Towards solving the Cold Start and Explainability Challenges in Recommender Systems Using Knowledge Graphs and User Demographics Data

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***Abstract*—Recommender Systems (RS) play a crucial role in helping users navigate vast amounts of digital information. However, these systems face persistent challenges, particularly the cold start problem and the lack of explainability in recommendations. This paper introduces X-KAREN-D, an *eXplainable Knowledge-based ATtention ensemble REcurrent Network with Demographics*, designed to address these issues. X-KAREN-D incorporates user demographic information to mitigate the cold start problem, improving personalization and recommendation accuracy. Additionally, it enhances explainability by leveraging a knowledge graph (KG) structure to provide path-based explanations, allowing users to understand the rationale behind recommendations. Through extensive experiments, we evaluate various Knowledge Graph Embedding (KGE) techniques to assess their impact on recommendation accuracy. Our results demonstrate that the proposed model outperforms the state-of-the-art baseline, achieving an MAE of 0.030 and an RMSE of 0.041. These findings highlight the significance of incorporating structured knowledge and user demographic data to improve both the performance and interpretability of recommender systems.**

***Index Terms*—Recommender systems, Knowledge Graphs, Demographic data, Explainability**

I. Introduction

As digital data on the Internet grows exponentially, users face increasing confusion when choosing items and services, making the decision-making process more challenging. To address this, commercial websites and service providers implement recommendation systems to enhance user experience and streamline decision-making [1]. As Internet usage continues to shape various aspects of life, users increasingly depend on Recommendation Systems (RS) to efficiently access relevant information, particularly in areas like online booking, social networking, and e-commerce. Recommender systems (RS) have become widespread and highly influential in recent years [2] due to their ability to predict user interests and preferences. Their applications extend across several domains, including tourism, e-government, e-learning, e-commerce, and social media [3]. Although, RS provide effective solutions for mitigating information overload, they still face several significant challenges, including the cold start problem and explainability issue [17], [18]. The cold start problem refers to the challenge of generating accurate recommendations in scenarios where limited or no historical data is available, particularly for new users who lack historical interactions or new items that have not yet received ratings. This limitation hinders the ability to deliver personalized suggestions [17]. On another side, the explainability challenge refers to the difficulty of making recommendation processes transparent and interpretable for users. In fact, RS operate as "black-box" models, making it challenging for users to understand the rationale behind recommendations. This lack of transparency can reduce trust and user engagement. Enhancing explainability by providing clear and interpretable justifications for recommendations fosters user confidence and improves overall system usability [18].

In our previous work [8], we introduced a personalized recommendation model for e-learning, designed to provide tailored suggestions that align with individual learner preferences. Our approach leverages: (1) an educational Knowledge Graph (KG) to encode background domain knowledge and capture complex semantic relationships between entities describing items (i.e., educational ressources), and (2) an ensemble learning framework that integrates a Bidirectional Long Short-Term Memory (Bi-LSTM) network and an Artificial Neural Network (ANN) through an attention mechanism to enhance recommendation accuracy. The integration of the Knowledge Graph enables the model to exploit contextual dependencies between items and their associated concepts. Despite these advancements, persistent challenges remain in the e-learning domain, particularly concerning the cold start problem and the imperative for generating explainable recommendations [25], [26].

In this paper, we extend our approach by incorporating demographic data to mitigate the cold start issue by categorizing users more effectively, thereby enhancing personalization and improving recommendation accuracy. Furthermore, we conduct a comparative analysis of widely used KG Embedding techniques to assess their impact on recommendation accuracy. Finally, we explore path-based explanations to improve recommendation transparency and interpretability.

The main contribution of this paper can be summarized as following:

- Proposing an enhanced recommendation framework that effectively addresses the cold start problem by integrating user demographic information. Experimental results demonstrate notable improvements in recommendation quality, personalization, and accuracy compared to our previous approach.
- Conducting a comprehensive evaluation of various Knowledge Graph embedding techniques to assess their impact on recommendation accuracy.
- Proposing a path-based explanation that leverages the Knowledge Graph (KG) structure to enhance transparency and interpretability in recommendations.

The remainder of the paper is structured as follows: Section II reviews related research works on RS, highlighting how the cold-start and explainability challenges are addressed in literature. Section III present in further details the proposed X-KAREN-D model. Section IV presents the experimental study. Section V provides a discussion on the role of demographic data, the use of synthetic attributes, and outlines future directions for evaluating explanation effectiveness. Finally, Section VI concludes the paper.

II. Related works

Recommender systems are broadly classified into four main classes [21]: content-based, collaborative, demographic, and hybrid filtering. Content-based filtering generates recommendations by comparing item descriptions with a user's profile, suggesting items similar to those the user has previously liked [23]. Collaborative filtering, one of the most widely used techniques, identifies users with similar preferences based on shared interests or rating patterns, assuming that like-minded users will have similar tastes [22]. Demographic filtering personalizes recommendations based on user demographic profiles, under the assumption that individuals within the same demographic group tend to have common interests [24]. Hybrid recommender systems combine multiple filtering approaches to improve recommendation accuracy and effectiveness, employing various hybridization techniques [21] such as weighted, switching, mixed, feature combination, cascade, feature augmentation, and meta-level hybridization.

A. Cold-start problem in RS

The Cold Start problem is a significant challenge for recommender systems, which typically perform well with abundant user and item data but struggle when faced with limited information [17]. Researchers have extensively studied this challenge, aiming to address the gaps caused by missing data and incomplete item listings. In [14], the authors propose a framework to address the cold-start issue by using demographic data such as age, gender, and occupation for generating recommendations. This approach aims to mitigate the initial lack of item ratings for new users by leveraging available demographic information to provide personalized suggestions. Instead of relying on rating history, which is unavailable for new users, the system assumes that users with similar demographic profiles will have similar preferences. In [15], the proposed model enhances recommendation accuracy for new users by generating personalized feature-based user profiles from past interactions. It consists of three key steps: (1) Creating User Feature Profiles by analyzing past ratings to generate genre-based scores, (2) Calculating Similarities using Pearson Similarity to identify similar users, and (3) Generating Recommendations based on highly rated items from similar users. This approach leverages feature-level preferences, improving accuracy in cold-start scenarios. In the same context, the POSO [16] (Personalized Cold Start Modules) model tackles the cold start problem, where new user features get overwhelmed due to data imbalance. POSO introduces user-group-specific sub-modules and personalized gating networks to enhance personalization in existing models like MLP, MHA, and MMoE with minimal overhead.

In conclusion, the cold-start problem remains a major challenge in recommender systems, prompting various solutions to address the lack of initial user data. Leveraging demographic information to infer preferences and feature-based user profiling using past interactions has shown promise in mitigating this issue [26].

B. Explainability in RS

Explainable RS (XRS) addresses the problem of why such items are recommended [4]. Explanations in recommendation systems (RS) can be categorized into two models based on their interpretability [5]. The model-intrinsic approach integrates explainability directly within the model architecture, ensuring that the reasoning behind predictions is inherently transparent. This allows users to understand the decision-making process without additional computations. In contrast, the model-agnostic approach treats the model as a black box and generates explanations externally after predictions are made. This flexibility allows it to be applied to any model, but it requires extra processing to analyze input-output relationships and derive meaningful insights. Post-hoc explanations are a type of model-agnostic approach that generate interpretability after a model has made its predictions. Since the model itself remains a black box, post-hoc methods analyze the relationship between inputs and outputs to provide insights into the decision-making process [6]. A notable example of a post-hoc explanation is LIME [7], which builds a surrogate model to approximate and explain the predictor's behavior after the prediction has been computed.

A promising direction for increasing the transparency of black-box models involves leveraging semantic information to enhance explanation quality. The use of structured knowledge, such as knowledge bases or KG, enables a more organized and flexible form of transparency, allowing for deeper insights into the model's reasoning processes. Integrating semantic information is, therefore, a key enabler for improving both the interpretability and overall effectiveness of machine learning models in real-world applications [13]. The Knowledge-aware Path Recurrent Network (KPRN) [19] enhances recommendations by reasoning over knowledge graph (KG) paths. It extracts user-item paths, encodes entity and relation semantics using an LSTM, and applies weighted pooling to prioritize informative paths. This improves recommendation accuracy and explainability. In the same context, Path-enhanced Recurrent Network (PeRN) [20] improves recommendation accuracy and explainability by leveraging Bi-LSTM for path encoding and an entropy encoder to weigh path contributions using metapaths. A weighted pooling layer integrates path scores for final predictions. PeRN also introduces a bidirectional path extraction algorithm for efficiency.

In this paper, we enhance our previously proposed KA-ERN model [8] by introducing X-KAREN-D (eXplainable Knowledge-based ATtention ensemble REcurrent Network with Demographics), which addresses the cold start problem using user demographic information. X-KAREN-D also improves transparency and interpretability by leveraging a kG structure, enabling users to understand the reasoning behind recommendations. Furthermore, we evaluate our model with different knowledge graph embedding techniques to assess their impact on recommendation accuracy.

III. Our Proposed Approach

To conquer the cold start problem and enhance recommendation explainability, we propose the X-KAREN-D model. This model integrates user demographic data to improve recommendations for new users while leveraging the Knowledge Graph (KG) structure to provide transparent and fair suggestions, along with clear justifications.

In Section III-A, we present the problem formulation, and in Section III-B, we describe in further detail the proposed approach.

A. Problem Formulation

In recommender systems, we model historical user-item interactions, such as purchases, clicks, and ratings, as a user-item bipartite graph G, where nodes consist of users $\mathcal{U}$ and items $\mathcal{I}$. Each interaction is represented as a triplet (u, y_{ui}, i), where y_{ui} denotes the nature of interaction from a predefined set. In our approach, our primary goal is to integrate user and item information to achieve effective and explainable recommendations. Therefore, our approach relies on an enriched User-Item Knowledge Graph, formally defined as:

$$\mathcal{G}_D = \{(h, r, t) \mid h, t \in \mathcal{E}, r \in \mathcal{R}\}$$

where:

- $\mathcal{E} = \mathcal{E}n \cup \mathcal{U} \cup \mathcal{I} \cup \mathcal{D}$ includes entities, users, items, and demographic attributes $\mathcal{D}$.
- $\mathcal{R} = \mathcal{R} \cup \{y_{ui}\} \cup \{r_d\}$ extends relations to include user-demographic associations r_d.

By integrating demographic information into the knowledge graph, we aim to explore the impact of demographic data on recommendation accuracy.

B. Proposed Approach

The proposed approach is composed of five main steps: Data preparation, KG construction, KG embedding, and recommendation generation, as described in Fig. 1.

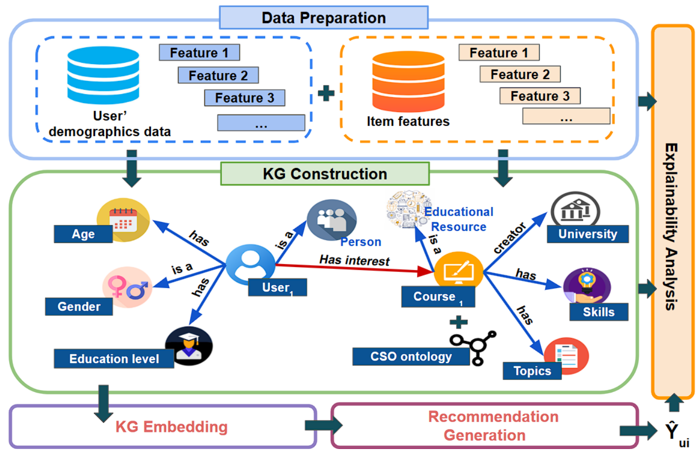

Fig. 1. Workflow of the proposed approach

1) Data preparation: The dataset used in our experiments was scraped from publicly available information on the Coursera website[1]. It is provided in CSV format, containing 3,533 rows with various attributes, including Course Name, University, Course Rating, Course URL, Course Description, and Skills. For our experiments, we assigned unique course IDs to each entry and generated user demographic data; table I shows the different attributes and their values. . Additionally, we synthesized ratings to create user-item interactions.

TABLE I
List of demographic attributes and their values

Attribute	Values
Age	[20-50]
Gender	Masculin, Feminine
Education Level	PhD, Bachelor's, Master's, High School
Location	UK, Brazil, Canada, USA, France, Germany, India

2) KG Construction: The constructed KG is an RDF-based graph developed as part of this research to enhance personalized learning recommendations and interpretability. It integrates **user-item interactions** and **structured knowledge** extracted from the textual content of Coursera courses, including *titles, descriptions, and related skills* and **user demographic data**. The construction of the KG follows a structured pipeline consisting of three main steps:

- **Course Concept (CC) Extraction**: This step identifies significant **keyphrases (KPs)** from course descriptions using a **KeyPhrase extraction model** based on KBIR [27]. The model, fine-tuned on the *Inspec benchmark dataset*, leverages the RoBERTa architecture to achieve state-of-the-art performance in extracting meaningful

[1]https://www.coursera.org/

course concepts. These extracted keyphrases form the foundation for structuring the knowledge graph.

- **Concept Disambiguation and Linking**: To ensure consistency and semantic clarity, extracted keyphrases are **disambiguated and linked** to external **Linked Open Data (LOD) sources**, such as **DBpedia** and the **Computer Science Ontology (CSO)**. Various *matching techniques* (e.g., exact and fuzzy matching) map these keyphrases to standardized scientific concepts, enriching EduKA with hierarchical and semantic relationships that enhance its expressiveness and knowledge representation.
- **KG Modeling and Generation**: The **RDFLib Python library** is used to construct the RDF graph, structuring course metadata (e.g., title, difficulty level) according to **Schema.org** and **Dublin Core** standards. Each course is further **semantically enriched** by linking it to relevant CSO topics using the *eduka:hasKnowledgeTopic* property. Additionally, **user-item interactions** are integrated into the graph, categorized into three levels—*eduka:smallInterest*, *eduka:mediumInterest*, and *eduka:highInterest*—to capture varying user engagement levels with courses. The constructed graph also contains the user demographic data using the properties ;*schema:person*, *schema:gender*, *schema:educationalLevel* and *schema:location*.

3) KG Embedding: To generate meaningful representations of entities and relations within the knowledge graph (KG), we begin by extracting triplets from the constructed KG. These triplets, typically represented as (head, relation, tail), serve as the foundational input for learning embeddings. The goal of knowledge graph embedding (KGE) is to map these symbolic representations into continuous vector spaces while preserving the semantic and structural characteristics of the graph.

To enhance the quality and applicability of the embeddings, we explore several well-established KGE techniques from the literature. These include:

- DeepWalk [9]: Performs random walks on the graph to generate sequences of nodes, which are then treated similarly to sentences in natural language processing. A skip-gram model is used to learn node embeddings based on their co-occurrence within these sequences.
- node2vec [10]: Introduces a more flexible and biased random walk strategy that balances between breadth-first and depth-first graph traversal. This allows the method to capture more nuanced local and global structural features.
- rdf2vec [11]: Designed for RDF-based knowledge graphs, rdf2vec extends the idea of sequence-based embedding by performing graph walks to transform the RDF graph into sequences suitable for training word embedding models.
- TransR [12]: Models entities and relations in distinct vector spaces, allowing for a more flexible and accurate representation of diverse relationships.

These KGE techniques are explored in our study, with detailed experiments and results presented in Section IV.

4) Recommendation generation: Inspired from our previous research [8], this module processes user-item interactions and user demographic information along with knowledge graph (KG) embeddings to generate recommendations. It consists of multiple key components: the input sequence layer, Bi-LSTM layer, attention mechanism layer, and fully connected layers. We employ a Bi-LSTM architecture to effectively model sequential dependencies in user interactions, capturing both forward and backward contextual information. The addition of an attention mechanism allows the model to prioritize more relevant user interactions, enhancing interpretability and recommendation accuracy. Finally, fully connected layers refine the learned representations and produce the final recommendation scores.

5) Explainability Analysis: One of the main key component of our approach is the educational KG that captures and represents semantic relationships among users, educational resources, and domain-specific concepts. In this section, we explore here how KG sub-structures (paths and sub-graphs) can be used to generate explanations of why a specific educational resource is recommended to a given user.

The explainability is intrinsic, as the recommendations are inherently interpretable due to the structure of the Knowledge Graph.

As illustrated in Fig. 2, the recommendation process is explainable through these semantic relationships. For instance, *Course_3* was recommended to *User_1* because they have a high interest in *Course_1*, which is associated with the knowledge topic *Data Analytics*. This topic is a super-topic of *Big Data*, which is also a knowledge topic of the recommended course. This demonstrates that the user is likely to be interested in *Course_3* since it shares relevant topics with a course they have already shown interest in.

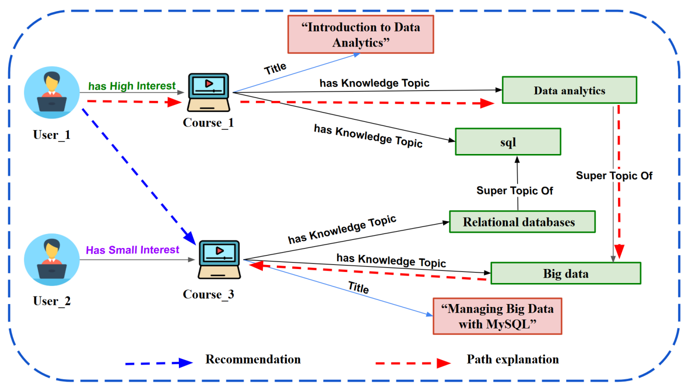

Fig. 2. Path-based explanation of our approach

IV. Experiment and Results

In this section, we present the experimental results evaluating our proposed model. We analyze the impact of different embedding techniques on recommendation accuracy, compare our proposed approach against SOTA approach [8], and conduct an explainability analysis to demonstrate that our model can generate interpretable recommendations.

A. Performance evaluation results

In this section, we present the results of our proposed model. The performance of X-KAREN-D is measured using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) :

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{2}$$

where:

- N is the total number of predictions,
- y_i is the actual value for instance i,
- $\hat{y}_i$ is the predicted value for instance i.

Table II compares the performance of the proposed approach using the Knowledge Graph Embedding (KGE) techniques: DeepWalk [9], node2vec [10], rdf2vec [11], and TransR [12]. Among these methods, TransR demonstrates the best performance, achieving the lowest MAE (0.030) and RMSE (0.041), indicating higher recommendation accuracy. rdf2vec follows with an MAE and RMSE of 0.063, outperforming both node2vec (MAE = 0.078, RMSE = 0.078) and DeepWalk (MAE = 0.087, RMSE = 0.088). The results suggest that TransR is the most effective embedding technique for improving recommendation accuracy.

TABLE II
PERFORMANCE COMPARAISON OF X-KAREN-D USING DIVERSE KGE TECHNIGUES

Embedding techniques	MAE	RMSE
DeepWalk	0.087	0.088
node2vec	0.078	0.078
rdf2vec	0.063	0.063
TransR	**0.030**	**0.041**

To evaluate the performance of our proposed model, we compare it against KA-ERN. Our model incorporates user demographic data, whereas KA-ERN considers only item features in the recommendation process. Fig. 3 demonstrates that X-KAREN-D outperforms KA-ERN, achieving a MAE of 0.030 and an RMSE of 0.041. These findings highlight that integrating user information into the recommendation process enhances accuracy. Additionally, combining both user and item features leads to more personalized recommendations tailored to each user's needs.

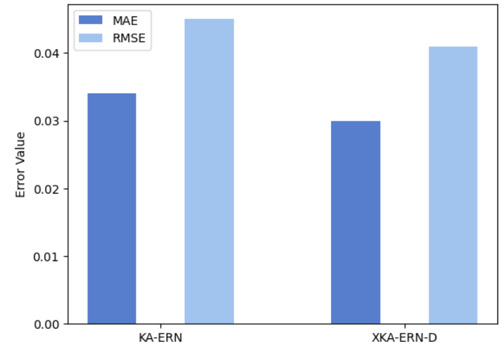

Fig. 3. Performance comparison between KA-ERN and X-KAREN-D

V. Discussion

In this section, we discuss the role of demographic data in addressing the cold start challenge, acknowledge limitations related to data generation, and outline future directions for evaluating the interpretability of our model.

In our approach, demographic features are integrated into the user-item knowledge graph, enriching the representation space and enabling similarity-based reasoning across users with shared attributes. This integration allows the system to make informed recommendations for users with no historical interaction data, thus effectively mitigating the cold start issue through demographic profiling. It is important to acknowledge that the demographic data used in this study was synthetically generated to simulate diverse user profiles. While this allowed for controlled experimentation and proof of concept, it inherently limits the empirical generalizability of the results. As part of future work, we plan to evaluate our model using real-world demographic datasets. Another key feature of X-KAREN-D is its ability to generate path-based explanations derived from the structure of the knowledge graph. These explanations are designed to improve transparency, build user trust, and increase satisfaction by clarifying the rationale behind recommendations. While the interpretability of these paths has been demonstrated through illustrative examples, their effectiveness from the user's perspective has not yet been formally evaluated. To address this, we intend to conduct a user study to assess the perceived usefulness, intuitiveness, and trustworthiness of the provided explanations.

VI. Conclusion

In this paper, we introduced X-KAREN-D, a novel recommendation approach designed to address two major challenges in recommender systems: the cold start problem and explainability. By incorporating user demographic information, our approach enhances personalization and improves recommendation accuracy for new users compared to the baseline method. Furthermore, the integration of a knowledge graph allows for path-based explanations, making recommendations more transparent and interpretable. Experimental results show that our model significantly outperforms baseline approaches in terms of accuracy and explainability, demonstrating the benefits of leveraging both structured knowledge and demographic attributes.

Despite these advancements, several areas for future work remain. First, we plan to explore the inclusion of additional contextual factors, such as user behavior patterns and temporal dynamics, to further refine personalization. Second, while our approach improves explainability, user studies could be conducted to assess the impact of different explanation techniques on user trust and engagement.

References

[1] Çano, E., & Morisio, M. (2017). Hybrid recommender systems: A systematic literature review. Intelligent data analysis, 21(6), 1487-1524.

[2] Singh, P. K., Pramanik, P. K. D., Debnath, N. C., & Choudhury, P. (2019). A Novel Neighborhood Calculation Method by Assessing Users' Varying Preferences in Collaborative Filtering. In CATA (pp. 345-355).

[3] Ge, Y., Liu, S., Fu, Z., Tan, J., Li, Z., Xu, S., ... & Zhang, Y. (2024). A survey on trustworthy recommender systems. ACM Transactions on Recommender Systems, 3(2), 1-68.

[4] Zhang, Y., & Chen, X. (2020). Explainable recommendation: A survey and new perspectives. Foundations and Trends® in Information Retrieval, 14(1), 1-101.

[5] Das, A., & Rad, P. (2020). Opportunities and challenges in eXplainable Artificial Intelligence (XAI): A survey. arXiv preprint arXiv:2006.11371.

[6] Shmaryahu, D., Shani, G., & Shapira, B. (2020). Post-hoc Explanations for Complex Model Recommendations using Simple Methods. In IntRS@ RecSys (pp. 26-36).

[7] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should i trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1135-1144).

[8] Boubaker, N. B. H., Kodia, Z., & Ayadi, N. Y. (2024). Personalized E-Learning Knowledge Graph-based Recommender System using Ensemble Attention Networks. In 16th International Conference on Management of Digital EcoSystems (MEDES 2024).

[9] Perozzi, B., Al-Rfou, R., & Skiena, S. (2014). Deepwalk: Online learning of social representations. In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 701-710).

[10] Grover, A., & Leskovec, J. (2016). node2vec: Scalable feature learning for networks. In Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 855-864).

[11] Ristoski, P., Rosati, J., Di Noia, T., De Leone, R., & Paulheim, H. (2019). RDF2Vec: RDF graph embeddings and their applications. Semantic Web, 10(4), 721-752.

[12] Lin, Y., Liu, Z., Sun, M., Liu, Y., & Zhu, X. (2015). Learning entity and relation embeddings for knowledge graph completion. In Proceedings of the AAAI conference on artificial intelligence (Vol. 29, No. 1).

[13] Dragoni, M., & Donadello, I. (2022). A knowledge-based strategy for XAI: The explanation graph. Semantic Web Journal.

[14] Agarwal, G., Bahuguna, D. H., & Agarwal, D. A. (2017). Solving cold-start problem in recommender system using user demographic attributes. International Journal on Emerging Technologies (Special Issue NCETST-2017), 8(1), 55-61.

[15] Uyangoda, L., Ahangama, S., & Ranasinghe, T. (2018). User profile feature-based approach to address the cold start problem in collaborative filtering for personalized movie recommendation. In 2018 Thirteenth international conference on digital information management (ICDIM) (pp. 24-28). IEEE.

[16] Dai, S., Lin, H., Zhao, Z., Lin, J., Wu, H., Wang, Z., ... & Liu, J. (2021). POSO: personalized cold start modules for large-scale recommender systems. arXiv preprint arXiv:2108.04690.

[17] Mohamed, M. H., Khafagy, M. H., & Ibrahim, M. H. (2019). Recommender systems challenges and solutions survey. In 2019 international conference on innovative trends in computer engineering (ITCE) (pp. 149-155). IEEE.

[18] Zhang, Y., & Chen, X. (2020). Explainable recommendation: A survey and new perspectives. Foundations and Trends® in Information Retrieval, 14(1), 1-101.

[19] Wang, X., Wang, D., Xu, C., He, X., Cao, Y., & Chua, T. S. (2019). Explainable reasoning over knowledge graphs for recommendation. In Proceedings of the AAAI conference on artificial intelligence (Vol. 33, No. 01, pp. 5329-5336).

[20] Huang, Y., Zhao, F., Gui, X., & Jin, H. (2021). Path-enhanced explainable recommendation with knowledge graphs. World Wide Web, 24(5), 1769-1789

[21] Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. Egyptian informatics journal, 16(3), 261-273.

[22] Sohail, S. S., Siddiqui, J., & Ali, R. (2017). Classifications of recommender systems: A review. Journal of Engineering Science & Technology Review, 10(4).

[23] Son, J., & Kim, S. B. (2017). Content-based filtering for recommendation systems using multiattribute networks. Expert Systems with Applications, 89, 404-412.

[24] Liao, M., Sundar, S. S., & B. Walther, J. (2022, April). User trust in recommendation systems: A comparison of content-based, collaborative and demographic filtering. In Proceedings of the 2022 CHI conference on human factors in computing systems (pp. 1-14).

[25] Akanbi, M. B., Okike, B., Owolabi, O., & Hammawa, M. B. (2024). A Comparative Study of Explainable AI Techniques for Bias Mitigation and Trust in E-Learning Recommendation Systems: Comparative Study of Explainable AI Techniques for Bias Mitigation and Trust in E-Learning. Journal of Institutional Research, Big Data Analytics and Innovation, 1(1).

[26] Jeevamol, J., & Renumol, V. G. (2021). An ontology-based hybrid e-learning content recommender system for alleviating the cold-start problem. Education and Information Technologies, 26, 4993-5022.

[27] Kulkarni, M., Mahata, D., Arora, R., & Bhowmik, R. Learning rich representation of keyphrases from text. CoRR abs/2112.08547 (2021). URL: https://arxiv. org/abs/2112.08547.