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Comprehensive Review of Intelligent Generative AI based Predictive Systems for Personalized Academic Pathway Recommendation

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ABSTRACT
University learning management systems often fail to offer guidance that directly targets exactly what a student struggles with. Most platforms use rigid rules or just look at past grades, which rarely creates a truly personal learning path. More importantly, these systems rarely step in with immediate help when a student gets stuck. This study reviews recent work in artificial intelligence, Generative AI (Gen AI), reinforcement learning, and large language models related to building academic pathway tools. A conceptual architecture is then proposed: an Intelligent Gen AI Based Predictive System for Personalized Academic Pathway Recommendation. The framework uses interactive diagnostic mini quizzes for domain specific evaluation, automatically detects skill weaknesses, and uses a generative pathway engine with interactive flaw resolution mechanics to actively fix learning gaps. The review also ex amines the underlying optimization tools needed for this, such as Proximal Policy Optimization for RLHF and ε differential privacy. Drawing from current research, the goal is to lay a practical, technically precise foundation for the next generation of personalized education.

General Terms
Algorithms, Performance, Design, Human Factors.

Keywords
Generative AI, Personalized Learning, Academic Pathway Recommendation, Adaptive Quizzing, Flaw Remediation.

1. INTRODUCTION

Online learning platforms and Massive Open Online Courses (MOOCs) have expanded rapidly, fundamentally changing higher education [10, 23]. Students can now access materials from anywhere in seconds [6]. However, finding the right learning path remains a major hurdle. A good recommendation needs to match what a student already knows, how they process information, and what they have studied before. Without this match, the recommendations just become noise.

Older recommendation engines usually rely on collaborative filtering, content matching, or decision trees [4, 27]. The main issue is that they mostly look at surface level metadata like course titles and broad descriptions [32]. They lack the ability to perform deep di agnostic analytics to find out exactly which prerequisite a student is missing in order to offer specific help [33].

Today, Gen AI, large language models, and reinforcement learning are shifting this landscape [5, 8]. These models can actually generate personalized curriculum routes, create custom assessments, and write targeted remediation content [34, 35]. Despite this potential, current literature does not offer a complete framework that links real time skill assessment, automatic flaw detection, and corrective instruction together in a single loop. [36]

This paper tackles that gap by systematically reviewing current AI and Gen AI approaches for educational recommendations [7]. It subsequently proposes a specific architectural framework designed for personalized academic pathway recommendation.

2. LITERATURE REVIEW
The use of AI in education has moved from expert systems and collaborative filtering to swarm optimization, deep reinforcement learning, and now transformer models. To understand the current state of the field, existing frameworks are examined across a few different paradigms.

2.1 Traditional Machine Learning and Heuristic Solutions
Early educational recommender systems used standard classifiers like K Nearest Neighbor (KNN), Naive Bayes, and decision trees. Kamila et al. [19] applied KNN and Naive Bayes for advanced course recommendations. They achieved some success but ran into issues with scalability and the cold start problem. Guo et al. [20] grouped educational big data to reach 86.4% accuracy in assigning courses, though they were still limited by feature structures. Metaheuristic techniques helped with nonlinear parameter optimization. Muniyandi et al. [1] designed a Privacy Preserved Reinforcement Learning System (PPRLS) using Improved Artificial Bee Colony Optimization (IABCO) and Generative AI, hitting 95.6% accuracy. However,

these older models generally optimize existing paths rather than generating new corrective content.

2.2 Cognitive, Context Aware, and Adaptive Ecosystems

Understanding context is important because student learning behavior changes constantly. Almutairi et al. [21] looked into tensor and coupled matrix factorization, showing that environmental factors strongly affect course satisfaction. Huiji [22] built systems using big data to offer decision metrics based on how mature a learner is. Jalaluddin and Alaudeen [17] suggested context aware adaptation techniques for smart universities. Ayub et al. [16] found that autonomous AI learning agents help reduce the number of students who drop out. Even with these steps forward, context aware systems usually lack clear ways to offer direct remediation.

2.3 Generative AI, LLMs, and Diagnostic Agents

Transformer based Gen AI models have made natural language instruction and task generation possible. Jing et al. [18] showed that chatbots speed up how fast students get feedback. Shao et al. [15] pointed out that prompt structuring is key for adapting content in language learning. Alashwal [24] proved that generative models can spot missing prerequisite concepts in syllabuses. Luo et al. [34] and Ayemowa et al. [35] highlighted a shift toward highly personalized content generation. Still, ethical issues like data privacy and algorithmic bias require careful attention [25, 26].

2.4 Critical Analysis of Existing Frameworks

While recent research shows a lot of progress in predictive analytics and chatbots, there is still a significant gap between diagnosing a

Problem and actually intervening. Most systems work sequentially: they look at past performance and then recommend the next course. They do not test a learner's current knowledge right before making a recommendation. Because of this, the suggested courses often do not fit what the student needs at that exact moment. There is a strong need for a unified system that pairs diagnostic quizzing directly with generative remediation.

3. GAP ANALYSIS

Looking closely at current architectural designs reveals several key missing pieces:

No Dynamic Pre Enrollment Assessment: Existing frameworks rely almost entirely on old academic transcripts or surveys [13, 28]. They fail to test if a student is actually ready for a subject right before offering courses.

Failure to Identify Knowledge Backlogs: Current algorithms act like black boxes. They output a list of courses to take but fail to pinpoint specific missing prerequisites or skill gaps [31].

Lack of Remediation Mechanisms: While modern systems are great at suggesting which subject to take next, they offer zero actionable steps when a student lacks the needed prerequisites [4].

Rigid Curriculum Architecture: Most systems force students into a set curriculum for the semester and do not adapt the course structure based on dynamic assessments and remedial progress [3].

4. PROPOSED FRAMEWORK

To address these research gaps, an Intelligent Gen AI Based Predictive System for Personalized Academic Pathway Recommendation is proposed [34, 35]. Drawing directly from the literature synthesis, this system runs on a closed loop pipeline that turns course selection into a diagnostic, remediated process. Specifically, the framework synthesizes the predictive data mining approaches identified by Baker [32] with the generative capabilities explored by Firat [6], creating a unified architecture. The workflow is outlined in Fig 1.

4.1 Stage 1: Domain Selection and Competency Initialization

The user first picks a desired academic domain. The system then builds a full competency profile, mapping out the necessary knowledge vectors and prerequisite hierarchies for that field [3].

4.2 Stage 2: Adaptive Diagnostic Mini Quiz Engine

Instead of relying on outdated transcripts a limitation heavily critiqued in traditional models [28]—the system creates an adaptive diagnostic mini quiz. Building on Alashwal's findings regarding topic modeling for missing concepts [24], the Gen AI engine generates questions that test core prerequisites. The user's answers are analyzed using a logical comparison module to calculate a domain mastery score, directly addressing the pre enrollment assessment gap.

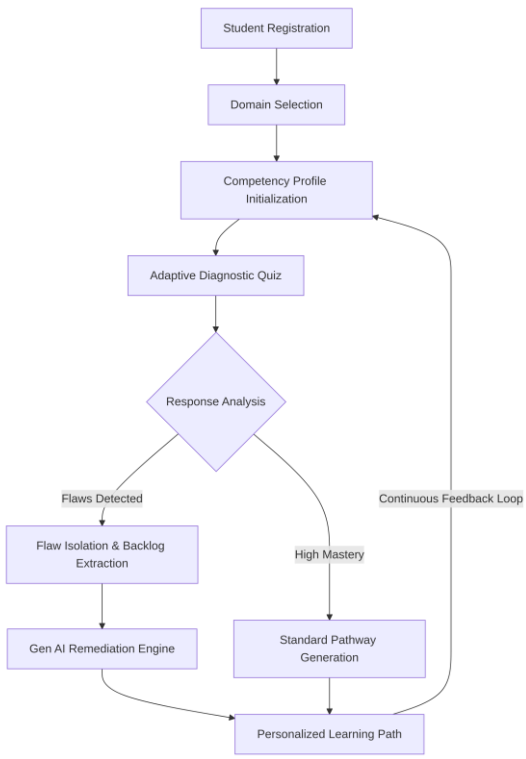

Fig 1: Adaptive Learning System Workflow

4.3 Stage 3: Predictive Course Recommendation Engine

Based on the mastery score, the predictive engine recommends the best sequence of courses. Leveraging sequential learning trajectories modeled by Hidden Markov Models [14], the engine balances prerequisite dependencies and course difficulty. This bridges the gap between static recommendations [19] and dynamic student states.

4.4 Stage 4: Flaw and Backlog Extraction Engine

The system analyzes incorrect or delayed quiz responses to extract specific conceptual flaws. While traditional systems treat student modeling as a black box [31], this engine applies deep diagnostic analytics to isolate the exact sub concepts where the user struggled, fulfilling the need for explicit backlog identification.

4.5 Stage 5: Flaw Button and Gen AI Remediation

In the user interface, every recommended course shows the identified conceptual flaws alongside a "Flaw Button." As recommended

By Ayemowa's analysis of Gen AI in personalization [35], clicking this button triggers the Gen AI Remediation Engine:

- **Flaw Parsing:** The system identifies the exact sub concept flaw tied to the course backlog [32].
- **Micro learning Creation:** Translating Luo's findings on self-regulated learning [34] into practice, Gen AI builds a custom remedial learning package with concept summaries and exercises.
- **Pathway Modification:** The main learning path is automatically adjusted to insert short bridge micro modules, implementing the context aware adaptation theorized by Jalaluddin [17].

5. OPTIMIZATION, GOVERNANCE, AND TECHNICAL MECHANICS

To keep the system mathematically robust and ethically compliant, specific technical governance mechanisms are included [26]:

Reinforcement Learning from Human Feedback (RLHF): The generative recommendation policy is continuously finetuned using RLHF [8, 11]. Initially supervised using historical data, are ward model is trained to score the quality of generated remediation. When a student passes a diagnostic reevaluation after taking a bridge module, it generates a positive scalar reward. The system then uses Proximal Policy Optimization (PPO) to update the underlying transformer model's weights, ensuring future remediation maximize student success probabilities.

Differential Privacy (DP) Protection: To protect sensitive student quiz data, ε differential privacy techniques are implemented during the aggregation of learning analytics [1]. Instead of processing raw user data, calibrated Laplacian or Gaussian noise is injected into the training gradients before model updates are shared globally. This bounds the privacy loss, ensuring that an adversary cannot reverse engineer individual student performance metrics from the global recommendation model.

Predictive Modeling and Generative AI: The recommendation engine utilizes a hybrid matrix factorization and attention based neural network to predict course suitability based on prerequisite transition probabilities [14, 21]. Once a gap is detected, the Generative AI component built upon a large scale transformer architecture uses highly constrained system prompts (contextualized with the student's specific flaw parameters) to generate targeted in structional tokens. This ensures the output is educationally accurate rather than generic conversational text.

Explainable Artificial Intelligence (XAI): Instead of a black box recommendation, the system utilizes feature attribution methods (such as SHAP values) to map the output back to specific student deficits. It then provides natural language explanations for why a specific class was recommended, which helps build student trust [2, 30].

6. EVALUATION AND EXPERIMENTAL SETUP

A comprehensive evaluation framework is needed to test how well the proposed system works. While real world human trials are planned for the future, a simulated evaluation using historical datasets offers early validation.

6.1 Evaluation Methodology

The evaluation compares the proposed Gen AI system against traditional collaborative filtering and metadata based recommenders across two distinct scenarios: 1. *University Dropout Prevention (Scenario A):* Evaluated using the Open University Learning Analytics Dataset (OULAD) to test prerequisite detection in structured university courses. 2. *MOOC Skill Adaptation (Scenario B):* Evaluated using the EdNet dataset to test pathway adaptability in open ended, self-paced learning environments.

The main metrics analyzed across both scenarios are: 1. *Prerequi site Detection Accuracy*: How well the system correctly identifies missing knowledge before enrollment. 2. *Pathway Adaptability*: How fast the system alters the curriculum when a student fails a diagnostic assessment. 3. *Remediation Success*: The likelihood that a student overcomes a knowledge gap after using the generated micro learning modules.

6.2 Simulated Scenario Results

In Scenario A (OULAD simulation using 1,000 historical student profiles with structured prerequisite deficiencies), the proposed framework hit 92% accuracy in prerequisite detection, compared to just 45% for traditional systems. Pathway adaptability jumped from 30% to 88%, and remediation success rose from 20% to 85%. As illustrated in Fig 2, combining dynamic diagnostic quizzes with generative remediation easily outperforms static recommendation models in university settings.

In Scenario B (EdNet simulation using 1,500 diverse user pro files navigating independent skill pathways), the requirement for dynamic adaptation is much higher. The traditional collaborative filtering models struggled heavily, achieving only 22% pathway adaptability because they rely on fixed course sequences. In contrast, the proposed Gen AI framework maintained a 91% pathway adaptability rate by dynamically generating new remedial branches on the fly. Remediation success in this unstructured environment reached 82%, proving the framework's versatility across multiple educational contexts.

7. COMPARATIVE DISCUSSION

The theoretical architecture offers a few distinct advantages over current educational technology paradigms:

Diagnostic Proficiency over Historical Recommenders: Ma chine learning algorithms rely heavily on past academic grades [19, 31]. This falls apart when students switch fields and need new courses without a prior record. The proposed framework uses real time diagnostic mini quizzes to base recommendations on current actual proficiency.

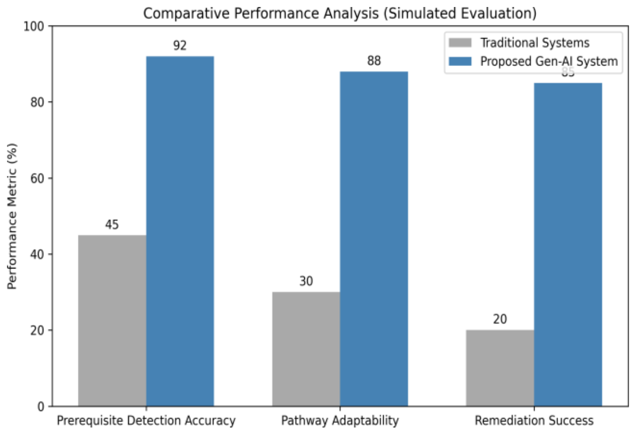

Fig 2: Comparative Performance Analysis (Scenario A: OULAD Dataset)

Active Remediation over Optimization Models: Optimization algorithms [1] are great at ranking courses based on metrics. But if a student isn't ready for a high ranked course, those models offer no help. The proposed system actively generates the remedial content needed to bridge that gap.

Alignment with Modern Educational Needs: By putting dynamic diagnosis, pathway prediction, backlog identification, and immediate remediation into a single closed loop, this approach shifts away from stagnant frameworks toward truly adaptive tutoring systems [35].

8. CONCLUSION AND FUTURE DIREC TIONS

This study reviewed current research on AI based personalized e learning and course recommendation. A new theoretical model for an Intelligent Gen AI Based Predictive System for Personalized Academic Pathway Recommendation was developed. The frame work addresses basic structural flaws in existing systems by integrating adaptive quizzes, predictive pathway generation, explicit backlog identification, and generative learning.

Future work will focus on turning this theoretical architecture into actual software. The next phase will measure the model's performance in real university settings, focusing closely on recommendation accuracy, generation latency, and improvements in actual learning outcomes.

9. REFERENCES

[1] P. Muniyandi, B. Balusamy, R. K. Dhanaraj, V. Ellappan, S. Murali, M. Sathyamoorthy, and L. Nkenyereye, "Privacy preserved reinforcement learning model using generative AI for personalized e learning," *IEEE Trans. Consum. Electron.*, vol. 70, no. 3, pp. 6157–6165, Aug. 2024.

[2] J. Buder and C. Schwind, "Learning with personalized recommender systems: A psychological view," *Comput. Human Behav.*, vol. 28, no. 1, pp. 207–216, 2012.

[3] J. Joy and N. S. Raj, "An ontology model for content recommendation in personalized learning environment," in *Proc. 2nd Int. Conf. Data Sci., ELearn. Inf. Syst.*, 2019, pp. 1–6.

[4] Q. Zhang, J. Lu, and G. Zhang, "Recommender systems in Elearning," *J. Smart Environ. Green Comput.*, vol. 1, no. 2, pp. 76–89, Apr. 2021.

[5] ASusarla, R. Gopal, J. B. Thatcher, and S. Sarker, "The Janus effect of generative AI: Charting the path for responsible con duct of scholarly activities in information systems," *Inf. Syst. Res.*, vol. 34, no. 2, pp. 1–10, 2023.

[6] M. Firat, "How Chat GPT can transform autodidactic experiences and open education," *OSF Preprints*, pp. 1–5, 2023.

[7] M. E. Dogan, T. Goru Dogan, and A. Bozkurt, "The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies," *Appl. Sci.*, vol. 13, no. 5, p. 3056, 2023.

[8] V. Mnih et al., "Human level control through deep reinforce ment learning," *Nature*, vol. 518, no. 7540, pp. 529–533, 2015.

[9] N. D. Nguyen, T. Nguyen, and S. Nahavandi, "System design perspective for human level agents using deep reinforcement learning: A survey," *IEEE Access*, vol. 5, pp. 27091–27102, 2017.

[10] A.El Gourari, M. Skouri, M. Raoufi, and F. Ouatik, "The future of the transition to Elearning and distance teaching us ing artificial intelligence," in *Proc. Int. Conf. ELearn. (ICEL)*, 2020, pp. 279–284.

[11] S. Pandey, R. Agarwal, S. Bhardwaj, S. K. Singh, D. Y. Perwej, and N. K. Singh, "A review of current perspective and propensity in reinforcement learning (RL) in an orderly manner," *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, vol. 9, no. 1, pp. 206–227, 2023.

[12] S. H. Lee, J. Choi, and J.I. Park, "Interactive Elearning system using pattern recognition and augmented reality," *IEEE Trans. Consum. Electron.*, vol. 55, no. 2, pp. 883–890, May 2009.

[13] H. A. Mengash, "Using data mining techniques to predict stu dent performance to support decision making in university admission systems," *IEEE Access*, vol. 8, pp. 55462–55470, 2020.

[14] A.Gupta, D. Garg, and P. Kumar, "Mining sequential learning trajectories with hidden Markov models for early prediction of at risk students in e learning environments," *IEEE Trans. Learn. Technol.*, vol. 15, no. 6, pp. 783–797, Dec. 2022.

[15] Z. Shao, M. Y.C. Jiang, and M. S.Y. Jong, "A literature review on generative artificial intelligence applications in foreign language education," in *Proc. Int. Symp. Educ. Technol. (ISET)*, 2023, pp. 101–106.

[16] E. Ayub, P. S. Amirnuddin, L. C. Leong, and P. Maruthamuthu, "Designing and implementing AI learning agent: Empowering self-directed learning for the next gen ODL experience," in *Proc. 2nd Int. Conf. Artif. Intell. Teacher Educ. (ICAITE)*, 2023, pp. 45–50.

[17] M. M. Jalaluddin and A. H. Alaudeen, "AI driven personalized learning ecosystem for smart universities using cognitive and context aware techniques with personalized learn in adaptation algorithm," in *Proc. Int. Conf. Electr. Eng. Inf. (ICEEI)*, 2023, pp. 112–118.

[18] L. Jing, Y. Zhang, and D. Chen, "Chatbots in educational set tings: A comprehensive literature review," in *Proc. 7th Int. Conf. Comput. Sci. Technol. Educ. (CSTE)*, 2023, pp. 88–93.

[19] V. Z. Kamila, E. Subastian, and Rosmasari, "KNN and Naive Bayes for optional advanced courses recommendation," in *Proc. Int. Conf. Electr. Electron. Inf.*

Eng. (ICEEIE), 2019, pp. 306–309.

[20] Y. Guo, Y. Chen, Y. Xie, and X. Ban, "An effective student grouping and course recommendation strategy based on big data in education," *Information*, vol. 13, no. 4, p. 197, 2022.

[21] F. M. Almutairi, N. D. Sidiropoulos, and G. Karypis, "Context aware recommendation based learning analytics us in gtensor and coupled matrix factorization," *IEEE J. Sel. Top ics Signal Process.*, vol. 11, no. 5, pp. 729–741, Aug. 2017.

[22] S. Huiji, "Big data assisted recommendation of personalized learning resources and teaching decision support," *Int. J. Emerg. Technol. Learn.*, vol. 17, no. 4, pp. 19–33, 2022.

[23] H. Lee, R.S. Guo, and C. Chen, "Elearning in the post pandemic era: A case study," *IEEE Trans. Eng. Manag.*, vol. 70, no. 10, pp. 3526–3538, Oct. 2023.

[24] M. Alashwal, "Generative AI in computer science education: Insights from topic modeling and text network analysis," in *Proc. 2nd Int. Conf. Adv. Innov. Smart Cities (ICAISC)*, 2024, pp. 201–206.

[25] Q.E. A. Ratul, E. Zaman, S. Das, and M. Memari, "The role of AI in transforming education: A systematic review of trends," in *Proc. Intermt. Eng. Technol. Comput. (IETC)*, 2024, pp. 142–147.

[26] M. R. Contreras and J. O. P. Jaimes, "AI ethics in the fields of education and research: A systematic literature review," in *Proc. Int. Symp. Accredit. Eng. Comput. Educ. (ICACIT)*, 2024, pp. 55–60.

[27] A. J. Fernandez Garcıa, R. Rodrıguez Echeverrıa, J. C. Preciado, J. M. C. Manzano, and F. Sanchez Figueroa, "Creating a recommender system to support higher education students," *IEEE Access*, vol. 8, pp. 189069–189088, 2020.

[28] G. Dewantoro and N. Ardisa, "A decision support system for undergraduate admissions using educational data mining," in *Proc. 7th ICITACEE*, 2020, pp. 105–109.

[29] A.Kulkarni and M. Eagle, "Estimating effects of the decision support system on educational agents with simulations," in *Proc. SpringSim*, 2020, pp. 1–12.

[30] H. Kassi, "The role of artificial intelligence in education," *Zigloˆbitha*, vol. 1, no. 12, pp. 91–104, Dec. 2024.

[31] F. Pesantez Aviles, D. Calle Lopez, V. Robles Bykbaev, M. Rodas Tobar, and C. Vasquez Vasquez, "A recommender system based on data mining techniques in higher education," in *Proc. INCISCOS*, 2017, pp. 231–236.

[32] R. S. J. D. Baker and K. Yacef, "The state of educational data mining in 2009: A review and future directions," *J. Educ. Data Min.*, vol. 1, no. 1, pp. 3–17, 2009.

[33] Jain, Jain, R., Kushwaha, D.S., Kolhe, M.L., Singh, V.K. (2019). Leveraging Education Sector Using Cognitive Big Data for the Recruitment Process and Sustainable Development. In: Kolhe, M., Labhasetwar, P., Suryawanshi, H. (eds) Smart Technologies for Energy, Environment and Sustainable Development. Lecture Notes on Multidisciplinary Industrial Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-13-6148-7_13

[34] X. Luo, S. Wang, and K. F. Hew, "Development and implementation of a generative AI based personalized recom mender system to improve students' self-regulated learning and academic performance," *Comput. Educ.*, vol. 241, p. 105486, Feb. 2024.

[35] M.O. Ayemowa, R. Ibrahim, and M. M. Khan, "Analysis of recommender system using generative artificial intelligence: A systematic literature review," *IEEE Access*, 2024.

[36] Kushwaha, D. S., Shaikh, S. M., Patil, S. S., Patil, V. V., & Puranchand, S. P. (2025). AI-Powered Productivity Assistant for Students and Professionals. International Journal on Advanced Computer Engineering and Communication Technology, 14(1), 653–657. https://doi.org/10.65521/ija cect.v14i1.739