AIREG: Enhanced Educational Recommender System with Large Language Models and Knowledge Graphs

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Abstract. In the nowadays modern digital era, the overwhelming amount of available online data has established challenges for individuals seeking personalized educational and career pathways with relevant skill dependencies, especially when surfing e-learning and online recruitment platforms. This challenge emphasizes the need for novel advancements in knowledge-enhanced Recommender Systems, offering more personalized, accurate, and timely recommendations. Recently, the rapid development of Large Language Models (LLMs) with their broad knowledge and complex reasoning skills, has significantly enhanced the ability of these systems to offer precise and knowledge-based suggestions. It highlights their potential to enrich these systems using their vast amount of knowledge and sophisticated reasoning capabilities, to leverage them as an alternative to structured knowledge bases like knowledge graphs (KGs). However, LLMs have still limitations for knowledge-based content generation, especially when it's a domain-specific case. To address this issue, researchers propose to enhance the system with explicit factual knowledge from KGs. This research aims to explore advanced technological developments in knowledge-enhanced conversational Recommender Systems to propose a novel system, named **AIREG** for the educational and career development sectors.

Keywords: Recommender System · Large Language Model · Knowledge Graph · Knowledge Extraction

1 Introduction

In the evolving educational technology landscape, with the rapid expansion of digital education and career development, Recommender Systems plays a vital role in providing relevant and personalized learning materials and career pathways [1]. For instance, consider a scenario where a learner is exploring topics in software development for upskilling or reskilling to find a suitable learning or career path. Traditional Recommender Systems mostly recommend resources based on their popularity or keyword matching and rely on conventional machine-learning techniques [2]. These systems often provide general recommendations that may not be aligned with the unique interests or demands of a job seeker since they fail to take into account the semantics of user interactions and academic backgrounds.

The rapid evolution of the job market and the increasing demand for digital skills pose significant challenges in career development, necessitating effective reskilling and upskilling strategies [3]. However, current Recommender Systems fall short of dynamically integrating structured data such as interactions data, about evolving education opportunities, career paths, and individual user profiles. This limitation prevents personalized, proactive career guidance and educational recommendations, emphasizing the need for an advanced approach that combines the capabilities of Large Language Models (LLMs) and knowledge Graphs (KGs), with user's profile and their interaction data to enhance Recommender Systems' effectiveness in navigating the complexities of career advancement and continuous learning. This gap emphasizes the importance of developing innovative approaches that leverage the latest advancements in artificial intelligence (AI).

The emergence of LLMs and KGs, and their integration into Recommender Systems, can significantly improve the accuracy and relevance of educational recommendations. LLMs, with their deep understanding of context and user-generated content [4], along with KGs that provide a semantic web of interconnected data, can significantly enhance the personalization and accuracy of recommendations delivered to users. However, many current approaches consider KGs as static entities, unable to update their knowledge base dynamically [5].

The combination of LLMs and KGs unlocks these limitations. In addition to providing a deep understanding of natural language, user intentions, and preferences, LLMs can provide structured data from unstructured one. On the other hand, KGs will validate and check the feasibility of the extracted information through their reasoning ability. This integration enables Recommender Systems to not only understand the latent and nuanced educational needs of learners but also to align their needs with the most appropriate educational material and resources based on the learner's learning journey and style [6]. Meanwhile, integrating other AI approaches such as Generative adversarial networks (GANs) models enables the system to predict future market trends, which is essential for reskilling and upskilling in the competitive labor market of today [7]. Furthermore, by applying other aspects of the data beyond the structural information in KGs, such as semantics, temporal, and multilingual features through KG Embeddings (KGEs), the Recommender Systems will be able to provide highly personalized recommendations, highlighting the need for enhanced KGEs [6].

However, integrating these technologies to develop an effective Recommender System poses significant challenges, including the dynamic updating of KGs with real-time data, optimizing user interaction data for more relevant recommendations, and ensuring the system's adaptability to diverse user needs and market conditions. This research aims to explore these challenges and propose a novel Recommender System framework that makes the way easy for people to choose their educational and career paths, improving accessibility, individualization, and alignment with the changing labor market for career growth and lifelong learning. Section introduces the proposed Recommender System, **AIREG**, which combines the AI capabilities of LLMs with KGs.

The rest of the paper is organized as follows: Section 2 introduces the background and related works to provide insights into the integration of Recommender Systems with LLMs and KGs, and explores the enhanced educational Recommender Systems (AIREG), designed especially in education. Section 3 defines the problem and outlines the contributions of this research. Section 4 delves into the methodology, detailing the innovative approaches and technologies employed. Section 5 presents our experimental evaluation plan and metrics to assess the effectiveness of the proposed system. Finally, section 6 summarizes the proposed approach, and provides insights into our plan for this Ph.D. thesis.

2 State of the Art

The evolution and impact of Recommender Systems in the field of education reveal a significant shift from traditional methods to AI-driven approaches, highlighting significant advancement in personalizing learning experiences and enhancing educational outcomes, especially with the advent of the Covid-19 Pandemic and accelerating adoption of online education [8]. Many literature and studies emphasize the role of Recommender Systems in adapting to the diverse needs of learners. These systems track learners' past activities, and preferences, and provide personalized recommendations to enhance learning outcomes [9].

A significant advancement in this field started with the release of models such as OpenAI's GPT (Generative Pre-trained Transformer) and Google's BERT (Bidirectional Encoder Representations from Transformers) in the late 2010s. These models, which are trained on big volumes of data and complex neural network architectures, showed previously unprecedented capabilities in understanding and producing writing that is human-like [10]. Recently many studies have explored the potential of leveraging LLMs as structured knowledge bases such as KGs. Nevertheless, while LLMs are performing very well in understanding and processing natural language and mimicking human behavior, they still have issues in recalling some facts while generating knowledge-based contents [11]. To bridge this gap, the integration of LLMs with KGs emerged as a promising approach. Recent studies such as the one conducted by [12] present an overview of integrating LLMs and KGs, which can be considered as a groundwork for the new generation of AI-driven educational tools to provide more accurate, dynamic, and personalized recommendations. They propose a road map in which they discuss how to utilize the combination capabilities of LLMs and KGs for improved inference, knowledge representation, and reasoning.
Accordingly, leveraging the integration power of advanced computational models such as LLMs and KGs has gained significant attention in recent research. These systems aim to use the extensive knowledge encoded in LLMs and explicit relations in KGs to enhance Recommender Systems' performance [13]. The objective of this integration is to leverage KGs' structured, semantic information along with LLMs' contextual understanding and generating capabilities to pro-

vide more personalized recommendations. Many studies have been done so far to investigate whether and how the integration of Recommender Systems with LLMs and KGs technologies could enhance recommendations, especially regarding learning experiences in education.

A recent study by [11], proposed the idea of integrating explicit factual knowledge from KGs into pre-trained LLMs (PLMs), which led to the creation of KG-enhanced large language models (KGLLMs). The study also investigates the integration of LLMs into Automatic Speech Recognition (ASR) systems to improve transcription accuracy. Another study conducted by [14], proposes the CHAT-REC framework, an LLM-Augmented Recommender System, which converts user profiles and historical interactions into prompts to enable in-context learning and improve the performance of the system. CHAT-REC also manages cold-start scenarios with new items through prompt-based injection of information into LLMs. In a study by [15], the authors demonstrated that using LLMs, such as ChatGPT, they can generate text from KG data, which shows the ability of LLMs to convert structured knowledge into human-readable text. Also, an experiment conducted by [16], investigates how LLMs, such as ChatGPT, can facilitate KGEs by contributing to the development and management of KGs.

For e-learning platforms, content-based recommendation systems—which employ a multi-agent method to suggest courses—are prioritized. [17] proposes the development of a system that improves e-learning experiences by helping students discover courses that match their interests and academic needs more effectively. The development of explainable Recommender Systems that use KGs to provide transparency in the recommendation process is also gaining attraction in this research area.

A further step forward is the development of KGs and Recommender Systems for suggesting reskilling and upskilling options. An experiment by [7] explores the development of KGs and Recommender Systems to assist individuals in identifying online possibilities for reskilling and upskilling. The RS can offer personalized learning pathways based on users' skill gaps and career goals. A study conducted by [18], proposes a multi-objective fused personalized recommendations for educational resources to improve recommendations' diversity and accuracy. The system employs a recommendation layer including SOM-CNN and ITEM-SOM models to provide a recommendation list based on learner users' presentation features and education resources' representation features. To improve the user experience by providing more relevant and varied educational content, this approach represents a significant advancement in recommending personalized educational resources.

The development of explainable Recommender Systems that use KGs to provide transparency in the recommendation process is also gaining attraction in this research area. Such systems help users understand the reason behind recommendations, which increases their trust and engagement with the system. A study by [19], explores the development of Recommender Systems that utilize KGs to enhance the explainability of their recommendations. They also discuss how KGs can be effectively used to improve the trustworthiness and acceptance of Recommender Systems by users through better explainability. According to this article, by integrating KGs, the system can provide users with clear and logical reasons for its suggestions, which makes the recommendation process more transparent and understandable.

3 Problem Statement and Contributions

This thesis aims to explore and address the challenges of effectively integrating diverse advanced technologies, such as LLMs, KGs, and Generative adversarial networks (GANs), to enhance a recommender system for job and educational opportunities and material such as courses. In this study, we investigate the synergy between various technologies to develop a comprehensive system that can provide personalized, accurate, and timely recommendations for reskilling and upskilling. By leveraging the capability of KGs for structured knowledge representation, LLMs for their natural language processing and deep understanding and content generation abilities, and GANs for simulating and predicting job market trends, with this approach we aim to revolutionize the way people navigate their careers and learning paths.

3.1 Research Questions

To explore and investigate the defined problem and its challenges, this research will focus on addressing the following research questions:

RQ1: Does the integration of external knowledge bases such as KGs enhance the performance of LLM-based Recommender Systems in providing personalized recommendations for employees and learners, while ensuring a high level of penalization and accuracy?

RQ2: What methodologies could be deployed to dynamically update KGs and LLMs with real-time job market data and user interactions?

RQ3: How could we optimize the user input and interaction data to refine and enhance the quality and relevance of recommendations provided by the proposed framework?

3.2 Main Contributions

The main contribution of this research is its novel integration of cutting-edge technologies, such as KGs, LLMs, and GANs within the semantic web framework to implement a highly adaptive recommender system for career and educational pathways. Furthermore, using the ESCO database—as a European classification of skills, competencies, and Qualifications[1]— as an input to the KG construction, we employ a standardization framework for learning outcomes documentation and ensure the interoperability and possibility to explore possibilities across

[1] https://esco.ec.europa.eu/en

Europe. The proposed Recommender System (AIREG) might be considered a groundbreaking approach that provides personalized job and educational opportunity recommendations, based on the European standards, embedded into the ESCO database. We hypothesize that this integration not only enhances the system's ability to provide personalized and accurate recommendations but also introduces a dynamic framework for continuously updating the system with real-time job market and educational data.

4 Methodology

In this section, we delve into the details of the proposed AIREG system and its components. As shown in Fig. 1, AIREG has the following five main components:

1. **User profile enhancement:** To complete and improve the quality of the user's resumes, we utilize a prompting approach leveraging the LLM's knowledge and ability in natural language processing based on the [3] benchmark. The component itself includes two other sub-components:
   - **Interactive resume completion** We leverage LLMs with a designed prompt associated with the recommendation field. The LLM gets triggered by a command in the prompt and it aims to fill gaps and suggest additions or improvements in the user's resume that are compatible with current industry standards, in two phases: 1) Simple resume completion, 2) Interactive resume completion.
     The model makes use of a self-description text that's associated with a user or job position. With adopting an embedding model, we concatenate the original text positional ordering with the actual text, to create a semantic embedding of the description text as the user's embedding. In the simple resume completion phase, the user's embedding will be passed through the LLM using the prompt for the first round of resume improvement.
     However, to alleviate the fabricated and hallucinated generation of LLMs, the model utilizes users' interactive behaviors with Recommender Systems to provide more information for the LLM for better user profiling and improving the model's accuracy in resume completion. In the second phase, the model concatenates users and jobs of their interest embeddings with their interactive behavior embedding along with their enhanced resume from the single resume completion phase to improve the user's resume.
   - **Resume quality alignment (GANs-based model)** To enhance the quality of resumes and provide a more comprehensive user profile, we'll make use of a GAN model based on the [3] benchmark to mimic creating realistic job descriptions, educational content, and user profiles for training the recommender system. Through this capability, the system will be able to forecast future market requirements and provide recommendations that are not only relevant at the time but also aligned with future developments, enhancing the system's predictive accuracy and relevance.

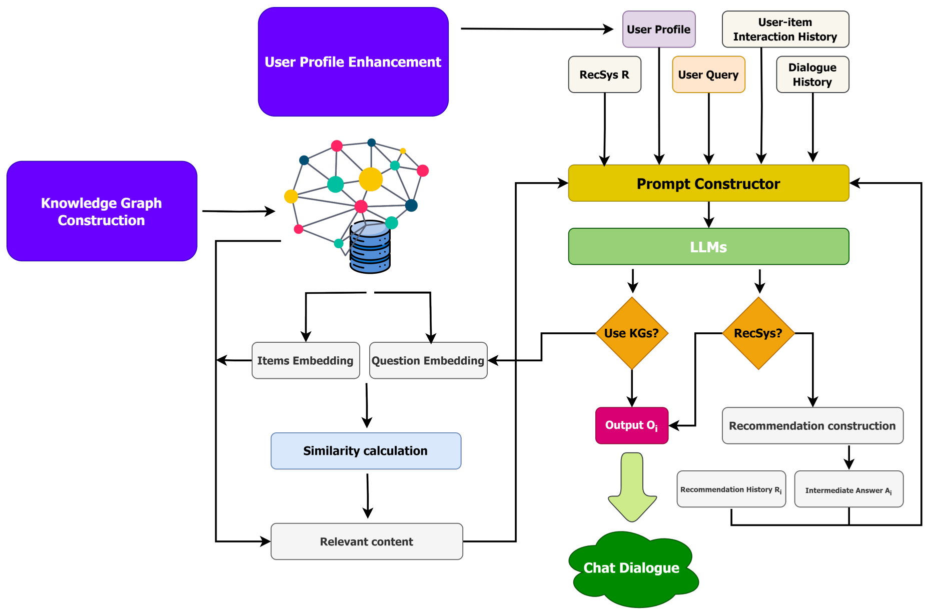

Fig. 1: The architectural design of the AIREG system

2. **Knowledge graph construction:** The KG construction involves gathering data from various education providers' websites to create a comprehensive graph based on the [7] as our benchmark as our KG construction method. This model uses different techniques such as entity recognition, entity linking, and slot filling to systematically organize and integrate data about educational programs, prerequisites, skills, and learning objectives into a KG. This graph then facilitates semantic searches and complex queries, enhancing the system's ability to provide focused recommendations for continuing education.
3. **Integrating the recommender system with LLM:** Our proposed framework leverages the recommendation method called LLM-based GANs Interactive Recommendation (LGIR), introduced by [14] as our benchmark, which combines LLMs and GANs. This method transforms user profiles and historical interactions into prompts for LLMs, facilitating a conversational interface that can dynamically adapt to user preferences. The system efficiently learns user preferences using in-context learning and provides individualized recommendations across different domains. Hence, improving the system's ability to manage cold-start scenarios. This integration represents a significant advancement in Recommender Systems technology providing a more engaging and user-centric experience.
   As shown in Fig. 1, the model takes as input user-item history interactions, user profile, user query, and history of dialogue before the current query and incorporates all in a designed prompt through the prompt constructor

module which triggers the LLM. The LLM then interfaces with any recommender system R. As the user profile, we use the enhanced user profile provided by the user profile enhancement process. The proposed framework introduces how to use the external information about education providers along with ESCO information to enrich the model with more information about educational requirements, hence, mitigating cold-start scenarios.

5 Evaluation Plan

To implement the proposed integrated approach effectively, many datasets, and evaluation metrics based on the baselines would be essential. In this section, we describe the plan for evaluating the performance and effectiveness of the AIREG system based on different datasets and evaluation metrics.

5.1 Datasets

- For this thesis, we will leverage multiple datasets to construct the KG, enhance user profiles, and evaluate the recommender system's performance. These datasets are essential to ensure that the AIREG system can provide accurate, personalized, and timely recommendations for users aiming for reskilling and upskilling opportunities.
- **Knowledge Graph Construction:** the primary datasets to create a KG include information from education providers' web pages, an occupational knowledge dataset such as ESCO and x28 occupation database , and online course platforms such as Udemy, and Coursera.
- **User Profile Enhancement:** enhancing the user's profile relies on datasets containing information from historical user interaction data with Recommender Systems (like real online interaction logs for job recommendation), and user-provided information such as resumes, educational backgrounds, and job experiences).
- **Career Path Recommendation:** To evaluate the career path recommendations, we can use the publicly available CareerCoach 2022 gold standard dataset.

5.2 Proposed Evaluation

To evaluate the performance of the proposed system, we will consider a multifacet evaluation plan:

Qualitative Evaluation: To evaluate the performance of the component in enhancing user engagement, we employ the Usability evaluation approach [20], which investigates metrics such as Learnability, Efficiency, Memorability, Errors, and Satisfaction.

Quantitative Evaluation:

1. Top-K recommendations metrics, using widely used metrics such as Precision, Recall, F1-score, Normalized Discounted Cumulative Gain (NDCG), mean average ranking precision (MAP), and mean reciprocal rank (MRR) to evaluate the Top-K recommendations of the system.
2. Ranking prediction metrics, such as Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to evaluate the ranking of provided recommendations.
3. Investigating the performance of the system with different LLMs and recommendation methods
4. Knowledge Graph Construction, assessment using popular metrics such as Precision, Recall, and F1-score.

6 Conclusion

This symposium paper explores the challenges of integrating state-of-the-art technologies such as Large Language Models (LLMs) and Knowledge Graphs (KGs) to develop a new kind of Recommender Systems within the realms of education and career. The objective is to tackle the limitations of existing Recommender Systems by leveraging the unique capabilities of these technologies to provide more personalized, accurate, and timely educational and career pathways. The proposed Recommender System, AIREG, which combines the AI capabilities of LLMs with KGs and associated components was discussed in (Section 4). Given that we are at an early stage of the entire thesis research and the conceptualised AIREG system, the datasets and evaluation criteria might change, we are looking forward to discussing this research with our mentor and the possibility of establishing long-term collaboration with our institute in the field of Semantic Web and KG.

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