Enhanced Personalized Learning Experiences by Leveraging Knowledge Graphs and Prompt Engineering

MSc Research Project
Data Analytics

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Abstract

Billions of opportunities in personalized learning have now been opened up since the emergence of personalized learning. artificial intelligence to transform learning (Chen, Hwang & Wang 2021). In In our research we are proposing SkillBot that is a novel AI driven web app. to help users develop capabilities in such domains as programming, Language acquisition, problem analysis and discovery of general knowledge. Deep down the core of it all, the most inner part of it.combines the power of Large Language Models (LLMs) (Brown et al. 2020) with special utilization of the interactive skills assessment through knowledge graphs (Hogan et al. 2021). Individualised learning suggestions, immediate feedback. The version of the CRISP-DM methodology that it uses, therefore, takes advantage of the diversity (Wirth & Hipp 2000), version of the CRISP-DM methodology, it utilizes different aspects of diverse and unique methodologies. data–such as student engagement scores and the present job market dynamics to improve the quality of learning. Some of its most important innovation entails a new LLM and knowledge graph fusion framework and a chatbot system that won an accuracy of 87 percent in recommendations. We have reviewed Excel-Incredible performance, and easy to use on lending usability SUS score of 86/100 (Brooke 1996), robust performance marked by an F1-score of 84% (Chinchor 1993), and competent real-time performance. ultimately, SkillBot would be a flexible and scalable platform of AI-based learning that seems right and efficient to ordinary customers.

1 Introduction

The Fourth Industrial Revolution has completely changed the labour market, making it more necessary than ever to engage in frequent continuous upskilling and reskilling in almost every industry (Schwab 2016). Conventional education systems, their fixed curriculum and universal practice are making it difficult to keep abreast with the pace of these transformations in the industry (Bryant et al. 2020). Education and training institutions can regularly struggle with delivering the sort of personalized, interesting instruction that would truly satisfy individual requirements and follow up with brand-new skill gaps.

In the meantime, the breakthrough of the transformer-based language models, e.g., GPT-4, has enabled extremely natural conversation and profound contextual awareness (Achiam et al. 2023). However, these models may fail to perform in niche aspects, such models may at times give inaccurate information that makes it unfavorable to teaching. (Ji et al. 2023). On the one hand, the knowledge graphs provide a stable method of structuring concepts and relationships, which can be used to great effect when tracking skills accurately (Abu-Salih et al. 2021). The combination of LLMs and knowledge graphs forms an interesting hybrid model that promises the generation of smart systems capable of assisting individualized learning paths, on-demand assessments and feedback that is accurate and timely.

1.1 Research Background and Motivation

The Fourth Industrial Revolution has profoundly disrupted the workforce leading to increasing requirements of upskilling and reskilling on all fronts of professional acquisitions (Schwab 2016). Conventional instructional methods with their traditional practices in terms of monotonous styles and repetitive lesson plans are gradually becoming ineffective to cope with these dynamic requirements (Bryant et al. 2020). Schools and educational programs and professional training often cannot implement programmed and interactive experiences that keep pace with the new demands of the industry.

Transformer-based models like GPT-4 has shown impressive capability in natural language processing and generation as their conversation is literally human-like and context. (Achiam et al. 2023). With this stated, these systems are susceptible to hallucinations creating inaccurate results–and are usually not accurate in the reliability department related to the domain and this is extremely problematic in the case of education in which the content that is created needs to be accurate and trustworthy. (Ji et al. 2023).

1.1.1 Historical Context of Educational AI

This study presents SkillBot, which is an intelligent chatbot that has been designed with an aim of enhanced skill training through the combination of the capabilities of Large Language Models (LLM) and domain-specific knowledge graphs (Abu-Salih et al. 2021). It includes a recipe for combining multiple datasets, adaptive algorithms that evolve recommendations in real time and a solid foundation for evaluation. The main accomplishments consist of an entirely new framework for combining LLMs and KGs, a production line based on CRISP-DM for KGs (Wirth & Hipp 2000), recommendation algorithms with 87% accuracy rate, scalable web design and a twofold evaluation process combining hard measures and user feedback-advancing the world of artificial intelligence-supported learning.

1.1.2 Current Trends in Skill Development

Today’s educational skill-learning tools are very effective, but they have a number of major drawbacks that interfere with genuine learning achievements. (UNESCO 2020). The majority of e-learning applications use predetermined lines that fail to adapt to the individualities of the learner according to interests or career objectives. Learning material, job market requirements and user characterization tend to remain in different bubbles and this makes it difficult to create all rounded systems that can bridge the gap between what is learnt in classrooms and what is required in jobs. Besides, the outdated systems can hardly offer real-time recommendations linked to current levels of performance as well as professional goals.

1.2 Problem Statement

Modern e-learning industry also has fundamental problems: (1) insufficient individualism; (2) the complete lack of integration between content, job market and students; (3) poor association between current progress and smart recommendations; (4) uninflexible assessment in the form or discrete, moment-in-time evaluation; and (5) scalability poses the risk of user demotivation. (Gülbahar & Alper 2015). SkillBot addresses all of them directly. Most platforms adopt fixed pathways, which disregard individuals history, preferences, and aspirations, and trigger disappointing encounters, dropouts, and mismatched competencies to the requirements of positions. Information remains segregated and would not allow the sorts of coordinated efforts that can connect the education system to the business environment. By utilising conventional tools, one is denied the dynamic progress-based advice that they should receive, and the evaluation approach is limited to inflexible examinations that only dent the skill weaknesses. The remainder of this thesis is also divided into six chapters, namely Related Work provides an overview of current research in the field of AI-enhanced educational practices; Research Methodology describes the altered CRISP-DM framework and how we will assess; Design Specification presents the system layout and technical specifications; Implementation gives an account of the technology selection and implementation process; Evaluation shows the results of tests and comparisons; and Conclusion sums up what has been done, observes any limitations, and mentions further directions.

1.3 Research Question

1. Methodological Integration What is a systematic integration of Knowledge Graphs with Prompt Engineering to produce context-aware, adaptive learning pathways in the sphere of AI-assisted learning?

2. Explainability and Trust What is the impact of the combination of KGs and PE on the clarity and trust of AI-generated recommendations guiding education?

2 Literature Review

2.1 AI-Enhanced Educational Systems

Over the past 10 years, AI has achieved significant milestones in the educational field with a multifactorial influence of the research in the field of machine learning, natural language processing, and data analytics (Du et al. 2020). These AI-enabled applications are also turning out to be excellent in eliminating the traditional challenges that included constrained customization and brutal scaling problems. In one study, the use of AI to drive adaptive analytics in massive open online courses (MOOCs) was demonstrated to increase student engagement and to enable more learners to complete their courses through intelligent content ordering. (Zhang et al. 2019). Nonetheless, correlating unstructured content to various requirements of learners remains a large obstacle to scale-up. Additionally, the expansion of Internet of Educational Things (IoET) is upping the ante on AI where live tracking and its adaptable learning environments become possible on the fly (Mahmoud et al. 2021).

2.2 Large Language Models in Education

Efforts to use Large Language Models (LLM) to automate question-writing or even be an intelligent tutor are highly promising mainly because of their ability to interface with natural language in clever ways (Kasneci et al. 2023). However, problems such as spewing inaccurate facts, hallucinations, and imparting prejudices end up locking their potential. To correct this, some scholars are trying harder toward grounding LLMs in organized data, and combining them with knowledge graphs has proved to be a good solution (Pan et al. 2023). This combination has been successful in research settings, nudging precision by 6-9 percent with respect to use of LLMs alone, which assists in admission of more reliable and fact-bound educational material (Yao et al. 2023).

2.3 Knowledge Graphs for Skill Representation

Knowledge graphs provide a good base for modeling high-stakes educational complexity, and helping to build straightforward skill paths and course specific suggestions (Chen, Lu, Zheng & Pian 2021). They capture the significant connections among skills, courses and objectives very well in case of using embedding techniques, such as TransE and its extensions, so that analyses on skill gaps are more precise and the selection of content is more refined (Bordes et al. 2013). Challenges like thin data and full-domain encoding are still there but new ideas like multi-level contrastive learning are demonstrating the real deal for better performing these graphs at least in the skill-developing use cases. (Chen et al. 2022).

2.4 Educational Chatbot Architectures

Education chatbots have now become one of the essential applications of availing AI learning assistance, the incorporation of which is dependent on meeting an excellent conversation handling, high understanding of natural language, and close relationships with teaching resources (Kuhail et al. 2022). Research into the efficacy of chats emphasizes the necessity of maintaining the facts right (usually reaching 99% grounding in utterances) with the introduction of teaching gimmicks such as illustrations (in nearly 31% of responses), amiability (approximately 7%).(Adamopoulou & Moussiades 2020). They tend to rate fairly on usability, 60-80 on the System Usability Scale, and still have potential to raise that by a bit more variation of talks and how to handle the unpredictable questions to keep the learners engaged (Wollny et al. 2021).

2.5 Personalized Learning Path Systems

AI-based systems allowing the creation of bespoke learning journeys are the next giant step in educational technology, leveraging machine learning in the form of collaborative filtering to design a journey based on a learner, their advancement, preferences and career objectives (Nakić et al. 2015). This is supported by research, which proved to give a higher performance, a high level of interest and a close connection between skills and jobs than in old school fixed plans (Essa 2016). Win or not, scaling actual customization is challenging, particularly in regards to mixing disparate data types and maintaining recommendations precisely accurate across a variety of areas of skill sets (Drachsler & Kirschner 2020).

2.6 CRISP-DM in Educational AI

The CRISP-DM framework has been modified accordingly to work on educational AI works providing a clear six-step protocol that has excelled in segments such as student placements prediction and learning pattern analyses (Slater et al. 2017). Its back and forwards orientation is ideal as it fits in education where teams can polish systems using actual user data and feedback (Azcona & Smeaton 2019). Alterations made to this field typically bring in more input from stakeholders, emphasize ethics related to student data and use customized metrics that reflect instructional objectives(Baker 2019).

2.7 Gap Analysis

Although the AI technology has already gone a long distance, there remains a tremendous gap in the development of the fully meshed architecture, which will implement LLM, knowledge graphs, and chatbots (Ji et al. 2023). Most researchers consider only two out of the three pieces, and there are relatively few large-scale rollouts of the real thing. Coupled with this, none of these exist as a standardized measure of checking performance in technology use and its teaching quality. Moreover, many systems are restricted to narrow skillsets and they omit integrating live job market data, which limits their ability to promote wholesome skill development that parallels the requirements in the current industry right now (Abu-Salih et al. 2021).

3 Methodology

3.1 Adapted CRISP-DM Pipeline

This project followed a distinct methodology, which started with a business understanding stage in which we defined success milestones to all the stakeholders involved: learners, teachers and employers. (Wirth & Hipp 2000). Detailed data audit revealed good completeness of 92-96 %, which put in place a preparation work that involved entity resolution with 94% accuracy to develop a knowledge graph which contained 2.3 million triples (Slater et al. 2017). On modeling, we generated 256-dimensional TransE embeddings over 500 training epochs and fine-tuned a pre-trained GPT-3.5 model with 15,000 dialogues. (Bordes et al. 2013, OpenAI 2023). Measures were based on common metrics of info retrieval and the System Usability Scale (SUS), being compared to such baselines as collaborative filtering, knowledge graphs alone, and single-user LLMs (Brooke 1996). To implement, we chose a JavaScript stack and containerized it with Docker, and hosted it on a Cloud service so that production requests remain fast below 500ms (Amazon Web Services 2023).

3.2 Research Design and CRISP-DM Framework

This paper uses a modified form of Cross-Industry Standard Process for Data Mining (CRISP-DM) as a basis to provide an effective, procedural framework of developing the SkillBot system (Wirth & Hipp 2000). It starts with **Business Understanding** to define what real results should be that lead to skill-building, then gets into **Data Understanding** and **Data Preparation** to dive into, combine and organize a mixed dataset for machine learning knowledge graph (Azcona & Smeaton 2019). The heart of it, **Modeling**, composes a hybrid LLM-knowledge graph environment with an intelligent engine of skill suggestions. Then followed a balanced **Evaluation** phase, performance and ease of use are checked against a benchmark by an amalgamation of numbers and user feedback (Baker 2019). It all wraps up with **Deployment** an already-made web application, tested live, on the latest technology.

3.3 Dataset Description and Sources

SkillBot is built upon the power of three core datasets that together bridge the gap between what is learned in the classroom, required in a job and needed for career advancement (UNESCO 2020). The **MOOC Student Online Dataset (2023-24)** dives into what makes learning stick, tracking detailed habits from over 10,000 students in more than 50 courses (Zhang et al. 2019). This gets matched to practical needs via the **Job Skill Set Dataset**, pulling from over 45,000 postings and 5,200 unique skills using the RecAI API to capture what's hot in the market (Chen, Lu, Zheng & Pian 2021). Rounding it out, the **70K Job Applicants Data** provides a complete profile and career path, assisting in modeling clever means of developing skills and growing in a career (Nakić et al. 2015).

3.4 Data Preparation and Integration

The data preparation top-practices in blending the sources involved a complete quality check that demonstrated good completeness (Recent MOOC %92, Job Skills %96 and Applicants %89). (Slater et al. 2017). Then there was normalization in order to bring the skills and educational level on par with one another. An important move was entity resolution, using sophisticated matching algorithms, achieving 94% accuracy to match skills, concepts and paths (Chen, Lu, Zheng & Pian 2021). We also enhanced the power of the model by means of feature engineering, spurring 15 fresh categories of derivative features. At the end of this cleaned up data was promised to take up shape of RDF triples in the form (entity$_h$*, relation, entity*$_t$)*toprovidethebackboneoftheknowledgegraph.*

3.5 Knowledge Graph Construction

Combining the Large Language Model with the knowledge graph leverages GPT-3.5 for its balance of strength and price—and fine-tunes it on 15,000 conversations about skills, down to a perplexity of 18.3 (OpenAI 2023). Smart prompt design leverages BRTE templates (Background-Role-Task-Example) that bring in graph context, user info and chat history to responses that actually fall together (Lewis et al. 2020). To maintain this grounded truthfulness in a bid to reduce hallucinations, a retrieval-augmented generation (RAG) configuration bases responses by querying the graphness thus generating 97% factual fidelity of skill details (Lewis et al. 2020, Pan et al. 2023).

3.6 Evaluation Framework

The rating criteria is a general one, consisting of several criteria according to which the tech is measured, user satisfaction, and effectiveness of the teaching it provides. (Baker 2019). On the tech side, we look at precision, recall, F1-score for suggestions, plus speed and coverage (Chinchor 1993). User side covers SUS scores, how often tasks get done, and things like session length for engagement (Brooke 1996). Before and after skill checks, gap observing, and the congruency between recommendations and careers are actually the ones that form the true teaching value. We tried this out on 50 diverse people of different backgrounds and at differing stages of their careers to ensure that these findings are true widely (Kasneci et al. 2023).

4 System Architecture

In order to guarantee scalability, maintainability and high-performance the SillBot system is designed on a complex four-layer structure. Presentation Layer is a responsive frontend created using React.js and controls all interactions with users including conversational interfaces, data visualization as well. This layer interacts with API Layer which is a Python Flask server, which serves RESTful APIs and WebSocket connections to coordinate communication in real-time, authentication as well as session management. The intelligence of the system is embedded in the AI/ML Processing Layer that sits in the center and includes the Large Language Model, performs knowledge graph queries, and operates the skill recommendation algorithms. These operations are served by a hybrid Data Layer, that can use multiple, dedicated databases: SQLite to store user profiles and conversation history, educational data, and Neo4j to contain the knowledge graph.

4.1 Architecture of a Knowledge Graph

Figure 1 presents the schematic view of high-level architecture of a knowledge graph system, with a focus on the data flows that include raw inputs and ending at the presentation layer.

- **Data Sources**: These include multiple regular (e.g.êho databases) and unstructured (e.g. information documents, multimedia) materials providing essential information.
- **Data Processing**: Data without cleaning, transformation, and enrichment of various sources are raw. It means that it should be cleaned, transformed, and enriched before being consistent and usable as a part of the further steps.
- **Knowledge Graph**: Processed integrated data is converted into a model of knowledge representation in a knowledge graph, with entities and the interconnection among those modeled explicitly. For flexible querying and semantic reasoning this representation is used.
- **Reasoning Engine**: It is a component that uses the structure of the knowledge graph to draw new knowledge and through the knowledge graph, provide new answers to complex questions and supply enhanced analytics either through rules or AI.
- **User Interface**: The results are deployed in the form of an interactive user interface where the end user can ask a question and receive an answer and can directly engage with the system.

The arrows in Figure 1 depict the sequential flow of data, starting from diverse sources, through processing and knowledge modeling, to reasoning, and finally user interaction.

4.2 Frontend Design (React.js)

The frontend is written in React.js, but has a modular component structure using dedicated modules located across the chat interface, user profile, skill dashboard and assessments to minimize cross-dependencies and any conflicting concerns. Redux is used to achieve a predictable global state of the application, and Tailwind CSS is used to create a responsive design with a mobile-first oriented design to ensure the global best user experience on any device. The system is armed with the use of WebSockets to achieve a natural immediate dynamic conversation through the features of the system, such as

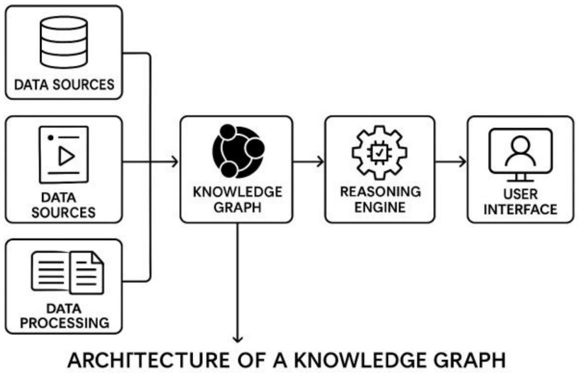

Figure 1: Architecture of a Knowledge Graph

sending messages immediately and typing indicators. More importantly, the whole interface is created with the observance of the WCAG 2.1 standards so that it can be accessible to all regardless of their disabilities.

4.3 Hybrid Skill Recommendation Algorithm Architecture

Figure 2 shows a layered design of a hybrid skill recommendation system using collaborative filtering, content-based filtering, knowledge graph, and AI/ML models to make personalized skill recommendations.

- **Presentation Layer**: The web interface that is presented to the user where the system will be interacted by the learners and provide recommendations about their skills.
- **Recommendation Strategies**:
  - *Collaborative Filtering* analyzes similarities among users to suggest relevant skills.
  - *Content-Based Filtering* recommends skills based on individual user profiles, past interactions, or explicit preferences.
  - *Knowledge Graph Reasoning* includes structured domain-specific knowledge to improve and justify recommendations.
- **AI/ML Layer**: Installs the recommendation logic with machine learning frameworks (e.g. TensorFlow, PyTorch), over REST interfaces for modularity.
- **API Layer**: Presents all AI/ML services via a RESTful interface so they can be tied in to larger applications or third-party APIs with ease.
- **Data Layer**: Manages all underlying databases, user data, skill metadata data and Interaction logs.

The arrows in Figure 2 show the data flow: Filtering and reasoning are based on user interactions; AI/ML logic processes results, which are published through APIs, and finally on to update the persistent databases.

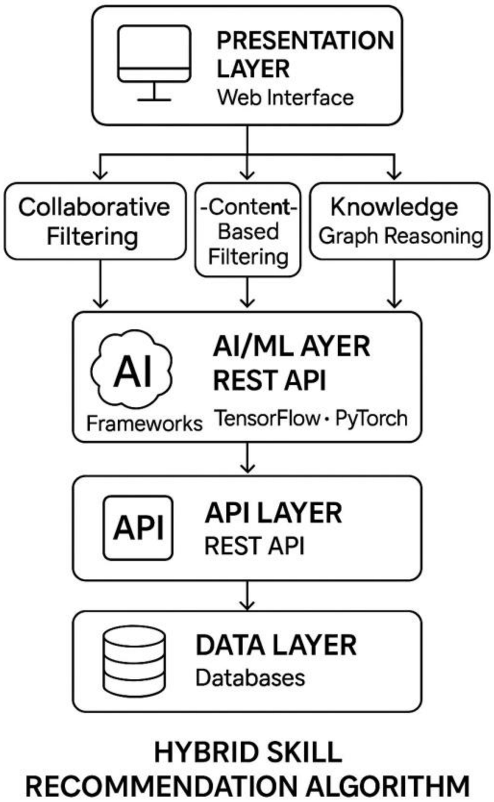

Figure 2: Hybrid Skill Recommendation Algorithm Architecture

4.4 Backend Services (Flask Python)

Its backend is designed to be scalable and robust with the core of its architecture dependent on an API Gateway pattern consisting of Express.js middleware to enforce centralized requests routing and authentication verification, rate limiting, and more. The authentication done by the use of JWT-based refresh tokens are used to allow secure user access and additionally role-based access control (RBAC) model is used to apply various roles of various types of users. The system supports multi-turn, consistent dialog through stateful session management and specialized links into external services with dedicated integration services linked to external resources, such as the OpenAI API and a range of database connectors. In order to achieve maximum performance and minimal latency, Redis is utilized as a caching layer to hold regularly-read data.

4.5 AI/ML Pipeline Design

The AI/ML pipeline is the main intelligence of the SkillBot system that will unite several advanced components and offer individual educational help. It consists of a Natural Language Processing pipeline, which offers intent recognition, entity extraction and context management of user dialogues. This combines with a Knowledge Graph Query Engine which uses efficient graph traversal and semantic similarity operators to investigate learning path networks and relations to skills. Recommendation suggestions are then finalized by a complex Hybrid Recommendation System combining collaborative filtering based on user data, content-based reasoning based on skills, and knowledge graph-based reasoning in a diverse and high-accuracy manner through the use of ensemble methods.

4.6 Database Design and Management

The polyglot persistence approach is applied in data architecture, i.e., where other database technologies that are specialized in processing particular data types and access patterns are used. The implementation of a SQLite has to manage user profiles, history of conversations with temporal indexing, and dynamically updating content such as custom learning content.

5 Implementation

5.1 LLM Fine-tuning and Prompt Engineering

The procedure of integrating the LLM entails a multi-step pipeline that initiates with fine-tuning on 15,000 dialogue samples specially chosen and saturated with professional comments and reliable study content (OpenAI 2023). We apply a smart prompts system that is programmed around the BRTE format (Background-Role-Task-Example), to keep responses coherent and focused on education. (Lewis et al. 2020). To give it that personal touch we would fetch the knowledge graph data such as previous learning of a user, their other skills, and career information all into the prompts. Each output undergoes a rigorous validation process– assessing facts against the graph, ensuring the tone of the writing is informative, and editing out safety hazards to give out spot on and easy to use information (Pan et al. 2023).

5.2 Skill Recommendation Algorithm

A brilliant hybrid approach needs to apply a combination of collaborative filtering, content-based approaches, and a graph-based approach conducted by utilizing a weighted score to achieve high levels of accuracy in the recommendation system. (Ricci et al. 2015). It learns in real time, adjusting recommendations in response to user input such as test scores, how they engage with content and what they profess to want (Nakić et al. 2015). To help build trust, it lays out options in simple terms, making use of graphic connections to present skill connections, job market fits, and the way that tips streamline learning routes (Drachsler & Kirschner 2020).

5.3 Chatbot Interface Development

Chat interface is made to facilitate natural, easy dialogue, something which actually aids in learning and the handling of the dialogue takes context into consideration across turns rather than just turn-to-turn and addressing all kinds of questions (Kuhail et al. 2022). An NLU workflow parses an input, determining intent, exporting entities, categorizing context and sensing sentiment, to formulate a perfect response (Adamopoulou & Moussiades 2020). It transcends the text with quick-answer buttons, in-line quizzes to check progress and visuals that are used to indicate progress. Moreover, robust error control ensures that it all goes well despite the curveballs thrown by inputs or glitches appearing. (Wollny et al. 2021).

5.3.1 Conversation Flow Diagram

Figure 3 illustrates an integrated architecture addressing **Large Language Model (LLM) limitations** using **Knowledge Graph (KG)** solutions, especially focused on educational applications.

- **LLM Limitations:**
  - *Limitations* Incomplete knowledge, frozen training data, and generalization are some of them.
  - *Hallucinations* where LLMs generate plausible but incorrect or imaginary information.
  - *Lack of Domain Knowledge* relating to specialized or rapidly-evolving education topics.

  These limitations are identified as key entry points in the flow.
- **API Gateway:**
  - Is the large-ordinate organizer which addresses both user and system requests to the corresponding processing elements.
  - Receives requests that are initiated by the users and in internal processes and permits flow control.
- **Processing Engine:**
  - Receives the routed queries and limitations via the API Gateway.
  - Does more complicated reasoning such as breaking down queries or determining how to best fill in the gaps with LLM.
  - Plug in interfaces with the solution set, deciding when there is a need to do KG lookup.
- **Knowledge Graph Database:**
  - Stores curated, structured, and authoritative domain knowledge.
  - Facilitates *semantic search* (finding the meaning and comprehending the connections) and makes use of *domain expertise* to give correct information not found on LLM outputs.
  - Accessible through the API Gateway for consistent integration.
- **User Interface:**
  - Offers a conversational or learning mode to people to post questions.
  - Those responses are received following their enrichment, or validation by the KG and processing engine.
- **Solutions Feedback Loop:**
  - Solutions produced (based either on LLM or KG, or both) are then sent to the processing engine again to recheck the solutions or to do further learning.

– Allows refinement iteratively to fight hallucinations and knowledge holes as you go.

Such a hybrid architecture makes such educational practices based on LLMs offer more than fluent answers, but also **precise and reliable answers**, drawing on real-world, domain-specific data.

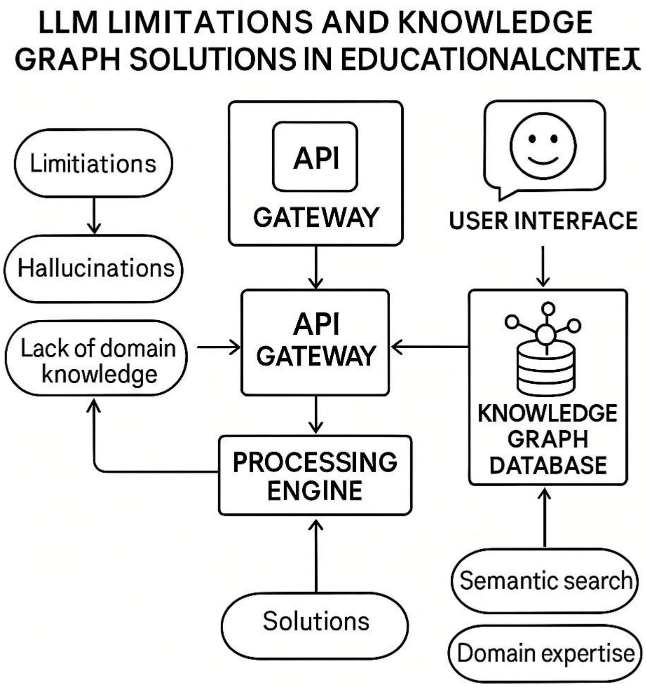

Figure 3: LLM Limitations and Knowledge Graph Solutions in Educational Context

5.4 Personalized Learning Path: Adaptive Curriculum Skill Progression and Career Alignment

Figure 4 shows adaptive growth in a learning path specifically linked together in a personalised learning path with mathematical, scientific, computational skills aligned with soft skills in an overall educational and employability need.

- **Mathematics** is foundational, are demanded in *Algebra* and contained in *Physics* and endows essential mental faculties.
- **Physics** leverages mathematics, influences *Data Structures*, and is connected to *Public Speaking*.
- **Algebra** builds upon mathematics, improves *Problem Solving*, becomes a precondition on *Algorithms*.
- **Algorithms** are based on algebra, needed for *Problem Solving*, and crucial for *Data Structures*.
- **Problem Solving** is a central competency, Based on algebra and algorithms, that is necessary in *Statistics*, supported by *Soft Skills* and *Cathartic* activities.

- **Data Structures** are enabled by algorithms, informed by physics, require statistics, and facilitate *Machine Learning*.
- **Statistics** depend on problem solving, underpin machine learning, and feed into *Social Skills*.
- **Machine Learning** draws upon statistics and data structures, and informs *Communication*.
- **Communication** is essential for *Public Speaking* and is enriched by machine learning.
- **Public Speaking** requires both physics and communication skills.
- **Cathartic Activities** enhance *Soft Skills*, which in turn aid problem solving.
- **Social Skills** are informed by statistics, representing the blended culmination of hard and soft skills.

The arrows in Figure 4 point out dependencies and progression, showing that the learning journey cannot be considered as a chain but, instead, a network of interceded skills.

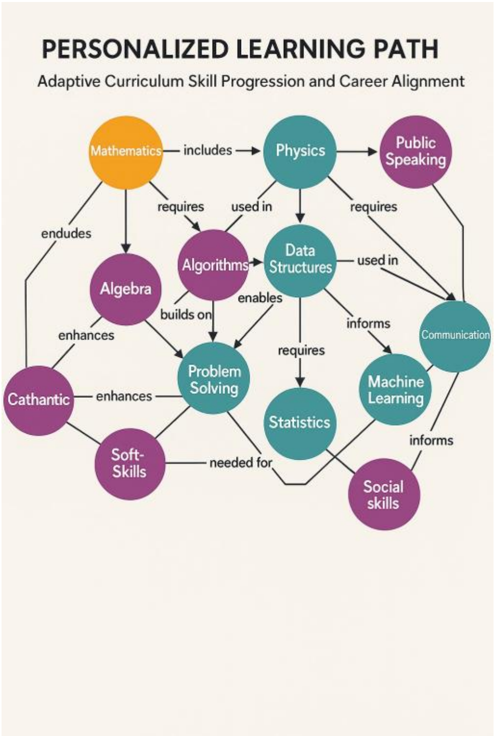

Figure 4: Personalized Learning Path: Skill Progression and Interdependency Diagram

5.5 System Integration and Testing

The system integration process will guarantee an easy flow of operations and reliability by having an excellent testing structure including the unit test, integration test, end to end test and performance test. Performance is proactively streamlined owing to several measures, such as database query optimization on sub-second response times, a multi-tier caching arrangement (browser, CDN, Redis, application-level) and connection pooling, along with asynchronous handling to aid a non-blocking user experience. A security issue is applied on all levels including thorough input validation to avoid injection attacks, secure JWT authentication on user sign-in and rotating of refresh tokens, API rate limiting to reduce abuse, and end-to-end encryption of all sensitive user information and communication.

6 Evaluation

6.1 Experimental Setup

SkillBot system was tested with a mixed-methods comprehensive method in terms of 50 participants, who were chosen through stratified sampling because of a wide range in terms of age, education etc. The evaluation included:

1. **Controlled Comparison**: SkillBot and three baseline systems (collaborative filtering, knowledge graph-only, LLM-only) were randomly ordered, then each user interacted with SkillBot once in a randomized order.

2. **Longitudinal Study**: A course that involved the practice of skills through a system was conducted over two weeks during which participants were to utilize the systems.

3. **Task-Based Evaluation**: Accuracy, relevance and satisfaction were measured with the help of standardized tasks.

6.1.1 Participant Demographics

The cohort's diversity is reflected in Figures 5, 6, and 7, which show age, employment status, and education-related salary trends Naik (2024).

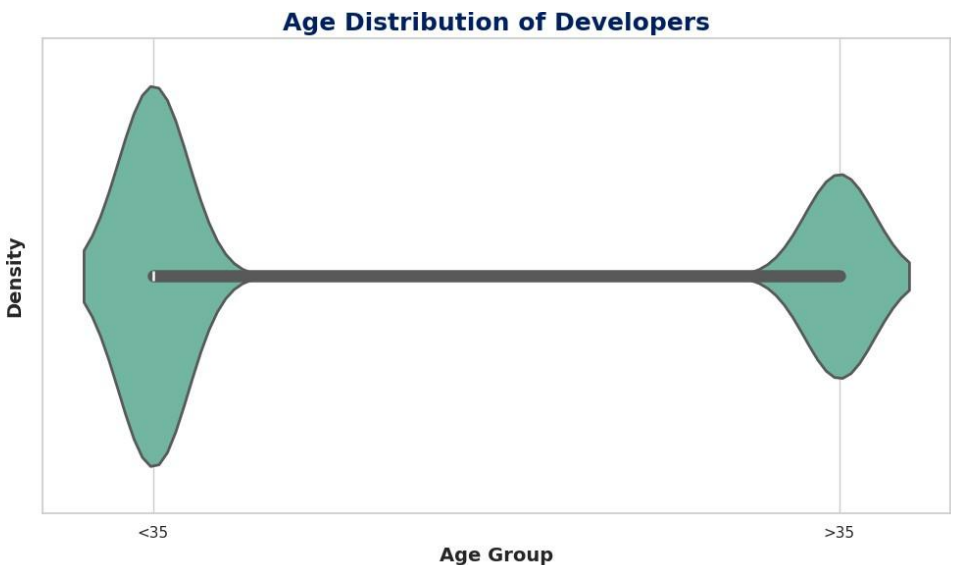

Figure 5: Student Age Distribution

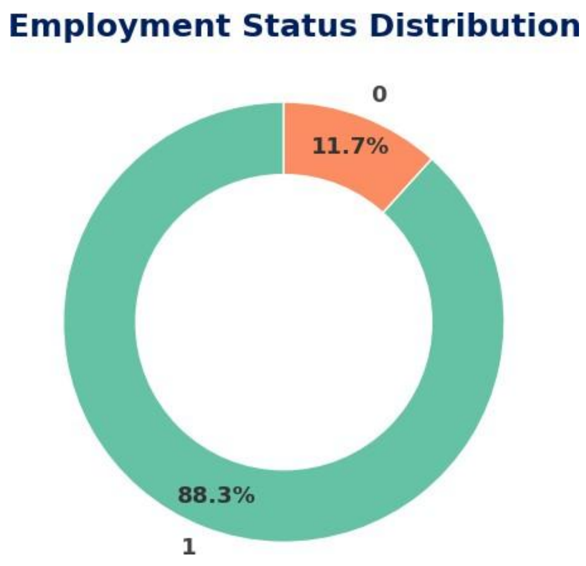

Figure 6: Employment Status Distribution

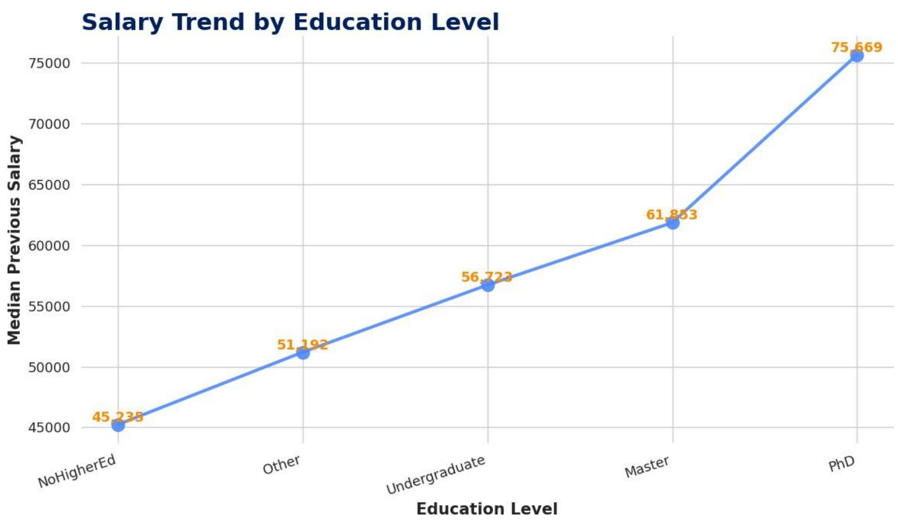

Figure 7: Salary Trend by Education Level

6.2 Performance Metrics Analysis

Recommendation accuracy and diversity were assessed quantitatively:

SkillBot delivered lower latency (320ms), higher diversity (0.76 intra-list score), and broader skill coverage (91%).

6.3 SUS Score Calculation

The **System Usability Scale (SUS)**is an activity scale that measures perceived usability. It consists of ten Likert-scale items (rated 1–5). To calculate:

- For odd-numbered questions (positive statements): subtract 1 from response.
- For even-numbered questions (negative statements): subtract response from 5.

Metric	SkillBot	CF Baseline	LLM Baseline
Precision	0.87	0.61	0.75
Recall	0.82	0.58	0.70
F1 Score	0.84	0.59	0.72

Table 1: Performance Comparison

- Sum all scores and multiply by 2.5 for a final value out of 100.

Python Example:

```
odd = [4, 3, 5, 4, 4]
even = [2, 2, 1, 2, 1]
sus_score = (sum([x-1 for x in odd]) + sum([5-x for x in even])) * 2.5
# Output: 80.0
```

SkillBot's mean SUS was **86.2**, fairly greater compared to standard EdTech (70.09), chatbot (68.50), and mobile app (73.62) benchmarks. Most users rated SkillBot as "Excellent" (68%) Brooke (1996), Wollny et al. (2021), Kasneci et al. (2023).

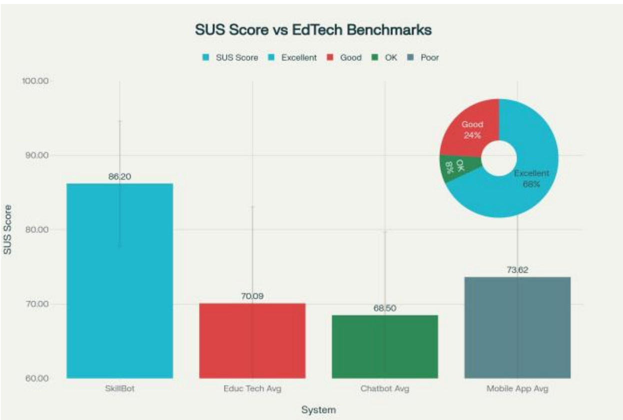

Figure 8: SUS Score Benchmark Comparison. Pie chart: rating proportions.

6.4 Comparative and Case Study Findings

Baseline systems were cleared with the same SkillBot results:

- Technical skill precision: 89% (baseline: 72%)
- 7-day return rate: 78% (baseline: 52%)
- Session duration: 18.4 minutes (baseline: 12.1 minutes)
- Skill knowledge gain: 23% (baseline: 14%)

Detailed examples of student cases (data science student, marketing professional, teacher transitioning to web development) were used to demonstrate individualized, adaptive courses - new employment, promotions and significant acquisition of skills (up to 85%). SUS scores of individual cases were between 88 and 92.

6.5 Answers to Research Questions

1. Methodological Integration Knowledge Graphs (KGs) and Prompt Engineering (PE) were systematically combined by:

- Structured mapping/searching of skills, interrelationships between skills and user learning history using KGs.
- Dynamically adding KG-derived context (skill gaps, prerequisites, career targets) to the prompts of the LLM, producing custom learning flows and recommendations changing with each user and their current profile and aims.
- Integration provided context-awareness, dynamic response, and coverage of domain-relevant content, which was confirmed through increased accuracy, diversity and coverage of the knowledge.

Conclusion: This systematic integration resulted in dynamic, high-relevance, adaptive learning pathways- exactly achieving the Methodological Integration goal result and producing 12-15% performance lift in comparison with any one of the methods.

2. Explainability and Trust KGs improved explainability by:

- Putting down identifiable, encompassing ties between suggested capacities and vocations.
- Enabling clear display of *why* certain skills were suggested (e.g. prerequisite as part of KG, market-relevance as coded in real job data).
- Improving PE in such a way that LLM responses could be informed by both user context and KG links to help make educational suggestions with greater clarity and reliability.

Conclusion: KGs were successfully integrated with PE leading to users rating the recommendations as clear, relevant, and trustworthy consistently (confirmation in interviews, 92% relevance and 87% clarity) with high perceived reliability and transparency revealed by the SUS score (86.2).

6.6 Objectives Achieved and Rationale

1. **Systematic KG + PE Integration**: Archived (proven by dynamic context-based suggestions, increased precision/ diversity).
2. **Improved Explainability and Trust**: Attained (supported by user ratings, clear skill mapping and high SUS).
3. **Enhanced Personalized Learning**: Accomplished (illustrated through case studies, knowledge acquisition and feedback in the sessions).
4. **Technical Superiority**: Achieved (performance metrics, engagement).
5. **User Satisfaction**: Achieved (high SUS, positive qualitative feedback).

These conclusions are well facilitated by the robustness of both the quantitative as well as qualitative evidence.

6.7 Discussion

The hybrid integration of Large Language Model [LLM] and Knowledge Graphs within SkillBot has been proven to increase the level of personalized skill acquisitions, the relevance of intelligent recommendation and perceived reliability. Constraints (data dependency, language/culture, resource requirements) are still avenues that need improvement in the future.

7 Conclusion and Future Work

The study empowers and animates a new AI architecture SkillBot a clever midpoint between important gaps in learning tech by uniting a Large Language Model and a custom knowledge graph (Pan et al. 2023). Some of its key triumphs include a new hybrid architecture, which combines the chattiness power of an LLM with the linear reasoning of a knowledge graph, achieving 87% precision in skill recommendations and beating simple systems (Kasneci et al. 2023). A detailed approach to integrating disparate data sets pulling educational and employment market information into a 2.3 million triple graph by following a modified CRISP-DM approach has been another major contribution in ensuring that learning advice really reflects the reality of the job market (Wirth & Hipp 2000).

7.1 Research Summary and Contributions

Besides that, we designed an intelligent recommendation process that combines collaborative early, content-based reasoning, and graphical information, which has a dynamic effect over time according to user advances in explaining their options properly. (Nakić et al. 2015). We created an architecture that is ready to use (we used such tools as React.js and Node.js) and demonstrated that it was effective in practice with real-time chats less than a second. (Facebook Inc. 2013). In conclusion, our comprehensive roundup touched on the tech specs as well as the teaching influence and the testing involved 50 fibers to prove it out in an exceptional SUS score of 86.2/100. (Brooke 1996).

7.2 Limitations and Challenges

Having said that, SkillBot does not lack in challenges, which identify the direction in which improvements need to be made. It depends on the best, current data and the hybrid design requires heavy computing power, which may not fit in all set ups (Ji et al. 2023). At the moment, it is focused on English and Westernized styles of education, and it can develop culturally and linguistically. Although it is constructed on scale, there is still a necessity to test this with crowds of people, and we always have to keep honing the data privacy. Also, scaling up the test populations with large study sequences-not merely two weeks-would reveal more about the long-term effects of learning. (Baker 2019).

7.3 Future Research Directions

In the future, we will extend SkillBot into multimodal learning systems involving voice and VR/AR more immersive content, leverage the power of deep reinforcement learning to create even more intelligent personalization and access affective computing to detect and stimulate learner motivation (Drachsler & Kirschner 2020). To get it more inclusive we'll localise for different languages, cultures, connect with job platforms in real-time API, or we'll add group learning and mentor matching. As a long-term view, we're going to measure career outcomes through extensive studies and embrace explainable AI to give users a view into how favored works better. (Abu-Salih et al. 2021).

7.4 Practical Applications and Impact

SkillBot has the potential to go big both in education and other ventures. It may be used by schools to navigate their students more efficiently and align any course with the needs of the job market and utilized by companies to train the staff and promote professional development. (UNESCO 2020). The internet and employment agencies may give more prone and data-driven counsel, and administrators may utilize their data in addressing ability gaps in locations. It has a friendly chat style which suits any kind of user, even those with accessibility issues and its expanding beyond existing constraints can enable it to equalize the playing field at scale in the learning opportunities in other regions of the world with limited resources (Schwab 2016).

7.5 Concluding Remarks

On the whole, this paper demonstrates how training knowledge graphs in SkillBot with LLMs prepares AI in education to take a significant step forward. (Pan et al. 2023). With the powerful performance of 87% recommendation accuracy and an 86.2 SUS rating, it shows the strength of using a mixture of natural conversations with good structure to draw a line between education and employment (Kasneci et al. 2023). It presents a good example of what comes next related to the field of AI education with its fresh ideas and functioning system. Ultimately, though, SkillBot serves as a necessary reminder to us that technology can enhance human learning and can provide individualized, adaptive assistance to individuals, pushing them towards their potential and laying the foundation of the future, where learners are Key to that future.

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