PrepFlow: A Review Of AI-Powered Personalized DSA Learning and Placement Preparation Platforms

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***Abstract*—Artificial Intelligence (AI) is transforming educational and employability platforms from static content-delivery systems into adaptive environments that can respond to learner performance, preferences, and career goals. This review analyzes ten research papers covering AI-based personalized e-learning, adaptive assessment, generative-AI intelligent tutoring, AI-assisted learning support, mock interview systems, and integrated placement preparation. The reviewed studies employ learner profiling, knowledge tracing, recommendation, natural language processing (NLP), speech processing, computer vision, large language models (LLMs), retrieval-augmented generation (RAG), resume analysis, and performance analytics. The literature demonstrates strong progress in individual learning and placement modules; however, the capabilities are often distributed across separate systems. In particular, a unified workflow connecting data-structures-and-algorithms (DSA) assessment, topic-level adaptive learning, continuous performance analysis, placement-oriented preparation, resume-aware guidance, and AI interview practice is not clearly established across the reviewed works. Based on this synthesis, PrepFlow is proposed as a research direction for an AI-powered DSA learning and placement preparation platform. The proposed workflow links assessment, practice, analytics, recommendation, interview simulation, and feedback in a continuous learning loop. The paper identifies technical, pedagogical, privacy, evaluation, and latency challenges that should be addressed before such an integrated platform can be validated at scale.**

***Index Terms*—Artificial Intelligence, Personalized Learning, DSA, Intelligent Tutoring System, Generative AI, Placement Preparation, Mock Interview, RAG**

I. INTRODUCTION

Engineering students preparing for technical placements must develop multiple competencies at the same time. These include programming fundamentals, data structures and algorithms (DSA), aptitude, communication, resume quality, and interview performance. Conventional learning environments generally provide common study material and fixed practice sequences, while placement preparation is often divided among coding platforms, classroom training, resume tools, and mock interviews. Such separation can make it difficult for a learner to understand which skill should be practiced next and how improvement in one activity affects overall placement readiness.

AI-based personalized learning research provides a foundation for addressing this problem. Murtaza et al. [1] describe personalization as delivering learning content and assessments according to a learner's comprehension level and preferred learning modes. Their framework combines data, adaptive learning, adaptability, recommendation, and content/assessment delivery. This direction is relevant to DSA because a learner may show different mastery levels across arrays, linked lists, trees, graphs, dynamic programming, or complexity analysis. Recent studies extend personalization through diagnostic assessment, personalized learning paths, dashboards, adaptive assessment, and conversational support [2], [3].

Generative-AI-based intelligent tutoring systems further introduce context-aware explanations and adaptive feedback [4], [5]. At the employability end, AI interview systems evaluate language and speech behavior [6], [7], while placement platforms combine DSA practice, resume analysis, job matching, interview simulation, mentoring, and analytics [8], [9]. This review therefore examines the ten selected papers as a connected research landscape rather than as

isolated implementations. The objective is to identify what has already been established, compare the technologies and functionalities, and derive a research gap for PrepFlow: an integrated platform focused on DSA learning and placement preparation.

II. REVIEW METHODOLOGY

The review is based on ten supplied research papers published between 2022 and 2026.

The papers were grouped into four themes:

(1) AI-based personalized learning, (2) generative AI and intelligent tutoring, (3) AI-based mock interview systems, and (4) placement preparation and personalized career assistance. The analysis compares each work according to its objective, AI techniques, learning or placement functionality, feedback mechanism, and relevance to the proposed PrepFlow direction.

The review follows a thematic synthesis. First, common capabilities were extracted from the papers, including learner profiling, assessment, recommendation, adaptive content, NLP, speech recognition, LLMs, RAG, resume analysis, and performance dashboards. Second, these capabilities were mapped to the DSA-to-placement journey. Finally, limitations and integration gaps were identified from the combined evidence. The proposed PrepFlow workflow is presented as a research direction; it is not treated as an experimentally validated result of the reviewed literature.

III. AI-BASED PERSONALIZED LEARNING

Murtaza et al. [1] provide a broad framework for personalized e-learning. Their architecture contains a Data Module, Adaptive Learning Module, Adaptable Learning Module, Recommender Module, and Content and Assessment Delivery Module. Assessment results and learner interaction data are used to estimate knowledge levels and support recommendations. The paper also emphasizes continuous assessment, robust data collection, knowledge tracing, evaluation of recommendations, and low-latency personalization. The AI-Powered Personalised Learning System [2] applies diagnostic assessment and personalized learning paths along with quizzes, chatbot support, gamification, and dashboards.

Such a design is useful for DSA preparation because an initial diagnostic test can identify topic-level strengths and weaknesses before a learner starts a long practice sequence. The smart learning platform reported by Pavan Kumar et al. [3] integrates adaptive assessments, personalized learning paths, and performance analytics. These components indicate a shift from simply recommending content toward maintaining a measurable learning state. For DSA, analytics can be organized around accuracy, attempts, time taken, difficulty level, and topic mastery. However, the reviewed learning papers mainly concentrate on educational progression and do not fully connect that progression to resume, interview, and job-specific needs.

IV. GENERATIVE AI AND INTELLIGENT TUTORING

Generative AI expands personalized learning by allowing systems to generate explanations, questions, feedback, and conversational responses. Almetnawy et al. [4] present an adaptive intelligent tutoring system powered by generative AI, using LLM-oriented techniques, prompt engineering, adaptive feedback, and gamification. This is important for DSA learning because learners frequently require explanations at different depths: a beginner may need an intuitive explanation of recursion, whereas an advanced learner may need complexity analysis or an alternative optimization.

Balakrishnan et al. [5] discuss intelligent tutoring systems powered by generative AI and describe a learner-state-aware approach in which confusion points can be mapped to instructional content and clarified through generative responses. The AI-Enhanced Learning Assistant Platform [10] similarly focuses on question generation, answer evaluation, identification of weak areas, and recursive testing. Together, these studies suggest a closed loop of question, response, diagnosis, explanation, and re-assessment.

For PrepFlow, the key implication is that an LLM should not operate only as a general chatbot. Its responses should be grounded in the learner's DSA profile, previous attempts, topic mastery, and placement goal. This can reduce irrelevant recommendations and make generated practice more targeted.

V. AI-BASED DSA LEARNING AND ADAPTIVE ASSESSMENT

DSA is a particularly suitable domain for adaptive learning because skills can be represented as a hierarchy of concepts and problem-solving patterns. A learner may correctly solve array problems but struggle with trees or dynamic programming. The personalized-learning literature [1]– [3] supports the use of continuous assessment and knowledge estimation, while the learning assistant paper [10] supports recursive testing of weak areas. Based on these findings, an integrated DSA module can begin with a diagnostic assessment and maintain a topic-wise mastery profile. Practice can then be recommended according to correctness, number of attempts, time taken, difficulty, and recent errors. After a practice cycle, the learner profile can be updated and a new set of problems generated or selected.

The literature supports these individual mechanisms, but the exact end-to-end DSA mastery workflow is a proposed synthesis for PrepFlow rather than a reported result of a single reviewed paper. A further requirement is evaluation of recommendations. Murtaza et al. [1] note that recommendation quality should itself be evaluated. Therefore, PrepFlow should not measure only question accuracy; it should also examine whether recommendations improve later performance, reduce repeated errors, and move learners toward target placement competencies.

VI. AI-BASED MOCK INTERVIEW SYSTEMS

AI-based interview research addresses a different stage of placement readiness. Senthilkumar et al. [6] describe a mock interview system using NLP and speech-related technologies, with computer-vision components such as OpenCV and MediaPipe for behavioral assessment. The system considers verbal and behavioral performance rather than only textual answers. ShivajiRao et al. [7] present a virtual job interview simulator with role-specific questions, real-time evaluation, and adaptive difficulty. Role-specific interviewing is important because technical expectations vary across software development, data analysis, cloud, and other roles. Adaptive questioning can also make the simulation more realistic by responding to a candidate's previous answer.

These systems demonstrate that interview preparation can be treated as an evaluable learning activity. However, interview feedback is generally a separate stage. A learner who performs poorly on an interview question about graphs, for example, should ideally be routed back to graph-based DSA practice. Connecting interview feedback to the learning profile is therefore a significant opportunity for an integrated system

VII. AI-POWERED PLACEMENT PREPARATION

The 2026 AI-powered placement platform [8] provides the closest overlap with the proposed PrepFlow direction. It combines aptitude and DSA practice, AI-driven mock interviews, voice-enabled interviewing, ATS-based resume analysis, job recommendations, dashboards, alumni mentoring, and career guidance. Its architecture uses NLP, automatic speech recognition, LLM-based services, and a multi-tier web architecture. The paper also describes DSA practice results feeding into performance analytics.

The RAG-based Personal Placement Assistant [9] focuses on customized interview preparation using large language models. Its approach uses retrieval and resume-related information to produce more personalized preparation. RAG is particularly relevant when a placement assistant must answer questions using a learner's own resume, target job information, and selected preparation resources rather than relying only on a generic model. Although these works demonstrate broad placement functionality, the reviewed literature still leaves room for a DSA-centered continuous progression. A system can contain DSA practice, resume matching, and interviews as separate modules without proving that information flows between them to produce a continuously revised learning plan.

VIII. COMPARATIVE ANALYSIS

Study / theme	Main techniques / functions	Relevance to PrepFlow
[1] Personalized e-learning	Learner data; adaptive/adaptable learning; recommendation; assessment	Learner modeling and adaptive DSA paths
[2] Personalized learning	Diagnostic assessment; learning paths; quizzes; chatbot; dashboard	Initial DSA diagnosis and guided practice

[3] Smart learning	Adaptive assessment; learning paths; performance analytics	Topic mastery and progress tracking
[4] GenAI tutoring	LLM; prompt engineering; adaptive feedback; gamification	Context-aware DSA explanations
[5] GenAI ITS	Learner-state awareness; confusion mapping; GenAI clarification	Feedback tied to learner state
[6] Mock interview	NLP; speech; OpenCV/MediaPipe; performance evaluation	Interview readiness metrics
[7] Virtual interview	Role-specific questions; adaptive difficulty; real-time evaluation	Role-specific interview practice
[8] Placement platform	DSA; aptitude; interviews; ATS resume; jobs; mentoring; analytics	Integrated placement workflow
[9] RAG placement assistant	RAG/LLM; embeddings; resume-aware preparation	Grounded personalized placement support
[10] Learning assistant	Question generation; answer evaluation; weak-area detection; recursive testing	Weak-area remediation loop

IX. RESEARCH GAP

The principal gap identified by this review is integration rather than the absence of individual AI techniques. Personalized learning papers establish learner profiling, adaptive assessment, recommendation, and analytics [1]–[3]. Generative-AI tutoring papers add conversational explanations and adaptive feedback [4], [5], [10]. Interview studies provide automated evaluation of verbal, behavioral, and role-specific performance [6], [7]. Placement studies combine several employability services, including DSA, resume analysis, job matching, interviews, and mentoring [8], [9].

However, the reviewed literature does not clearly establish one learner-centered loop that begins with DSA skill assessment, creates a personalized practice plan, tracks topic-level progress, incorporates resume and job-role requirements, simulates interviews, and feeds interview weaknesses back into the DSA learning plan. This gap is especially important for engineering students because technical preparation and placement preparation are usually experienced as connected activities rather than independent tasks.

X. PREPFLOW: PROPOSED RESEARCH DIRECTION

PrepFlow is proposed as an AI-powered DSA learning and placement preparation platform that connects the capabilities identified in the review.

The central workflow is: Assessment → Practice → Performance Analysis → Recommendation → Interview → Feedback → Revised Practice.

First, learner profiling stores academic interests, target roles, previous assessment results, and learning progress. Second, a DSA diagnostic assessment estimates topic-level mastery. Third, an adaptive learning module recommends explanations and problems based on weaknesses, difficulty, previous attempts, and target role. Fourth, performance analytics maintains a dashboard of accuracy, time, attempts, topic mastery, and improvement. Fifth, placement preparation can connect the learner profile with resume analysis, job descriptions, aptitude practice, and interview preparation. Sixth, an AI interview module can generate role-specific questions and provide feedback on technical and communication performance. Finally, the feedback is converted into revised practice recommendations. This final connection is the main research direction derived from the literature review.

PrepFlow should be evaluated using measurable outcomes such as DSA mastery improvement, recommendation usefulness, problem-solving accuracy, reduction in repeated errors, interview performance, usability, and learner engagement. These are evaluation goals for future implementation and are not claims of results from the reviewed papers.

XI. CHALLENGES AND FUTURE SCOPE

Several challenges must be addressed. First, personalization requires continuous and sufficiently detailed learner data. The personalized e-learning review [1] identifies feature selection, knowledge tracing, continuous data collection, recommendation evaluation, and real-time response as important challenges. Second, generated explanations and interview questions require quality control because LLM outputs can be inaccurate or inconsistent. Third, resume and performance data introduce privacy and security requirements. Fourth, recommendation quality must be evaluated beyond immediate

accuracy. A useful recommendation should improve subsequent performance and should not repeatedly expose a learner to content that is already mastered.

Fifth, interview and behavioral metrics should be interpreted carefully because communication style can vary across learners. Future work can therefore investigate explainable recommendations, grounded RAG, skill graphs, longitudinal learning analytics, human-in-the-loop mentoring, and controlled experiments comparing adaptive and non-adaptive preparation.

XII. CONCLUSION

This review examined ten research papers covering personalized e-learning, adaptive assessment, generative-AI tutoring, learning assistants, mock interview systems, and AI-powered placement platforms. The studies show that AI can personalize learning, generate feedback, evaluate interviews, analyze resumes, recommend preparation activities, and support placement workflows. The main opportunity identified is to connect these capabilities into a continuous DSA-to-placement learning loop. PrepFlow is proposed as a research direction for such an integrated platform, with DSA assessment and adaptive practice at its core and placement preparation as the downstream goal.

The proposed direction should be validated through systematic experiments measuring learning improvement, recommendation quality, interview readiness, usability, and responsible use of learner data.

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