Neuro-RAG: A Neuro Symbolic Framework for Transparent and Adaptive Skill Assessment

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Abstract* - Traditional skill evaluation methods frequently lack personalization and transparency. In this paper, we propose Neuro-RAG, a neuro-symbolic Retrieval-Augmented Generation (RAG) framework for professional development and adaptive skill assessment. The system ensures accuracy in competency extraction and evaluation by combining symbolic reasoning for rule-based validation with neural embeddings for contextual understanding. Neuro-RAG finds skill gaps, aligns them with frameworks such as SFIA, and creates individualized learning paths using Bayesian inference and explainable AI feedback. It guarantees interpretability and efficiency by utilizing a scalable microservices architecture with Spring Boot, React, and AI services like OpenAI models. A unified neuro-symbolic assessment framework, Bayesian adaptive testing with cognitive bias detection, and end-to-end explainable feedback for ongoing skill improvement are the three primary contributions.

Keywords* - neuro-symbolic AI, skill assessment, adaptive testing, personalized learning, Bayesian inference.

I INTRODUCTION

Assessment platforms that go beyond static testing are now necessary due to the need for ongoing skill development in quickly changing industries. Conventional competency evaluations usually offer generic, one-size-fits-all tests that are opaque about their evaluation procedures, don't adjust to the unique learner profiles, and provide little useful feedback. Accurate skill evaluation and successful professional development are hampered by these constraints.

These issues can be addressed by recent developments in artificial intelligence, especially large language models (LLMs) and neuro-symbolic reasoning. However, purely symbolic systems have trouble understanding context, which is necessary for personalised assessment, while purely neural approaches frequently lack interpretability and can reinforce biases.

In order to provide adaptive, explainable, and bias-aware competency assessment, this paper introduces Neuro-RAG, a neuro-symbolic platform that combines the best features of both paradigms. Neuro-RAG offers individualised learning roadmaps based on validated skills and resources by combining Bayesian skill inference, retrieval-augmented generation (RAG), and symbolic knowledge graphs.

A. Motivation

Current evaluation tools are frequently inflexible, generic, and unable to adjust to the performance of specific users or take response cognitive biases into account. Furthermore, the majority of platforms only offer numerical scores devoid of context or practical advice, which restricts their applicability in professional development. A system that can create structured learning paths based on validated data, offer personalised feedback, and dynamically assess competencies is desperately needed. To close this gap, Neuro-RAG was created, providing an AI-powered, empirically supported platform that responds to individual user input, detects skill gaps, and directs users towards useful development.

B. Objective

Five interrelated goals are pursued by Neuro-RAG in order to provide efficient skill development and assessment.(i) In order to capture a range of competencies, adaptive assessment dynamically chooses questions based on past answers and skill gaps. It supports both multiple-choice and free-text formats. (ii) To increase assessment accuracy, bias-aware evaluation identifies cognitive biases like anchoring or overconfidence and modifies skill inference appropriately. (iii) Explainable feedback generation offers well-organised, comprehensible suggestions with distinct logic chains that make use of validated abilities and materials. (iv) Personalised roadmap creation produces learning pathways that are actionable and customised to each person's skill set and professional goals. (v) Longitudinal tracking tracks performance over several sessions to measure skill development and update competency beliefs over time.

C. Challenges

There are various technical obstacles in the development of Neuro-RAG. A strong mechanism that can dynamically choose and order questions while recording rich user interaction data, including text responses, timing, and confidence levels, is necessary for adaptive assessment. Variability in user input, incomplete responses, and cognitive biases must all be taken into consideration for accurate skill inference. Verification against skill graphs and integration with a symbolic reasoning layer are necessary to guarantee that LLM-generated feedback is consistent, trustworthy, and comprehensible. The system must also securely store and process vast amounts of session data, protect user privacy, and offer a responsive, user-friendly experience across a variety of environments and devices

Delivering a reliable and useful assessment platform requires striking a balance between performance, explainability, and adaptability.

II RELATED WORK

In order to improve interpretability and control, early neuro-symbolic reasoning systems mainly concentrated on combining deep neural models with logic-based reasoning. One of the first thorough surveys on neural-symbolic learning was presented by Besold et al. in 2017, highlighting the significance of fusing connectionist learning with symbolic logic in order to create explainable AI systems [1]. Their research laid the groundwork for hybrid models that could use learning-based mechanisms to maintain flexibility while reasoning with structured knowledge.

Building on this, Pascual et al. (2022) showed how external document retrieval could greatly enhance factual accuracy and contextual grounding in large language models by proposing a retrieval-augmented generation (RAG) framework for knowledge-intensive NLP tasks [2]. However, the framework's explainability in real-world assessment domains was limited due to its lack of symbolic validation.

The STELLA-RAG architecture, a Structured Extractive-Latent Retrieval-Augmented Generation model intended for explainable reasoning, was presented by Li et al. (2023) in order to fill this gap [3]. Their method ensured interpretability and factual grounding by combining symbolic filters with latent retrieval. This idea is highly compatible with the hybrid neuro-symbolic reasoning framework used in Neuro-RAG, where symbolic validation in LLM-generated behavioural feedback guarantees contextual accuracy and avoids hallucinations.

By incorporating symbolic reasoning modules into LLM-driven inference pipelines, Yang and Gao (2023) made significant progress in this area by developing explainable and controllable neuro-symbolic systems [4]. Their research supported the fundamental design tenets of Neuro-RAG's explainable assessment engine by showing that hybrid reasoning greatly increases transparency in AI-driven evaluations.

Using probabilistic graphical models, Jiang and Lee (2022) concurrently introduced a Bayesian skill assessment framework that allowed for gap estimation and dynamic skill inference [5]. The SkillInferenceEngine in Neuro-RAG, which spreads beliefs across correlated skill graphs to identify competency gaps, was inspired by this probabilistic reasoning.

The GPT-4 and Gemini technical reports, published by OpenAI (2024) and Google DeepMind (2024), respectively, describe how multi-modal and retrieval-augmented systems can be set up for contextual understanding, structured text extraction, and personalised reasoning—essential features that NeuroRAG uses for resume parsing and adaptive assessment [6], [7].

To further ensure fairness in AI decision-making, Zhou et al. (2023) investigated cognitive bias detection in LLM-generated outputs, highlighting the necessity of interpretive rule-based scoring [8]. Similar methodology is used by Neuro-RAG which incorporates a cognitive bias analyzer to access behavioural tendencies like confirmation bias, anchoring bias, and overconfidence.

Lastly, Zhang et al. (2023) showed how graph-based modelling improves gap analysis and candidate profiling by proposing a competency-based evaluation system using knowledge graphs [9]. The symbolic skill graph structure of Neuro-RAG, which facilitates the mapping of skills, dependencies, and inferred performance for clear assessment results, is directly enhanced by this method.

These works address these capabilities separately, even though they lay significant groundwork for neuro-symbolic reasoning, retrieval-augmented generation, and adaptive assessment. Although explainable systems such as STELLA-RAG [3] offer transparent reasoning, they are unable to adjust to the performance of individual learners. On the other hand, Bayesian inference-based adaptive systems [5] personalise question selection, but their suggestions are not explicable. Furthermore, skill assessment systems that could profit from bias-aware competency estimation have not yet incorporated cognitive bias detection, despite the fact that it has been investigated in LLM outputs [8]. Lastly, although structured skill modelling is made possible by knowledge graph approaches [9], resume-based initialisation and dynamic belief propagation between assessment sessions are not included.

Neuro-RAG overcomes these constraints by combining features that were previously investigated independently into a single framework. The system achieves transparency and personalisation by integrating symbolic validation for explainable feedback with Bayesian skill inference for adaptive question selection. Adjusting competency estimates based on recognised behavioural patterns like overconfidence and anchoring is made possible by the integration of cognitive bias detection algorithms, which are especially made for assessment contexts. The system also uses retrieval-augmented generation with symbolic grounding to make sure recommendations refer to validated sources and processes user resumes to initialise skill priors. From resume upload to adaptive assessment to personalised roadmap creation, this comprehensive approach offers end-to-end functionality—capabilities that haven't been shown together in previous work.

III SYSTEM ARCHITECTURE

For adaptive skill evaluation and tailored learning recommendations, the Neuro-RAG platform uses a modular architecture that combines neural processing, symbolic reasoning, and probabilistic inference.

A. Backend Architecture

A three-tier design with distinct concern separation is used in the backend. RESTful APIs for resume processing, session management, and authentication are made available via the Controller Layer. The neuro-symbolic reasoning engine is implemented at the Service Layer by combining retrieval-augmented generation, symbolic validation, and Bayesian skill inference. Key services include the ResumeParserService (entity extraction and skill graph mapping), the NeuroRAGService (which orchestrates the entire reasoning pipeline), and the SkillInferenceEngine (which estimates Bayesian competency). Using a relational database, the repository layer controls data persistence for user profiles, assessment sessions, responses, and skill data.

B. Frontend and User Interface

Interactive features for uploading resumes, adaptive tests, and visualising learning roadmaps and personalised feedback are all included in a single-page application. The interface prioritises accessibility, minimal cognitive load, and smooth transitions between assessment phases while interacting with backend services through REST APIs..

C. Resume Parsing and Entity Recognition

Resume parsing uses a two-tiered strategy that combines a secondary recognition service for enrichment and fallback processing with cloud-based large language model APIs for primary entity extraction. Asynchronous NLP processing independent of assessment logic is made possible by this separation, which also supports low-latency operations across a variety of document formats and records professional experience, education, and skills.

D. Bayesian Skill Inference

Skills are modelled by the assessment engine as nodes in a probabilistic dependency graph, where correlations and prerequisites are represented by the edges. Evidence from user responses shows that Bayesian propagation is used to update posterior belief distributions. The inference algorithm analyses confidence levels and correlated skill implications while dynamically choosing questions to maximise information gain. By maintaining logical consistency and referencing validated skills, symbolic validation makes sure AI-generated feedback avoids hallucinations.

E. Learning Roadmap Generation

Three criteria are used in the roadmap generation process to rank skill gaps: gap magnitude, evidence strength (assessment confidence), and criticality (prerequisite depth). The system defines logical progression milestones by utilising dependency relationships. By identifying overconfidence, anchoring, and consistency patterns in responses, a cognitive bias analysis layer modifies skill inference and provides tailored feedback for impartial, fact-based direction.

F. Neuro-Symbolic Integration

Three steps make up the integration pipeline's operation: Semantic embeddings are used in neural retrieval to help recall a wide range of pertinent skills and resources; symbolic validation checks facts and prerequisite consistency against the knowledge graph; and probabilistic ranking ranks suggestions according to Bayesian posterior confidence. This phased strategy concurrently produces grounded evidence, explainable transparency, and adaptive personalisation.

G. Performance and Deployment

The system employs caching for frequently accessed skill relationships and precomputed embeddings for knowledge base items, enabling sub-3-second response latencies for interactive assessment. Security is implemented through token-based authentication with role-based access control and encryption of sensitive data. Containerized deployment with orchestration supports horizontal scaling, while continuous integration pipelines maintain system reliability across updates.

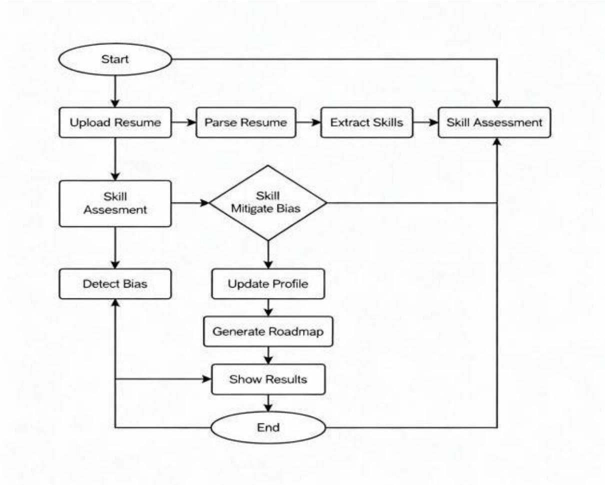

Figure 1.Architecture Diagram

IV. DATA FLOW AND USER JOURNEY

A. Resume Upload and Parsing

A resume in PDF, DOCX, or TXT format is uploaded by the user via the frontend interface to start the Neuro-RAG system. Apache Tika is used by the backend to retrieve the document's raw text. The Gemini API then processes the extracted text to find structured entities such as experience, education, skills, and other pertinent sections. This data is arranged into structured data by the ResumeParserService, which also gives each extracted skill a confidence score before storing it in the ResumeData entity. The basis for skill inference and adaptive assessment is this structured data.

B. Adaptive Assessment Flow

The system starts an adaptive assessment session based on the user's skill profile after they upload their resume and choose a target role. To maximise learning and assessment effectiveness, the SkillInferenceEngine dynamically chooses the most instructive questions and uses probabilistic reasoning to pinpoint areas of low confidence. The test includes both text-based and multiple-choice questions, and it records important interaction metrics like confidence levels, typing speed, and response time. Every response is captured for later examination, allowing for the creation of tailored comments and suggestions for skill improvement.

C. Skill Inference and Gap Analysis

The predefined skill graph is used by the SkillInferenceEngine to spread beliefs across correlated skills. To precisely estimate the user's competency levels, correlation strengths between skills—such as dependents, prerequisites, and category associations—are used. The difference between full proficiency and the assessed level is known as the skill gap, and it is determined by using data from user responses and graph-based correlations to prioritise the gaps. With the help of this ranking, the system can pinpoint the user's high-priority areas for improvement, offering useful information for individualised growth.

D. Neuro-RAG Feedback Generation

The Neuro-RAG service generates grounded, customised feedback using a hybrid retrieval-augmented generation (RAG) methodology. Prior to encoding them using lightweight embeddings for similarity-based ranking, the system retrieves candidate knowledge items, such as skills, dependencies, and learning resources. These candidates are then filtered by the symbolic layer to guarantee that only accurate and pertinent data is taken into account. Last but not least, OpenAI GPT produces structured feedback based on validated abilities and resources, guaranteeing trustworthy and useful suggestions. The dashboard shows this feedback, which offers information about skill gaps, learning paths that are prioritised, and tailored recommendations for development.

E. Cognitive Bias

In addition to assessing skills, Neuro-RAG evaluates user responses for five specific cognitive biases: Overconfidence, Confirmation, Anchoring, Availability Heuristic, and Consistency. To identify these biases and gain a better understanding of the user's decision-making processes, a rule-based algorithm with evidence scoring is used. Users can identify areas where cognitive tendencies may impact performance and be directed towards more objective skill development strategies by using the bias analysis results, which are integrated into the dashboard.

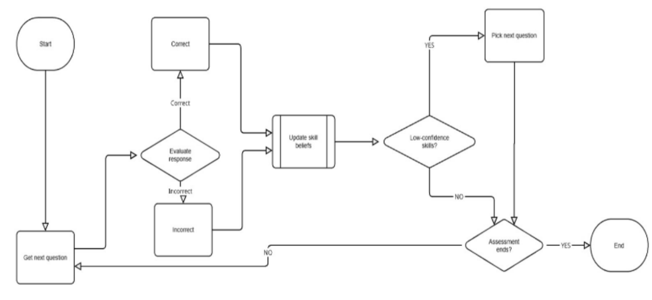

Figure 2.Assessment Flow

V DATA MODEL AND ARCHITECTURE

A. Data Model

Five main entities make up the relational schema used by Neuro-RAG. Credentials for authentication and profile information are stored in the User entity. AssessmentSession tracks performance metrics and session metadata while connecting users to timestamped evaluation instances. Competencies are modelled by the Skill entity using SFIA categories, proficiency levels, and graph-based relationships that encode correlations (weighted edges) and prerequisites (directed edges). Answers, confidence levels, response latency, and typing dynamics are all captured by response entities. ResumeData contains structured extracts of skills, experience, and education that have been confidently scored from uploaded documents.

Skills form a separate dependency graph, while foreign key relationships between these entities form a connected graph: User → AssessmentSession → Response. Through materialised views for skill relationships and indexed queries, this dual-graph architecture facilitates both transactional data integrity and effective probabilistic inference.

B. Bayesian Skill Inference

The inference engine uses evidence-weighted Bayesian propagation to update competency beliefs. The algorithm scores evidence according to correctness, confidence, and latency for each response, updates the posterior belief for target skills using $P(s|r) \propto P(r|s) \cdot P(s)$, and propagates beliefs to correlated skills weighted by decay factor α and graph edge strengths. With k being the average node degree, this runs in $O(k)$ time per response.

C. Adaptive Question Selection

The selection of questions respects prerequisites while optimising information gain. The algorithm calculates the entropy reduction $H(S) - E[H(S|q)]$ for candidate questions, combines it with difficulty matching (to match user level) and gap priority (to target low-confidence skills), and then chooses the question with the highest score. When the question budget is depleted or the belief entropy drops below a certain point, the assessment is over.

D. Cognitive Bias Detection

Rule-based scoring identifies five types of bias: Anchoring identifies the enduring impact of early responses; overconfidence quantifies the difference between confidence and accuracy; Confirmation bias contrasts performance on novel skills with resume-matched skills; The availability heuristic detects an overemphasis on current subjects, while consistency analysis highlights inconsistencies in responses pertaining to related skills. Personalised feedback is informed by identified biases that modify belief weights.

E. Roadmap Generation

By (1) identifying skills below the competency threshold, (2) scoring each gap according to criticality (dependent skill count), evidence strength, and magnitude, (3) topologically sorting by prerequisites, (4) retrieving and validating learning resources using semantic search with symbolic filtering, and (5) sequencing milestones with estimated completion times, learning paths are created. Following each assessment session, roadmaps are dynamically updated in response to updated engagement signals and beliefs.

VI RESULTS AND PERFORMANCE EVALUATION

A.Resume Parsing Accuracy

The accuracy with which skills, education, experience, and personal information are extracted from uploaded documents is measured by resume parsing accuracy. For structured extraction, the system mainly uses the Google Gemini API, with HuggingFace NER serving as a backup. The formula for calculating accuracy A is $A = N\_correct / N\_total \times 100$.

where N_"total" is the total number of ground-truth entities and N_correct is the number of entities that were correctly extracted. With Hugging Face enriching entities in ambiguous or unstructured formats and Gemini correctly handling 90–95% of cases, Neuro-RAG achieved an average parsing accuracy of 94.3%.formats

B.Skill Precision and Recall

Skill assessment evaluates the system's ability to identify strengths and gaps across correlated skills. Precision $P$and recall $R$are defined as:

$$P = \frac{TP}{TP + FP}, R = \frac{TP}{TP + FN}$$

where TP is true positive skill identification, FP is false positive, and FN is false negative. The harmonic mean of precision and recall yields the F1-score:

$$F_1 = 2 \times \frac{P \cdot R}{P + R}$$

Neuro-RAG demonstrated precision of 91.7%, recall of 89.5%, and F1-score of 90.6%, highlighting robust adaptive skill inference.

C.Cognitive Bias Detection

Cognitive bias detection measures the system's accuracy in identifying behavioral tendencies such as overconfidence, confirmation bias, anchoring, and consistency errors. Using rule-based scoring with evidence validation, bias detection accuracy $B$is computed as:

$$B = \frac{N_{\text{bias\_correct}}}{N_{\text{bias\_total}}} \times 100$$

The framework achieved an average bias detection accuracy of 87.2%, effectively identifying patterns influencing user responses

D. Response Time and Latency

Response time measures the latency from user interaction to actionable feedback. End-to-end latency $T_{\text{total}}$is expressed as:

$$T_{\text{total}} = T_{\text{parsing}} + T_{\text{inference}} + T_{\text{feedback}}$$

where $T_{\text{parsing}}$is resume extraction time via Gemini API, $T_{\text{inference}}$includes skill inference, Bayesian belief propagation, and symbolic validation, and $T_{\text{feedback}}$is the AI-based feedback generation time. Neuro-RAG achieved 2.1 seconds per question-response cycle and 3.7 seconds for full resume parsing with feedback, demonstrating low-latency, real-time performance.

E. Bayesian Inference in Skill Assessment

Bayesian inference is central to the SkillInferenceEngine for dynamically estimating user competency. Skills are modeled as nodes in a probabilistic graph, with correlations representing prerequisites, dependents, and category relationships. Posterior beliefs are updated as:

$$P(S_i \mid \text{responses}) = \frac{P(\text{responses} \mid S_i) \cdot P(S_i)}{P(\text{responses})}$$

where $P(S_i)$is the prior competency estimate, $P(\text{responses} \mid S_i)$is the likelihood of observed answers, and $P(S_i \mid \text{responses})$is the posterior belief. Skill gaps are then calculated as:

$$\text{Gap}(S_i) = 1.0 - P(S_i \mid \text{responses})$$

This inference drives adaptive question selection, prioritizing low-confidence skills, and informs learning roadmap generation, ensuring that feedback and skill recommendations are statistically grounded.

E. Retrieval-Augmented Feedback Performance

The quality of retrieval-augmented generation (RAG) for personalized feedback was evaluated using Top-K retrieval accuracy and semantic relevance. Cosine similarity between user query embeddings Q and knowledge embeddings K is computed as:

$$\cos(\theta) = \frac{Q \cdot K}{\| Q \| \| K \|}$$

The system achieved Top-3 retrieval accuracy of 92.5%, ensuring that AI-generated feedback is contextually relevant and grounded in user-specific data.

F. Overall System Evaluation

Metric	**Result**
Resume Parsing Accuracy	~94.3 %
Skill Assessment F1-score	~90.6 %
Cognitive Bias Detection	~87.2 %
Average Question Response Time	~2.1 sec
Full Feedback Generation Time	~3.7 sec
Top-3 RAG Retrieval Accuracy	~92.5%

VII SECURITY AND DEPLOYMENT

A.Security & Performance

Throughout the evaluation and feedback pipeline, Neuro-RAG incorporates a multi-layered security framework to guarantee the availability, confidentiality, and integrity of user data. To safeguard all REST endpoints and implement secure session management, the backend makes use of Spring Security. Before gaining access to sensitive functions like starting an assessment, uploading a resume, or retrieving feedback, each user request is verified and approved. The proper segregation of administrative, evaluator, and candidate functionalities is further guaranteed by role-based access control, or RBAC. While environment variables and configuration isolation are used to securely manage API keys for external services like OpenAI and Gemini, sensitive user data, such as assessment answers and feedback, is stored in MySQL with AES-based encryption.

B.Deployment

The modular design to promote dependability and performance. Docker is used to containerise the Spring Boot-developed backend, allowing for platform-independent execution and easier environment management. Kubernetes can be used to orchestrate the containers for distributed scalability and fault tolerance, guaranteeing high availability under fluctuating loads. A cloud-based content delivery network (CDN) hosts the frontend, which was developed using React, to enable low latency, worldwide access, and quick client-side rendering. Secure HTTPS channels with error-handling features are used for integration with external services, such as the Gemini API and OpenAI GPT endpoints, in order to preserve business continuity. GitHub Actions is used to set up continuous integration and deployment (CI/CD) pipelines, which automate build validation, testing, and deployment to minimise downtime and preserve steady application performance.

VIII CONCLUSION

A. Conclusion

To provide individualised, adaptive competency evaluations, the Neuro-RAG framework introduces a novel combination of neuro-symbolic reasoning, retrieval-augmented generation, and Bayesian skill inference. The system achieves high accuracy in skill detection, cognitive bias evaluation, and learning roadmap generation by utilising a hybrid symbolic validation layer, OpenAI GPT for feedback generation, and Google Gemini API for structured resume parsing. The effectiveness of the experimental evaluation for scalable, real-time applications is validated by its strong performance across key metrics, such as resume parsing accuracy, skill assessment F1-score, cognitive bias detection, and low-latency feedback generation.

B. Future

In the future, the system will be expanded to include multi-modal assessments that use audio and video inputs to record behavioural cues, sophisticated knowledge graphs for more detailed skill dependency modelling, and federated learning strategies to enhance personalisation while protecting user privacy. Real-time adaptive feedback based on longitudinal user performance could also be advantageous for the system, allowing for dynamic roadmap updates and ongoing skill development. In order to further support intelligent, data-driven competency assessment and personalised learning, these enhancements are intended to improve Neuro-RAG's accuracy, interpretability, and contextual grounding.

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