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A Survey of AI-Based Campus Placement Management: Gamified Learning, Resume Screening, Explainability, and Research Challenges

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ABSTRACT

The campus placement industry has evolved from manual processes to AI aided screening and gamification based learning. However current systems are fragmented with most placement portals not focusing on skill development, gamification based learning platforms not integrating with the recruitment process and AI screening being too opaque. This survey provides a summary of 10 sources, including 7 recent (2025-2026) studies and 3 seminal papers relating to fair, explainable, and effective hiring using gamification. These sources were grouped into four research areas; placement portals based on AI integration, Natural Language Processing/Machine Learning based resume screening and matching, AI recruitment (reviews, fair, and explainable), and gamification in education (AI enhanced gamification). Comparison was made between the studies based on the focus of the study, the types of evidence provided, features mentioned, and limitations. The review highlights areas of lacking evidence transfer between learning and recruitment, lack of evidence that gamified performance can be used to indicate employability, lack of explainability and assurances of fairness, issues with data quality and computational costs, and lack of common benchmarks. A conceptual framework is provided which demonstrates how the four research areas can be linked together to form a circle. Risks have been highlighted with suggestions for future research directions. This review is a narrative rather than systematic review, therefore only covers a limited amount of sources.

Keywords: Campus Placement, Gamification, Resume Screening, Explainable Artificial Intelligence, Skill-Gap Analysis, Large Language Models, Candidate–Job Matching, Learning Analytics, Survey

INTRODUCTION

Campus placements are a crucial part of an engineer's career, and one of the biggest challenges for TPO (Training and Placement) cells. Each season, TPO cells have to publish job drives, ensure eligibility, collect resumes, conduct tests and interviews, and provide results. Similarly, students will have to prepare for aptitude tests, technical rounds, and interviews. Much of this process is conducted using spreadsheets, messaging groups, and manual resume screening. This makes it time-consuming for recruiters.

Recent studies have explored the use of large language models (LLMs), natural language processing (NLP), and machine learning (ML) to improve campus placement portals, resume screening, and job matching [1]-[4]. Other studies have looked into creating engaging learning environments through gamification, often using AI [5][6]. There are still concerns around fairness, accuracy, and transparency using AI for recruitment [7][8]. Placement systems focus on resume screening and matching whilst gamified systems focus on engagement. These areas have been explored independently. There is a lack of cohesion within the research. Placement portals can be used to manage job drives and resumes, however they do not provide much structure for skill development. Gamified platforms create and track skills but cannot provide evidence to recruiters. AI models for resume screening can prioritise candidates but can be a black box. A recent review highlights the use of various techniques when researching using AI for recruitment [7]. Having a holistic understanding of the research can help to understand the differences between current techniques, what problems they are solving for campus placements, what evidence they are using, and what problems still need to be solved.

A. Motivation

There are multiple motivations for doing this work. Firstly, there are disjoint areas of research. The problem has been tackled using LLM assessments, student profiles, resume parsing, transformer embeddings and gamified e-learning. These have all been assessed separately with different data and different problems. We can find trends and issues in the methodologies. Secondly, we want to give students, recruiters and placement personnel more insight into why they received a score or ranked position in the screening results. This motivated us to consider a wider definition of screening. A useful screening system should give insight into why certain recommendations were made. Thirdly, rarely is learning data combined with recruitment data.

There is valuable information in quiz results, practice history, resume content, job requirements and hiring results. This suggests that combining them will improve preparation and screening (from the literature).

B. Objectives of the Survey

The goals of this survey are:

1. To understand existing techniques relating to AI assisted campus placement, CV screening and job matching.

2. To categorise the literature based on the main research directions.

3. To understand the characteristics of each category and the types of evidence described.

4. To compare the techniques used in placement portal, CV screening, explainable and gamification approaches.

5. Identify limitations and gaps within current works.

6. Identify potential research directions.

C. Contributions

Key contributions of this survey are:

1. A systematic categorisation of the 10 key sources (7 recent + 3 seminal) into 4 categories.

2. An overview of the different research in a representative number of areas (placement, screening, explainability and gamification).

3. An overview of the role learning evidence (and the absence thereof) can play in AI-based candidate screening.

4. An overview of fairness, transparency and explainability in the context of AI-based recruitment.

5. The identification of a research gap that is an architectural research gap. There is no loop between learning and recruitment.

6. A priority list of research gaps (including the validity of using gamification as an indicator of employability).

7. A conceptual reference framework based on the literature. This includes the risks associated with the literature, and suggestions for future research with the form of research questions.

D. Paper Organization

Background: This section gives a background of the placement process and associated techniques. Review Methodology: This section details the scope of work, sources and criteria used. Literature Survey and Classification: This section categorises and reviews the literature. Cross-Comparison and Taxonomy: This section compares the various studies and organises them. Research Gaps: This section covers the challenges that have not been solved. Conceptual Reference

Framework: This section shows how it would be designed as an integrated framework. This paper concludes with Future Research Directions, Discussion/Limitations and Conclusion.

BACKGROUND

A. Campus Placement Workflow

The process of placement usually includes posting job drives specifying skills and eligibility requirements. Student profiles and resumes are collected, shortlisted and then aptitude tests and interviews are conducted. All in all there are three parties involved, students, recruiters and the TPO/Placement Cell. The entire process is time consuming when done manually and the quality of screening depends on the quality and completeness of the data submitted by the students [2].

B. Natural Language Processing and Machine Learning for Resume Filtering

Resume filtering systems are used to convert unstructured data in resumes into structured information (such as skills, qualifications and experience) and compare with job descriptions. Initial implementations are based on keyword matching while more recent implementations use embedding and transformer based language models. This increases fairness by providing semantic similarity although adds to computation. This needs to be audited for fairness [4].

C. Interpretability and Fairness

AI driven systems for scoring and ranking raise concerns around fairness, bias and accuracy [7]. The use of algorithms in hiring should be considered carefully. Vendors may make claims about reducing bias and this should be verified. Fairness is dependant on the use of the system [8]. Interpretability techniques including SHAP explain the outputs of the model by assigning importance to the inputs [9]. Removing a protected attribute from the inputs does not guarantee that there will be no proxy effect. Correlated features can provide proxy variables. A common way to test fairness is to look at selection rates between different groups of applicants. Data protection and regulation around AI would also need to be considered when using this type of system (Responsible Deployment Considerations)

D. Gamification and Demonstrated Skill

Gamification is the application of game mechanics such as points, levels, streaks, badges and leaderboards to non-gaming situations. AI has been applied to gamification within education [5]. A meta-analysis showed that gamification had positive impacts on cognitive, motivating and behavioural learning outcomes though varied depending on design [6]. One potential source of demonstrated skill could be from quiz performance. However, this is still a proxy for employability and does not directly measure job related competence. Unproctored quizzes may have issues with people sharing answers, using external resources and chasing points so the word demonstrated has been used in this survey rather than verified.

E. Skill Taxonomy, Knowledge Tracing and Recommender Systems

There are three areas outside of the corpus that directly affect skill gap analysis. Using a common skill taxonomy to match students skills to job requirements, knowledge tracing to predict how much a learner knows based on their response history and recommender systems to rank learning materials by expected benefit. These provide a more principled approach however, none of the placement sources mentioned using any of these so they are considered as future work.

F. Evidence Levels

We can consider the evidence we have about candidates in 4 levels. Self reported evidence from resumes/profiles. Demonstrated evidence from measured performance such as quizzes. Requirement evidence from job drive descriptions and rules. Outcome evidence from interviews/offers. This makes it clear how different evidence can be used to produce similar rankings from two different systems. This is just a description and does not mean all systems in the review are using the same assumption.

REVIEW METHODOLOGY

A. Research Questions

We seek to answer the following research questions through this survey:

RQ1: What techniques have been proposed for AI assisted campus placement and recruitment?

RQ2: How can NLP/ML techniques be used for the screening and matching of candidates via their CVs?

RQ3: How is fairness, transparency and explainability achieved using AI based hiring techniques?

RQ4: How has AI driven gamification been used in educational contexts? Is there a link to recruitment?

RQ5: What are the limitations outlined in the literature?

RQ6: What are the research gaps and possible future directions that we can derive from our synthesis?

B. Scope and Sources

This is a narrative literature review rather than a systematic review. The scope was limited to ten sources which were selected due to them being key pieces of work. Seven of the sources were recent research (2025-2026), with the sources coming from journal articles, conference papers and one arXiv preprint. The other three are seminal works discussing the effectiveness of gamification [6], fairness of algorithmic hiring [8] and explainability [9]. We also focused on selecting sources that would cover all the four clusters and provide relevant information for a gamified, explainable placement process. This is not a systematic review, therefore we do not have a detailed protocol stating how many sources were filtered from multiple databases. As such our research gap should be seen as evidence-based positioning rather than a definitive statement. We included the seminal works as the recent placement literature did not mention any evidence of fairness, explainability or learning effectiveness. This is noted in Table II. Table I outlines how many sources there were in each cluster.

TABLE I: **DISTRIBUTION OF THE REVIEWED CORPUS BY CLUSTER**

Cluster	References	Sources
A: Integrated placement portals	[1]–[3]	3
B: NLP/ML screening and matching	[4]	1
C: AI in recruitment, fairness, explainability	[7]–[10]	4
D: Gamification in education	[5], [6]	2
Total		**10**

C. Inclusion and Exclusion Criteria

A source would be included if it contained any of the following areas: (i) AI supported campus placement/recruitment portals (ii) NLP/ML based resume screening (iii) Ensuring fairness/transparency/explainability with AI-based recruiting (iv) Gamification, and AI-based gamification/game-based learning. However, any source that does not fall under the hiring/placement/gamification areas would be excluded. As the corpus encompasses only 10 sources, sources will be prioritised that are up-to-date, peer-reviewed/high citation, and directly relate to gamification and explainability in a placement workflow.

D. Data Extraction and Synthesis

The focus, type of study, technique used, and any limitations mentioned have been extracted from each source. A qualitative synthesis has been performed here as the sources do not all contain the same dataset, tasks and evaluation method. Therefore, cannot combine into a single performance metric.Comparison of features. If a feature is not mentioned in the source then it will be marked as not being reported '–' rather than not present. Extracting the dataset and quantitative results from the full text will be done as future work (see section 6. Future Research Directions).

LITERATURE SURVEY AND CLASSIFICATION

The literature reviewed has been categorised into four main areas: (1) Integrated AI-based campus placement portals (2) NLP and ML based resume screening (3) AI in recruitment – Reviews, fairness and explainability (4) Gamification in education. Table II summarises the focus and any limitations mentioned for all sources. The fundamental sources can also be seen in the type column.

TABLE II: **STUDY-LEVEL SYNTHESIS OF THE TEN REVIEWED SOURCES**

Ref.	**Cluster**	**Type**	**Reported Focus**	**Limitation / Gap Stated or Implied**
[1]	A	System design	LLM-based resume intelligence, interview coaching, mentor discovery, administrative analytics	Fairness auditing and use of assessed evidence in shortlisting not reported
[2]	A	System	Placement prediction, resume scanning, RL-based job matching, role-based dashboards	Depends on historical student records; fairness and explainability not reported
[3]	A	System	AI resume screening, mock tests, interview preparation, job portal	Student-facing; recruiter analytics and fairness checks not reported
[4]	B	Method	Transformer embeddings with cosine-similarity resume ranking	Interpretability and computational efficiency left as open issues
[5]	D	Review, meta-analysis	Gamified AI-supported digital learning: personalization and engagement	Educational setting; not linked to recruitment decisions
[6]	D	Foundational meta-analysis	Effects of gamification on cognitive, motivational, and behavioral learning outcomes	Effects vary across designs and contexts; learning outcomes are not employability
[7]	C	Systematic review	Systematic review of AI in employee recruitment	Outlines the field and future directions; recruitment considered apart from learning

Ref.	Cluster	Type	Reported Focus	Limitation / Gap Stated or Implied
[8]	C	Foundational analysis	Evaluation of bias-mitigation claims and practices in algorithmic hiring	Concerns hiring in general; not tied to placement or to learning evidence
[9]	C	Foundational method	SHAP: attributing a model output to its input features	Explains a model's output, not the validity of its inputs; not reported in the reviewed portals
[10]	C	Framework	Context-aware, explainable multi-agent framework for LLM-based resume screening	Addresses transparency, but recruitment is treated in isolation from skill development

A. Integrated AI-Based Campus Placement Portals

These include multiple aspects of the placement process in one place. Recently a system has been designed to provide resume intelligence using LLMs, interview coaching, mentor discovery, and admin analytics [1]. However, fairness auditing and using evidence to shortlist were not mentioned as key points. A machine learning and reinforcement learning system provides predictive placement, resume scanning and job matching. However, it requires historical student data such as grades, internships and backlogs [2]. Campus-Connect provides AI based resume screening, mock testing, interview preparation, and job portal. However, recruiter analytics and fairness were not mentioned as key points [3]. Across all sources, evidence of assessment, screening and preparation were mentioned. However, no evidence of gamification to engage users was mentioned. Overall, the main issue with this cluster is that it relies on self-reported or historical data, and there was no mention of using evidence of skills to shortlisting.

B. NLP and ML for Resume Screening and Job Matching

These sources focused on resume screening. Using NLP and ML to parse resumes and rank candidates. Embedding resumes and job descriptions using transformer models and ranking using cosine similarity was found to perform better than a traditional applicant tracking system in most domains. However, interpretability and computational efficiency was an issue for large datasets [4]. The resume screening aspect was also included in the placement portals [1]-[3] however, no mention of fairness auditing or explanation of ranking was mentioned. Overall this provides motivation for using semantic matching with low computational cost and bias auditing. It was identified that having two stages would be beneficial with an initial low cost vector based filtering stage.

C. AI in Recruitment: Reviews, Fairness, and Explainability

A systematic review of AI in employee recruitment was performed providing an overview of the field and future research directions [7]. Fundamental work has been done into algorithmic hiring with caution required to independently audit claims of bias reduction by vendors. Fairness will depend on the use of the tool 8+. SHAP provides a general method to attribute model output to features [9]. A context aware and explainable multi agent framework has been designed for LLN based resume screening [10]. However, fairness and accuracy issues have been raised in recruitment [7],[8] and no fairness auditing was mentioned in the placement specific systems [1]-[3]. There is therefore established evidence that explainability should be included when shortlisting. However, these sources focused solely on recruitment and are not tied to the learning process.

D. Gamification in Education

Evidence of skill development can be seen from these sources. A meta analysis showed positive impacts from gamification on cognitive, motivational and behavioural learning outcomes. However, it varies depending on the design and context [6]. A systematic review and meta analysis was performed looking at personalised learning and engagement using gamified AI supported digital learning environments [5]. Overall these focus on using gamification in education. There is no evidence tying gamified learning to recruitment decisions.

E. Cross-Cluster Observations

Overall there are three key points to note from the clusters. Firstly, the information covered is complimentary. A-C cover how candidates are assessed and ranked whilst D covers skill development. Secondly, there are similar issues with data quality, fairness auditing and computational cost mentioned/implied in multiple placement and screening sources. Finally, there is unidirectional evidence. No evidence of learning systems providing evidence of skills to recruitment, or recruitment providing evidence of skills required to learning. This is where the research gaps will be found.

CROSS-STUDY COMPARATIVE ANALYSIS

A. Comparison of Methods

Table III highlights the focus, key advantage and disadvantage of each of the four research areas.

TABLE III: **COMPARISON OF KEY RESEARCH AREAS**

Direction	Main Strength	Major Limitation
Integrated portals [1]–[3]	Several placement tasks on one platform	Self-reported or historical data; fairness and analytics gaps
NLP/ML screening [4]	Automated parsing, ranking, and semantic matching	Fairness audits and explanations not reported; computational cost
AI-based hiring, fairness, and XAI [7]–[10]	Field overview; fairness caution; feature attribution; transparent screening	Recruitment isolated from learning
Gamification in education [5], [6]	Engagement, personalization, skill tracking	Educational setting; not linked to recuritment

B. Comparison of Reported Features

Table IV shows a qualitative comparison of the features of each system. Please note that '–' does not mean that the feature is not implemented in the system but that it was not mentioned as part of the key points of the source. The bottom row corresponds to the framework set out later in this paper and demonstrates what was intended in the design.

TABLE IV:**QUALITATIVE COMPARISON OF FEATURES IN CURRENT PLACEMENT AND LEARNING SYSTEMS**

System	Gamification.	Resume screening	Skill gap	Test / interview prep	Explainability	Recruiter analytics	Placement workflow
LLM-based placement portal [1]	–	✓	–	✓	–	P	P
ML/RL placement platform [2]	–	✓	–	P	–	P	P
Campus-Connect portal [3]	–	✓	–	✓	–	–	P
Resume2Vec screening [4]	–	✓	–	–	–	–	–
Explainable LLM screening [10]	–	✓	–	–	✓	–	–
Gamification in education [5], [6]	✓	n/a	P	–	–	n/a	n/a
Conceptual framework	✓	✓	✓	✓	✓	✓	✓

✓ = Feature mentioned. P = Partially mentioned. × = Not mentioned. – = Not mentioned in source. N/A = Not within scope. Bottom row shows what was intended in the design.

C. Evaluation Metrics

When evaluating the various methods in the literature, it is not possible to compare them based on a single accuracy metric due to variations in the tasks and data involved. The following metrics will be important when considering the future evaluation of methods:

Screening Quality: How well the AI shortlisted candidates match those shortlisted manually by the TPO/recruiter. Can be measured using precision, recall, F1 score and rank correlation. It does not measure how accurate the system is, rather how consistent it is with human practices. The manually shortlisted candidates may be biased.

Fairness: Selection rates are balanced between groups. For example the ratio between lowest and highest selection rates. This can be measured alongside accuracy.

Explainability: Stability of explanations to minor changes in inputs. How often the recruiters override the suggestions.

Predictive Validity: Whether the proficiency measured predicts interview and placement outcomes. This also considers whether this is true when controlling for integrity of the assessments.

Learning: How many quizzes were completed, how many streaks were maintained and how much skill was gained between pre and post assessments.

Cost: How long it takes to score each drive and behaviour as the applicant pool increases. This addresses concerns with the cost of transformer-based ranking [4].

TAXONOMY OF AI-BASED PLACEMENT APPROACHES

Current methods can be split up into three groups depending on the type of evidence used and the type of decision it is applied to. Figure 1 shows how self-evidence, evaluated evidence, and requirements/outcome evidence can be mapped to the screening, explaining and feedback stages. Self-evidence is collected from resume and portal information. Evaluated evidence is collected from gamified learning. Requirements/outcome evidence is collected from drives and outcomes. The decision stage will provide a scoring system for candidates. The explaining stage will provide insight into factors affecting decisions. The feedback stage will provide information back to learning about gaps.

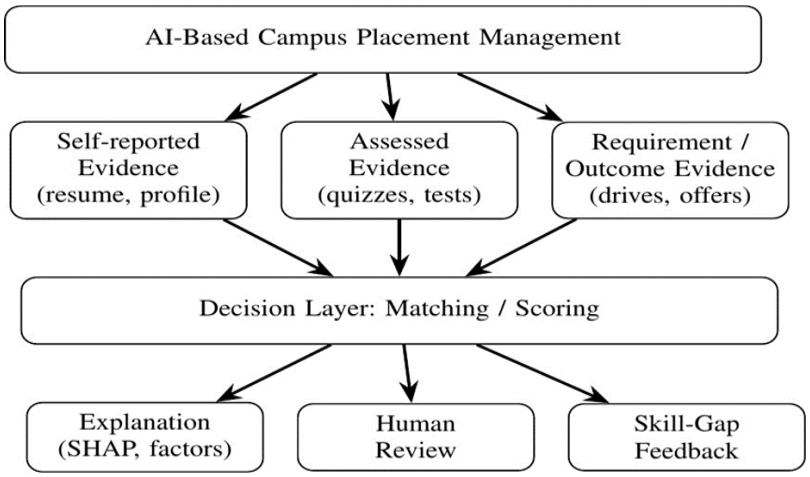


Fig. 1. Taxonomy of AI-based placement approaches. The layers are complementary rather than mutually exclusive.

RESEARCH GAPS

The synthesis of the reviewed literature highlights several gaps which still remain unresolved. Table V summarizes them with their supporting sources and the direction each points to; the subsections give the detail.

TABLE V: **PRIORITIZED RESEARCH GAPS**

Gap	Supporting sources	Impact	Direction
1. No learning–recruitment evidence flow	[1]–[3] portals; [5], [6] gamification	Preparation and screening cannot inform each other	Closed-loop exchange of skill evidence and requirements
2. Unvalidated skill signal	[2]–[4]; [6]	Screening bounded by self-reported data; assessed signal unproven	Predictive-validity studies with integrity controls
3. Limited explainability and oversight	[10] only; [1]	Opaque to students, recruiters, and staff	Factor-level explanation and human review
4. Fairness and proxy bias	[1]–[3], [7], [8]	Unequal opportunity, potential legal exposure	Group-level audits, context-specific proxies
5. Data quality and computational cost	[2], [4]	Poor input limits accuracy; heavy models do not scale	Tractable two-stage matching, data curation
6. No standard frameworks or benchmarks	[1]–[6]; differing datasets and protocols	Results not comparable across sources	Shared benchmark and evaluation protocol
7. Limited recruiter and TPO analytics	[1]–[3]	Staff lack cohort and drive insight	Role-based analytics on a shared data layer

A. No bidirectional learning-recruitment loops

Each component (integrated portals, NLP/ML filtering, explainable AI hiring and AI aided gamification) has a body of existing research. However, none of these sources present a complete learning-recruitment loop where evidence from gamified learning can be used for personalisation based on skill gaps, explainable filtering by humans for shortlisting, and role based analytics. There is no bidirectional sharing of evidence from learning to recruitment

systems and vice versa. This is only true for the sources reviewed. Due to the small amount of recent sources, it should be checked whether a system exists.

B. Unvalidated Skill Signals

The shortlisting process used in placement and filtering sources relies heavily on self-reported resume information. Hence the quality of the filtering processes are limited by the quality of the data provided [2]- [4]. While assessed evidence such as quiz based evidence could be used to increase the quality of evidence, there are still issues. Firstly,

none of the sources show that gamified evidence correlates with employability. Secondly, unmonitored assessment evidence may be shared, external tools used and points gained due to not being monitored. Leaderboards can also incentivise activity rather than competency. Finally, students may have varying levels of access to revision resources

meaning gamified evidence may be influenced by this factor. While gamification has been shown to impact learning outcomes through meta-analytic. evidence 6+ the learning evidence may not correlate with employability.

C. Limited Explainability and Human Oversight

Most filtering systems produce a score/ranking. Only one source shows explainable filtering 10+. A useful system would allow a clear pipeline from decision to evidence to reasoning to human review. Student evidence is not very transparent meaning they do not know what skills/gaps impacted their position. They simply receive a score.

D. Fairness, Bias, and Proxy Effects

Fairness and accuracy are mentioned in the recruitment literature [7]. None of the placement portals mention a fairness check [1]- [3]. Simply removing protected attributes may not guarantee fairness as other correlated attributes may be proxies. Claims of reducing bias in hiring tools should be independently verified [8]. In the Indian campus setting plausible proxy attributes would be college tier, gender, medium of instruction and regional background. Group level monitoring should be done and fairness should be independently validated. None of the sources mention this.

E. Evidence based on quality of past/student data and computational efficiency

Evidence is limited by reliance on quality of past/student data [2] and computational efficiency of transformer based ranking [4]. This has motivated tractable matching designs as only costly scoring is done following a cheap initial filter. However, comparisons are not available.

F. Different datasets/tasks/evaluation

Different datasets/tasks/evaluations are used. Gamification evidence varies depending on the design [6]. No standard framework exists to link gamified evidence with recruitment outcomes. Filtering does not have a standard benchmark to compare placement portals. Usually agreement with manual baselines is the only comparison. Future evaluations should include accuracy, fairness, learning impact and cost.

G. Limited Recruiter and TPO Analytics

None of the portals mention this as a key feature [1]- [3]. Only system performance and user engagement metrics are monitored [2]. Administrative analytics are mentioned [1]. Analytics at drive, cohort and student level using a common data layer are not mentioned.

CONCEPTUAL REFERENCE FRAMEWORK

Based on the literature, a holistic solution can be produced where multiple techniques are not being forced into solving parts of the problem. A conceptual reference framework has been created named GLAP-Portal (Gamified Learning and AI based Placement Portal) using the techniques described in this survey. No experiments were run and results collected for this framework. All parts of the framework have already been well documented (SHAP [9], Gradient Boosting, Sentence Embeddings, Vector Search, Gamification).

A. Design Principles

There are four design principles that have been derived from the previously mentioned issues. (P1) Evidence-Based: Student competency will be used as an evidence-based measure rather than proof. This will be provided as an additional signal and there will be checks in place to ensure the integrity. (P2) Bidirectional: Requirements and outcomes from the recruitment side of things will be passed onto the learning side and vice versa. (P3) Human-in-the-loop: While AI will provide the candidate rankings and explanations, they will be verified by HR and TPO. (P4) Efficient Matching: Costly scoring only happens once semantic filtering has occurred.

B. Layers

There are five layers, starting with the UI layer providing dashboards for students, recruiters and the TPO/Placement Cell with role-based features. The Application layer contains the Quiz and Learning, Gamification, AI Features and Placement Management. The AI/ML and Explainability layer contains Resume Parsing, Embeddings, Semantic Search, Candidate Scoring, SHAP explanations with confidence levels, Skill Gap Analysis and Mock Interviews. Finally, there is a Data Layer containing User Data, Quiz Data, Gamification Data, Placement Data, Analytics Data. Lastly, an Infrastructure and Security Layer containing encrypted communication, Role Based Access Control, Audit Logging and Backup. An overview of this can be seen in Figure 2.

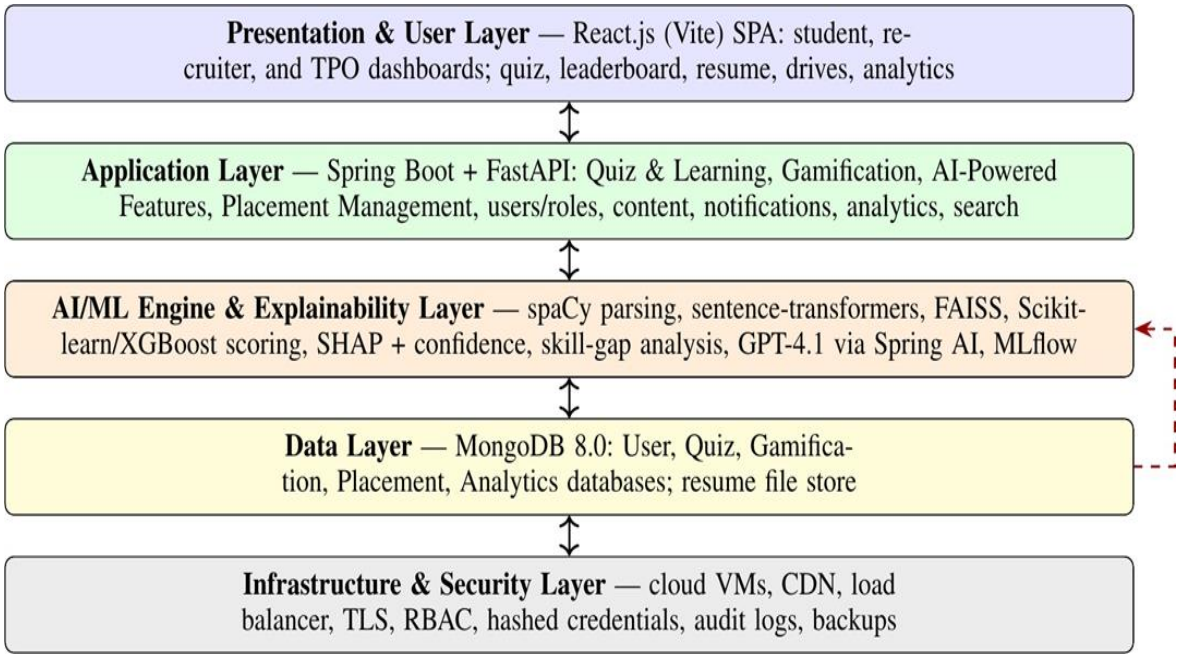


Fig. 2. Five-layer architecture of GLAP-Portal. The dashed arrow shows shortlists and recorded outcomes returning to the data layer to support periodic model re-validation and recruiter/TPO review.

C. Bidirectional Loop

The key feature of this framework is the bidirectional loop shown in Figure 3. Candidates will complete the gamified quiz and their competency level will be assessed. Once they have a competency level, this is combined with their resume semantics to provide candidate scoring. Each score will have explanations for each factor and confidence levels. If the confidence level is low, the candidates will be passed onto humans. The outcomes will then be recorded. This will be compared to current requirements in real time to show the skill gaps. From here, the most important skill gaps will be identified and used to recommend further quiz and content. However, this loop has been broken in one or more places in the sources reviewed.

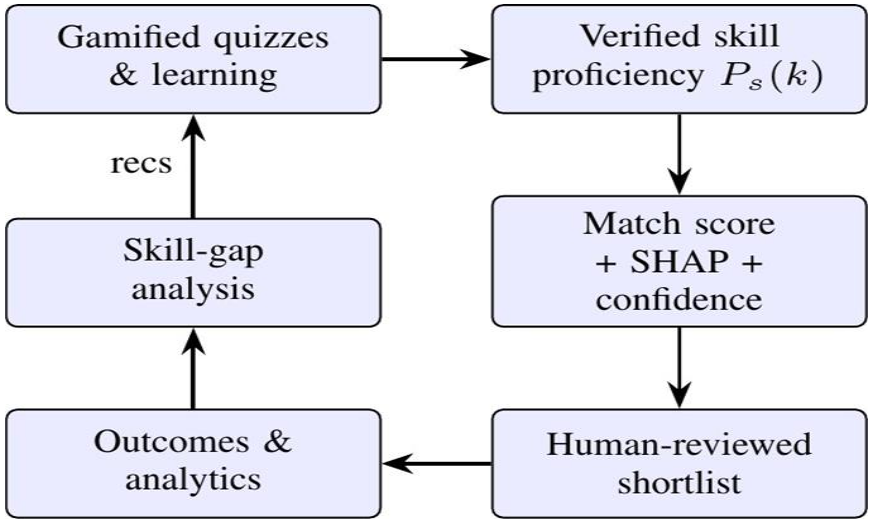


Fig. 3. Closed loop connecting gamified learning, assessed skills, explainable shortlisting, outcomes, and skill-gap-driven recommendations.

D. Alignment with the Reviewed Literature

Each part of the design has been included to overcome issues raised in the literature. Evidence based competency to overcome dependency on quality student data [2]-[4]. Two stage matching to overcome computational complexity [4]. Explainability, Confidence and Human Review to overcome fairness and transparency [7][8][10]. Gamification to provide evidence of employability to overcome the fact the sources are focussed on education [5][6]. Analytics per role to overcome lack of analytics for recruiters and tpo [1]-[3].

E. Risks and Open Issues of the Framework

The framework does introduce some risks that must be considered when implementing. Feedback Loop Bias: If the overrides made by the recruiters are recorded as labels to help validate the model, this could introduce bias as recruiters may have existing biases that will become more prominent. Low Recall of Pre-Filter: Due to the two stage matching, candidates may not get through to the scoring model. Therefore the recall of the pre-filter must be measured. Cheating and Integrity: Candidates may cheat in the unproctored quiz, share answers or use external tools to increase their competency. Therefore randomised question banks, proctored testing and verification of interview outcomes must be implemented. Access: Candidates may gain higher scores in the gamified quiz due to having access to resources to prepare. External LLM Dependency: Using an external API will increase the cost and latencies, whilst exposing privacy.

F. Responsible Deployment Considerations

As candidates will be screened for placements, responsible implementation must be considered. This includes obtaining consent and data minimisation in accordance with data protection laws. Protected attributes must not be used and group audits performed to avoid proxies [8]. Humans must be accountable and overrides must be auditable. Transparency must be provided to students. Personal data must be minimised/masked before using external LLM APIs. As AI systems used in recruitment are increasingly seen as high risk by regulators, legal requirements must be checked for each deployment. Learners may not want to be ranked so options to opt out or view leaderboards relative to their cohort must be provided. Gamification effects vary depending on context [6].

FUTURE RESEARCH DIRECTIONS

Each direction below is stated as a research question.

A. Evidence of skill acquisition and prediction

Is there evidence that the skill proficiency derived from weighted quiz performances can predict success in an interview and placement process, after controlling for resume information, whilst also maintaining predictive validity after integrity measures?

B. Personalisation using skill gaps

Can aligning skills to a common taxonomy and using knowledge tracing to model mastery give more accurate skill gaps? Can the recommendations be improved compared to just averaging skill proficiency using pre/post assessment skill improvement compared to the control group?

C. Explainable and fair shortlisting

Do the explanations provided at a factor level remain stable with minimal variance in inputs? Does it influence the recruiters' decisions? Does the shortlisting vary depending on the tier of the college, gender, medium of instruction and region?

D. Recruiter feedback and re-validation

Does labelling using override affect the accuracy of the matches without increasing existing bias? How can the feedback be audited?

E. Placement analytics

What indicators are used by TPO staff/recruiters at a driver, cohort and student level? Are they improving placement outcomes?

F. Benchmark and validation

Can having a common benchmark and methodology allow comparison between placement and gamification results using multi-institutional and longitudinal studies?

G. Improved review

The review should be conducted again following a documented protocol, using a PRISMA style method for searching multiple databases. Data and results should be extracted from full text articles. A larger and longer dataset will be used.

DISCUSSION

From the literature it was found that there are different approaches to using AI for campus placement. A common trend has been to move from manually managing campus placements to using LLMs to aid in screening candidates, using semantic methods to match resumes and providing explanations. AI has also been used to increase engagement with learning through gamification. The main findings were that each method is tackling a different aspect of the problem. Integrated placement portals are tackling the workflow and using NLP/ML to help screen candidates. Explainability is being tackled by various techniques and each have been well researched individually. However, there is no evidence of evidence flow within the methods and no evidence that gamification can provide valid information to show employability. Table VI shows how the research questions have been answered.

TABLE VI: **ANSWERS TO THE RESEARCH QUESTIONS**

RQ	Section	Finding
RQ1	Literature Survey (A)	Portals combine LLM assessment, skill-based matching, and test preparation, mostly on self-reported data
RQ2	Literature Survey (B)	Semantic matching helps, but fairness auditing, explainability, and cost remain open
RQ3	Literature Survey (C); Research Gaps	Fairness concerns recur; explainability is reported in one source
RQ4	Literature Survey (D)	Gamification improves engagement in education but is not linked to recruitment
RQ5	Table II	Data quality, fairness auditing, cost, and no shared frameworks
RQ6	Research Gaps; Future Research Directions	Seven prioritized gaps and research questions

A. Limitations of This Survey

The corpus size is limited with only 10 sources. The sources were purposefully chosen and most are recent (7 out of 10 are from 2025/2026). There is a pre-print and some sources are not well indexed meaning the identified gap should be reviewed as the literature will grow. Only 10 sources were retained meaning many relevant areas were not cited. These include skill taxonomies, knowledge tracing and data protection regulation. Some features are missing as they were extracted from the sources based on what they mentioned they focused on and their limitations. Therefore, the comparison between the features is based on what the sources state rather than fully tested benchmarks. Some features might be missing (-) due to how features were extracted. The conceptual framework was designed with no validation. Proficiency and XP are used as proxies for employability. The effect gamification has can vary depending on the design and context [6]. The framework was designed for an engineering college placement cell with 3 user roles meaning it would need to be validated to apply to other institutions.

CONCLUSION

AI assisted campus placements is an growing area with a fragmented literature base. This scoping review covered 10 key sources (7 recent and 3 fundamental) to provide insight into integrated placement portals, NLP/ML resume screening, AI aided recruitment with fairness and explainability and gamification in education. The main issues faced were no evidence flow between learning and recruitment, no evidence that gamification provides valid information to show employability, fairness and transparency, data quality and computational costs and no standardised benchmarks. Future work should focus on testing if proficiency can predict placement outcomes, connecting skills gap analysis with taxonomies and knowledge tracing, fairness should be audited within the Indian campus context and validation should be carried out. Future systems can combine placement portals, screening models, explainability and gamification learning to create a multi-layered system as long as the risks mentioned are addressed.

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