaptive assessment generation, and automated academic evaluation, where both accuracy and explanatory connections are important.
Transformer architecture based models such as **LLaMA3** and **GPT-4** shows a deeper context based understanding that results in higher accuracy in learner categorization,quiz generation, and automated evaluation while maintaining clarity and importance in generated explanations.
Mainly, open source models like **LLaMA** achieve near results on smaller-scale setups, that requirs relatively less computational resources when compared to private sourced models such as **Sonnet** or **GPT-4**,hence improving their dependency for institutional deployment.

A. Learner Categorization Performance

Early adaptive learning mechanisms, such as Bayesian Knowledge Tracing and Performance Factor Analysis, depending on static parameter estimation and simplifying assumptions about learner behavior. While these frameworks offered interpretability, their representational capacity was not enough for modeling complex, evolving learning paths. Subsequent machine learning techniques including ensembles like XGBoost has improved the prediction accuracy but remained less focused on the predefined targets without understanding the generalized context.
Recent studies instead shows that classifier models derived from large language architectures produce most improved with the overall outcomes. When evaluated against statistical and hybrid systems, LLM based model approaches improves the accuracy gains up to 13% in learner categorization tasks, as summarized in Table I. These improvements are achieved with reduced inference overhead, indicating favorable efficiency of performance trade-offs.Clearly, comparative analysis shows that moderately sized open sourced models attain F1-scores comparable to larger private based models, while it uses lower GPU which is an advantage as it directly impacts scalability in institutional deployments.

B. Question and Simulation Generation

Traditional educational content generation systems usually apply rule based logic, which will create difficulty when tasked with generating diverse or context based learning materials. In contrast to this generative transformer models such as

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GPT-3.5 and recent LLaMA models uses the various mechanisms to generate content that is both context-aware and semantically consistent.

As seen in the comparative results that is presented in Table II, transformer based generators meet or exceed existing methods in semantic fit while retaining the computational efficiency. Controlled hyper parameters, particularly on lowtemperature sampling systems, will enhance the reliable balance between creativity and determinism. This balance proves that these parameter are critical for applications including adaptive quiz construction, simulation based learning, and structured code exercises, where consistency and relevancy are equally important.

C. Automated Evaluation and Feedback

Automated evaluation systems based on earlier machine learning techniques such as BERT-QA basically depend on predefined response patterns or similarity thresholds. which is effective for small scoring tasks, these systems often lack transparency and produce less explanatory feedback. Transformer models contain reasoning based and long context modeling instead of generating evaluative outputs.

This results summarized in Table III show that open large language models achieve great precision and semantic score on par with premium systems while substantially reducing computational cost. In particular, open architectures demonstrate resource consumption reductions of approximately 50% relative to closed models such as LLAMA. This efficiency advantage will improve their suitability for the educational institutions and research organizations which are operating under the constrained API or cloud-computing budgets.

D. Aggregate Comparison of Adaptive Learning Systems

When evaluated overall, the reviewed research underscores the benefits of embedding Generative AI technologies within LMS infrastructures. The Aggregate comparisons (Table IV) reveal that open sourced LLaMA-centered systems deliver educational outcomes nearly same as those of high-cost commercial platforms, while bringing down the implementation and long-term operational expenditure by an estimated 65–70%. These findings shows that open transformer architectures effectively balance instructional quality, system performance, and affordability giving positioning as a viable solutions for largescale educational deployment.

E. Critical Observations

Although the research strongly supports the educational and operational advantages of the Generative AI integration within Learning Management Systems, there are several key challenges that persist and that must be addressed for sustainable adoption:

Fairness and Bias: Even open sourced large language models may also show underlying dataset biases. Giving the diverse and representative training data, along with fairness based fine-tuning methods which is also essential. Moreover, context-specific prompting plays an very important role for the the model and providing balanced outcomes.

Model Drift: As there is change in learner behavior and curricular, the models risk performance degrades over the time gradually. Periodic fine-tuning and adaptive learning capability updates are more essential to ensure the continued reliability and accuracy.

Explainability and Trust: The Transparent dashboards, interpretable model outputs and clear feedback mechanisms must be included in AI based educational systems to support the educator confidence and ethical accountability which provides student's performance and student's capabilities.

Overall, the reviewed research shows importance on the **Generative Transformer based LMS architectures** which are particularly open sourced model systems such as **LLaMA** which achieve performance levels comparable to or surpassing the proprietary solutions like **gpt-4**. They do so while the maintaining cost efficiency and promoting accessibility for institutions with limited computational resources.

These models form a robust foundation for the developing the **flexible, learner centered education systems** that align with the goals of **UN SDG 4: Quality Education**, advancing equitable and inclusive learning opportunities for all.

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VI. CONCLUSION

The sources have examined here and shows a definite pattern with a clear change in online learning, moving away from tje fixed structures toward the **dynamic, evolving systems** which enabled by automated tools. Personalized material is now distributed through the flexible, student based platforms powered by **Generative AI** and **transformer based architectures**.

Across multiple studies, The **Large Language Models (LLMs)** such as **GPT-4** and **LLaMA-3** have showed stronger performance in managing core learning tasks, including generating customized content, assessing the student progress, and providing the contextual based feedback.

By comparing with the traditional methods and machine driven approaches along with the generative transformer based systems, several consistent trends emerge

Enhanced Learning Accuracy and Context Awareness: LLM powered systems have achieved the higher categorization accuracy and improved knowledge based acquisition through the multimodal based models and contextual based reasoning models.

Increased Efficiency and Reduced Workload: Automated testing, interactive modules, and AI-driven feedback tools has been used to streamline the repetitive tasks and reduce educator workload, thereby ensuring consistent student assessment across the platforms.

Nevertheless, persistent difficulty remains which include ensuring the **fairness, clarity, and computational efficiency** while maintaining the ethical data practices. Achieving the transparency in the AI-generated feedback and also preserving the human oversight are important for responsible educational innovation.

In conclusion, the body of research reviewed confirms that **Generative Transformer based LMS frameworks** provide transformative educational value by adapting learning to individual needs while supporting scalable and easy deployment. When designed with a focus on clarity, accessibility, and ethics, such systems holds an strong potential for advancing the **United Nations Sustainable Development Goal 4 (Quality Education)**, promoting fair and responsive educational opportunities that improves both teaching effectiveness and learner success.

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TABLES

TABLE I: PERFORMANCE COMPARISON OF ADAPTIVE LEARNING MODELS

Model Type	**Accuracy (%)**	**F1-Score**	**GPU Usage Reduction (%)**
BKT / PFA	72.4	0.69	–
XGBoost	78.3	0.74	–
Sonnet-class (Commercial)	85.6	0.82	0
LLaMA-3.1-8B	86.9	0.81	45

TABLE II: COMPARISON OF GENERATIVE MODEL PERFORMANCE FOR CONTENT CREATION TASKS

Model	**Semantic Accuracy (%)**	**Consistency Score**	**Avg. Latency (s)**	**Cost Efficiency (%)**
Rule-based / Template Systems	68.2	0.71	5.4	100
GPT-3.5 (Baseline)	87.5	0.86	3.8	82
LLaMA-3.1	**89.3**	**0.89**	3.2	**92**

TABLE III: PERFORMANCE COMPARISON OF AUTOMATED GRADING AND FEEDBACK MODELS

Model	**Scoring Precision (%)**	**Feedback Clarity**	**Meaning Consistency**	**Compute Cost Reduction (%)**
BERT-QA (Baseline)	74.6	0.72	0.70	–
GPT-4 (Closed-source)	91.4	0.90	0.92	0
Sonnet (Commercial)	90.2	0.88	0.89	0
LLaMA-3.3-70B (Open)	**90.8**	**0.89**	**0.90**	**50**

TABLE IV: EDUCATIONAL EFFECTIVENESS AND COST COMPARISON OF GENAI-BASED LMS MODELS

Model Type	**Learning Gain (%)**	**Retention Rate (%)**	**Satisfaction Score (1–5)**	**Cost Reduction (%)**
Traditional LMS (Non-AI)	100 (Baseline)	68	3.7	–
GPT-4 / Sonnet (Proprietary)	142	85	4.5	0
LLaMA-3.3-70B (Open-Source)	**140**	**84**	**4.4**	**68**

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