AI-Based Personalized Multilingual Course Recommender System Using Large Language Models

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Abstract: This paper presents an AI-driven personalized course recommender system designed to enhance user engagement and learning outcomes on educational platforms. Leveraging the EU DigComp competency framework, the system constructs detailed user profiles through a chat assistant that guides users in identifying relevant competency areas and completing tailored surveys. Course recommendations are generated based on a hybrid scoring model that integrates semantic similarity and competency alignment, ensuring that course suggestions are both contextually and skill-relevant. For users seeking structured guidance, the system offers a learning path feature, utilizing a large language model to suggest subsequent courses that align with the user's interests and prior learning experiences. While traditional course recommenders often rely on simple keyword matching, our system dynamically combines user interests and competencies for nuanced recommendations across English and German courses. Screenshots of the system's live demo showcase key functionalities, including chatbot-led profile creation, multilingual support, personalized learning paths. This paper highlights the ongoing development of the recommender system and discusses future plans to further refine and expand its personalized learning capabilities.

1 INTRODUCTION

The rise of online learning platforms has revolutionized access to education, allowing individuals to learn at their own pace from a vast array of courses (Pappano, 2012). However, the abundance of available resources can overwhelm learners, leading to the need for personalized recommender systems to guide users toward relevant courses that match their interests and skill levels. Recommender systems, traditionally based on collaborative filtering and content-based filtering techniques, have shown promise in various domains, including e-learning (Burke, 2002; Manouselis et al., 2012). However, these methods often fall short when it comes to personalizing recommendations based on a learner's specific competency profile or learning goals (Adomavicius and Tuzhilin, 2005). The European Union's Digital Competence Framework for Citizens (DigComp) provides a structured approach to defining digital skills and competencies. The framework outlines 21 key competencies grouped into five dimensions, including information literacy, communication, digital content creation, safety, and problem-solving (Ferrari et al., 2014). By integrating this competency framework into an educational platform, it becomes possible to generate a profile for each learner that reflects their strengths and areas for improvement. This approach enables the design of personalized learning experiences that target specific skills, offering users more relevant and effective learning paths.

Recent advancements in artificial intelligence (AI) and natural language processing (NLP), particularly with the introduction of large language models (LLMs) such as BERT (Devlin et al., 2019), have transformed the landscape of recommender systems. LLMs have the capability to capture semantic nuances in textual data, making them ideal for matching course descriptions with user preferences and competency profiles. These models, pre-trained on vast amounts of multilingual text, allow for the development of AI-based recommender systems that surpass traditional keyword-based matching by leveraging contextual understanding (Vaswani et al., 2017).

In this paper, we present an AI-based personalized course recommender system for an educational platform. Our system uses the DigComp framework to assess user competency profiles and utilizes a fine-

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tuned BERT model to compute semantic similarity between user input and course content. Furthermore, we introduce a novel learning path generation method that builds customized course sequences for users, ensuring a progressive and effective learning experience. This approach represents a significant improvement over traditional recommender systems, addressing both the need for personalization and the challenge of competency-based learning in the digital age.

2 RELATED WORK

Research on recommender systems spans multiple domains, including e-commerce, entertainment, and education (Ricci et al., 2010; Adomavicius and Tuzhilin, 2005). In the context of education, the need for personalized course recommendations has driven innovation in both traditional and AI-based methods. This section outlines key advancements in three areas: traditional recommender systems, NLP-based approaches, and competency-based learning systems.

2.1 Traditional Recommender Systems

Traditional recommender systems fall into three primary categories: collaborative filtering, content-based filtering, and hybrid approaches. Collaborative filtering, one of the earliest approaches, relies on user-item interaction data to recommend items based on the preferences of similar users (Schafer et al., 2007; Ekstrand et al., 2011). This technique has been widely used in various domains but often struggles with the cold-start problem, where insufficient data on new users or items reduces its effectiveness.

Content-based filtering, by contrast, matches users with items based on item attributes, such as textual descriptions in the case of educational courses (Pazzani and Billsus, 2007; Lops et al., 2011). This method allows for more personalized recommendations by considering the specific features of each course, but it tends to lack diversity and novelty in the recommendations, often leading to overspecialization. Hybrid systems, which combine collaborative filtering and content-based approaches, have been developed to overcome these individual limitations, improving recommendation accuracy and coverage (Burke, 2002; Burke, 2007; Çano and Morisio, 2017).

2.2 Course Recommendation in Educational Platforms

In educational platforms, course recommendation systems have traditionally relied on simple keyword-based matching techniques (Manouselis et al., 2012; Lu et al., 2015). Rule-based systems that use algorithms like TF-IDF and cosine similarity to compare user queries with course descriptions are common (Colchester et al., 2017; Murtaza et al., 2022). While such methods provide basic semantic matching, they often fail to capture the full complexity of user intent or course content, leading to recommendations that may not fully align with the learner's needs (Anand and Mobasher, 2003; Zhang et al., 2020). Moreover, these systems do not account for the progression in a learner's knowledge or provide personalized learning paths, making them less effective in guiding users through a structured learning journey.

Some platforms have incorporated domain-specific taxonomies or ontologies to improve the matching process. For example, educational ontologies may categorize courses by subject or level of difficulty, but these approaches are often rigid and do not adapt dynamically to changes in user preferences or competencies (Manouselis et al., 2012). Educational platforms like *Coursera* (https://www.coursera.org/) and edX (https://www.edx.org/) employ comprehensive skills taxonomy and learning objectives based on different frameworks like Bloom's Taxonomy (Bloom et al., 1956), the Skills Framework for Information Age (Foundation, 2015), and the Skills Network (Anderson, 2017) to map out competencies and skills.

2.3 Advances in NLP-Based Recommender Systems

Recent advancements in natural language processing (NLP), particularly with the development of large language models (LLMs), have opened new possibilities for course recommendation systems. BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019), a pre-trained transformer model, has proven especially effective in understanding the semantic context of text, enabling more accurate matching between user queries and course content. BERT-based models capture bidirectional context, making them more suitable for tasks like semantic similarity, text classification, and information retrieval (Vaswani et al., 2017).

In education, LLMs have been applied to generate personalized learning plans, taking into account user input, course descriptions, and the user's progress. Studies (Sun et al., 2019; Wu et al., 2023) have demonstrated that BERT-based models significantly improve the accuracy of recommendations compared to traditional approaches by leveraging deeper contextual understanding (Zhou et al., 2018). Moreover, these models can support multilingual platforms, broadening the applicability of the recommender system to users from diverse linguistic backgrounds.

2.4 Competency-Based Learning and Frameworks

Competency-based learning frameworks have gained traction as a way to personalize education by focusing on the learner's skills and competencies rather than the content alone. The European Union's DigComp framework, for example, outlines 21 key digital competencies across five dimensions namely, *information and data literacy*, *communication and collaboration*, *digital content creation*, *safety*, and *problem solving* (Ferrari et al., 2014). These frameworks enable educational platforms to map courses to specific competencies, providing a structured and targeted learning experience for users.

Previous research (Justesen et al., 2019) has explored integrating competency frameworks into educational recommender systems, but many implementations are limited to matching courses based on predefined categories rather than dynamically analyzing user competencies and needs. Our approach builds upon this work by incorporating both the DigComp framework and AI-based semantic analysis, offering a more sophisticated method for matching user profiles with relevant course content.

2.5 AI-Driven Learning Path Generation

Another emerging area in educational recommender systems is the generation of personalized learning paths. Traditional recommenders typically suggest a list of courses without considering the order in which learners should complete them. However, recent AI-driven approaches are addressing this gap by using LLMs to dynamically generate learning sequences that align with the learner's progress and goals (Zhou et al., 2018). These systems can provide not only course recommendations but also a structured path that optimizes the learning experience by guiding users through progressively advanced material.

In our work, we extend this concept by employing LLMs like the *mistralai/Mistral-7B-Instruct-v0.2* model (Jiang et al., 2023) to generate personalized learning paths that account for the user's past learning experiences and future goals. This approach enables the creation of tailored, goal-oriented learning paths, enhancing the overall user experience in navigating complex educational ecosystems.

3 SYSTEM ARCHITECTURE AND METHODOLOGY

The system we developed for personalized course recommendations is composed of several interconnected components, each responsible for a specific aspect of the recommendation and learning path generation process. The architecture includes a Rasa (Bocklisch et al., 2017) intent-based chatbot for initial user interaction, a user competency profile based on the EU DigComp framework, a rule-based recommender, and an AI-based course recommendation engine using large language models (LLMs). In this section, we detail the design and functioning of each of these components.

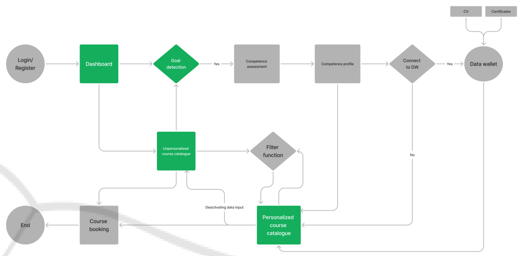

Figure 1: Flowchart of the important components in the system. (*Zoom in to read*).

3.1 User Interaction and Competency Profiling

The first step in the system is user interaction, facilitated by a Rasa intent-based chatbot (Bocklisch et al., 2017). The chatbot prompts users to describe what they are interested in learning. By analyzing the user's responses using intent detection and entity extraction techniques, the chatbot selects the relevant competency areas from the DigComp framework that the user should focus on. This process ensures that the user receives recommendations aligned with their learning needs and goals. This is a key advantage for users who may not be familiar with the DigComp competences, as it guides them through a tailored selection process.

Once the relevant competency areas are identified, the chatbot asks the user to complete corresponding surveys based on these competencies. The surveys are structured on a Likert scale, allowing users to self-assess their proficiency in various competency areas. The results of these surveys are then used to create a user competency profile, represented as a 21-length vector corresponding to the 21 DigComp competency areas (Ferrari et al., 2014).

Rasa was chosen for its customizable, open-source framework that allows detailed intent recog-

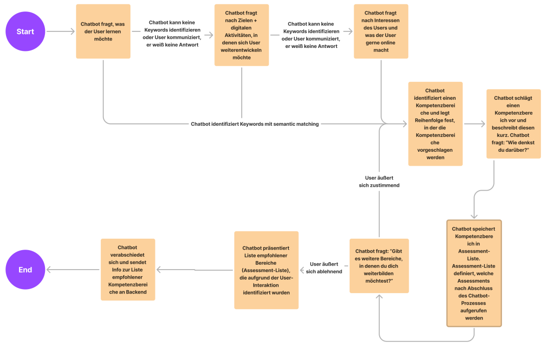

Figure 2: Flowchart showing the decision-making of the chatbot (in German). (*Zoom in to read*).

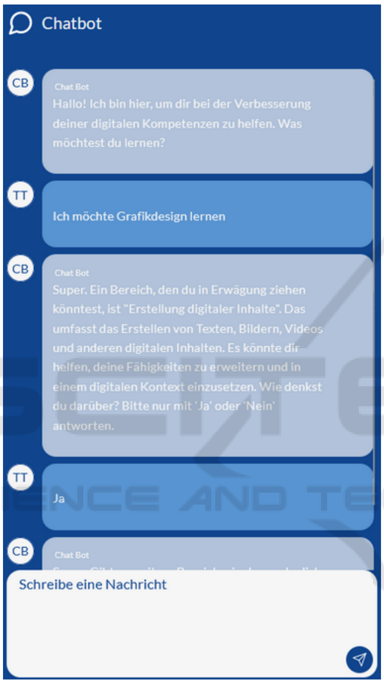

Figure 3: Chatbot interface (in German) providing user assistance with selected competences.

nition and seamless integration with external data sources. Since Rasa supports nuanced conversational flows, it was ideal for building a bot that could effectively guide users through selecting their competencies, improving the onboarding process and ensuring accurate profiling. Again, the DigComp framework was chosen because it is well-established for accessing digital competencies and is structured into 21 areas, allowing for a granular approach to competency-based learning. By using DigComp, our system can provide recommendations closely aligned with industry-recognized competencies, which increases relevance for both users and educational providers.

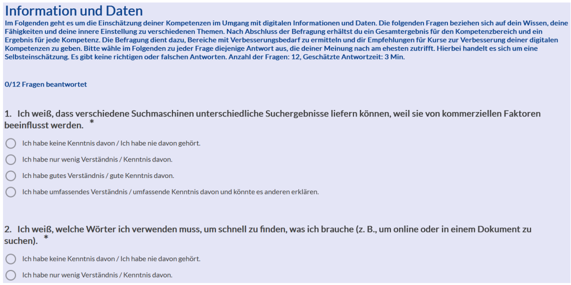

Figure 4: Survey form (in German) presented to the user for the *Information and Data* competence. (*Zoom in to read*).

Figure 5: User competence profile (in German) shows the overall competence levels of the user with a guide.

3.2 Course Data Collection and Annotation

The system's course database comprises approximately 800 courses from various online providers, with 374 of them manually annotated. These courses follow the MoocHub data schema (https://moochub.org/), which includes metadata such as course title, description, and provider information. However, these courses do not have DigComp-related annotations, requiring an additional step for competency mapping.

To bridge this gap, we employed ChatGPT based on the GPT-4 model (Radford et al., 2019; Brown et al., 2020) to annotate the 374 courses with difficulty levels (on a scale of 1 to 5) and competency areas from the DigComp framework. The annotation process involved extracting keywords from course descriptions and assigning appropriate difficulty ratings and competency areas based on the course content. This use of language models enabled efficient and consistent annotation across multiple providers, ensuring that the courses could be aligned with user competency profiles for personalized recommendations. ChatGPT based on GPT-4 is used here for annotation because of its advanced natural language understanding and adaptability in generating contextually relevant annotations. Without access to domain experts or teachers for manual annotation, GPT-4 provides an efficient alternative that leverages extensive pre-trained knowledge to identify course difficulty and competencies accurately. This choice allows for high-quality annotation at scale, addressing the need for a robust, consistent annotation process that would otherwise require considerable human expertise and resources. GPT-4's capabilities ensure consistent labeling across a large volume of courses, which is essential for maintaining annotation quality when scaling up the system. Additionally, using an automated model minimizes the time and cost associated with human annotation, making it possible to achieve comprehensive coverage across all courses without delays. This approach supports our goal of quickly developing a personalized recommendation system based on accurately classified and well-annotated course data. GPT-4's capacity for contextual understanding allows it to map course content to the DigComp competency areas effectively, ensuring that recommendations align well with the skills defined in this widely accepted framework. This alignment is key to ensuring that each recommendation supports relevant skill-building, which strengthens the educational value of the system for users.

3.3 Course Recommender System

Initially, a rule-based recommender system was implemented to offer basic course recommendations based on user-entered search queries. This system used term frequency-inverse document frequency (TF-IDF) and cosine similarity to calculate semantic similarity between the search query and course descriptions. A weighted score was computed for each course, which determined its rank in the recommendation list (Schütze et al., 2008). Although effective for simple query matching, the rule-based approach lacked the capability to adapt to individual user competencies and did not fully leverage semantic information embedded in course content.

To improve recommendation quality and incorporate personalization, an AI-based recommender system was developed using the pretrained DistilBERT ("distiluse-base-multilingual-cased-v1") (Devlin et al., 2019) model from HuggingFace. BERT's transformer architecture allows it to capture deep contextual relationships within text, making it ideal for calculating semantic similarity between user queries and course descriptions. We trained course embeddings on the course titles and descriptions for all 374 annotated courses and stored them in a searchable database. DistilBERT, especially its multilingual variant, offers a powerful yet computationally efficient approach for text embeddings, ideal for real-time course recommendation scenarios. Since the system needs to handle both English and German inputs, a multilingual transformer is necessary to ensure consistent quality across languages. DistilBERT's lightweight architecture provides an optimal balance between model performance and computational efficiency.

When a user enters a search query, the system calculates the semantic similarity between the query and the course embeddings, selecting only those courses that meet a predefined threshold of 78%. Courses above this threshold are then ranked based on the reverse Euclidean distance between the user's 21-length competency vector and the annotated competency vector for each course. This step ensures that the recommendations are not only semantically relevant but also aligned with the user's competency profile. The hybrid scoring model addresses limitations in both purely semantic and purely rule-based systems by combining contextual similarity with personalized competency alignment. This approach ensures that recommendations aren't only relevant in terms of content but are also tailored to each user's skill level, increasing the likelihood that recommendations will be meaningful and actionable for the user. The threshold of 78% is empirically chosen to strike a balance between relevance and inclusivity in recommendations. This level is set based on preliminary testing to ensure that users receive high-quality suggestions without overly limiting course options, allowing for a more diverse set of learning opportunities.

Figure 6: Course catalog (in German) showcasing the list of available courses. (*Zoom in to read*).

3.4 Personalized Learning Path Generation

In addition to recommending individual courses, the system generates personalized learning paths containing a sequence of 2–3 courses. After selecting the first course from the AI-based recommender, the system generates a customized prompt for the *mistralai/Mistral-7B-Instruct-v0.2* model (Jiang et al., 2023) from HuggingFace. The Mistral-7B-Instruct model is chosen for its capability to generate contextually relevant prompts that guide users

to their next steps in learning. By leveraging this model's generative capacity, the system can create a custom, adaptive learning path that considers users' past courses. This approach aligns with the goal of providing not only relevant but also sequential learning recommendations. The prompt includes information about the user's interests, previously completed courses, and goals, requesting the model to suggest the next step in the user's learning journey (Zhou et al., 2018).
Prompt: "A person searches for [*user search input*]. The person has taken the following courses: [*course names with course descriptions*]."
Question: "Write in a paragraph which topics this person should learn next."

The model's output provides key topics or skills for the next course, which is used as input to the AI recommender. This process repeats until the system constructs a complete learning path, allowing users to follow a structured, goal-oriented sequence of courses.

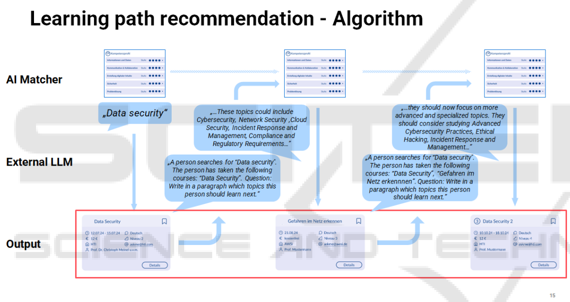

Figure 7: Flow of information in the learning path generation. (*Zoom in to read*).

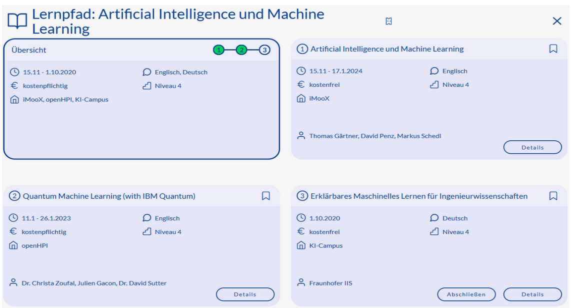

Figure 8: The learning path "*Artificial Intelligence and Machine Learning*" for a user profile. (*Zoom in to read*).

The system architecture integrates various components—from a chatbot-driven user interface to advanced AI-based recommendation models—to deliver personalized course suggestions and learning paths. The system's ability to dynamically generate competency-aligned recommendations and tailored learning paths represents a significant advancement over traditional rule-based recommenders, offering a more engaging and effective user experience.

4 FUTURE WORK

While the current system leverages content-based methods and language models to provide personalized recommendations, the recommendation quality could be enhanced by integrating a **collaborative filtering** approach. Collaborative filtering has been widely adopted in recommendation systems to identify patterns in user behavior, recommending items based on the preferences of similar users (Koren et al., 2009). Apart from real datasets, simulated datasets including user data can be used to initially validate the collaborative filtering algorithm (Herlocker et al., 2004).

Collaborative filtering has the potential to complement the existing content-based recommendation system by incorporating user-item interactions, which will help overcome limitations like the "cold start" problem inherent in purely content-based systems (Schein et al., 2002). By leveraging user similarities, courses can be recommended based not only on course content and competency profiles but also on the learning patterns of other users with similar interests and skill levels. This hybrid system—combining content-based filtering, AI-based matching, and collaborative filtering—has the potential to significantly improve recommendation relevance and engagement (Burke, 2002; Burke, 2007).

Using real user data at a later time point, the collaborative filtering model can be fine-tuned to work with live data. User feedback can also be integrated into the system, allowing for further refinement of recommendations based on explicit (e.g., course ratings) and implicit (e.g., click-through rates) signals. Additionally, reinforcement learning techniques could contribute to continuously adapt the learning paths based on user progress and outcomes (Zheng and Wang, 2022).

Beyond the education sector, the personalized recommender and adaptive learning path approach developed in this project are important assets which hold significant potential for other domains requiring tailored content delivery and skill progression. In corporate training, such a system could guide employees through customized learning paths aligned with career goals, role requirements, or skill gaps, ensuring that development resources are both relevant and impactful. Similarly, in healthcare, this approach could support personalized patient education by recommending articles, videos, or courses tailored to individual health conditions or treatment plans, thereby enhancing patient engagement and adherence to health protocols. Additionally, in sectors like e-commerce, personalized recommenders could suggest products or services based on past purchases or browsing behavior, while an adaptive path model could guide customers through complementary products or bundles in a curated sequence. The flexibility and contextual adaptability of this recommender system make it valuable across various fields where user-specific recommendations enhance engagement and satisfaction.

5 CONCLUSION

In this paper, we have presented an AI-based personalized course recommender system grounded in the EU DigComp competency framework. By using a combination of natural language processing techniques, large language models, and semantic similarity algorithms, our system provides tailored course recommendations based on users' competencies and interests. Additionally, a learning path generation module offers structured course sequences, further enhancing the personalized learning experience. The integration of a Rasa chatbot allows for an intuitive and interactive user interface, improving engagement by guiding users through competency-based assessments. The annotation of courses with DigComp competency areas, facilitated by LLMs, ensures that the recommendations are competency-aligned and relevant to individual learning goals.

As the project progresses, we plan to incorporate collaborative filtering algorithms to augment the recommendation engine. By leveraging both simulated and real user data, we aim to create a hybrid system that combines the strengths of content-based and collaborative filtering techniques. Ultimately, this system will enable more effective and personalized educational experiences, catering to a wide variety of learners and their evolving needs.

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REFERENCES

Adomavicius, G. and Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge and data engineering*, 17(6):734–749.

Anand, S. S. and Mobasher, B. (2003). Intelligent techniques for web personalization. In *IJCAI Workshop on Intelligent Techniques for Web Personalization*, pages 1–36. Springer.

Anderson, K. A. (2017). Skill networks and measures of complex human capital. *Proceedings of the National Academy of Sciences*, 114(48):12720–12724.

Bloom, B. S., Engelhart, M. D., Furst, E. J., Hill, W. H., and Krathwohl, D. R. (1956). Taxonomy of educational objectives: Cognitive and affective domains. *New York: David McKay*, pages 20–24.

Bocklisch, T., Faulkner, J., Pawlowski, N., and Nichol, A. (2017). Rasa: Open source language understanding and dialogue management. *arXiv preprint arXiv:1712.05181*.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., and Amodei, D. (2020). Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901.

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, 12:331–370.

Burke, R. (2007). Hybrid web recommender systems. *The adaptive web: methods and strategies of web personalization*, pages 377–408.

Çano, E. and Morisio, M. (2017). Hybrid recommender systems: A systematic literature review. *Intelligent data analysis*, 21(6):1487–1524.

Colchester, K., Hagras, H., Alghazzawi, D., and Aldabbagh, G. (2017). A survey of artificial intelligence techniques employed for adaptive educational systems within e-learning platforms. *Journal of Artificial Intelligence and Soft Computing Research*, 7(1):47–64.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*.

Ekstrand, M. D., Riedl, J. T., Konstan, J. A., et al. (2011). Collaborative filtering recommender systems. *Foundations and Trends® in Human–Computer Interaction*, 4(2):81–173.

Ferrari, A., Brečko, B. N., and Punie, Y. (2014). Digcomp: a framework for developing and understanding digital competence in europe. *eLearning Papers*, (38):1.

Foundation, S. (2015). Sfia6 the complete reference guide.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., and Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS)*, 22(1):5–53.

Jiang, A. Q., Sablayrolles, A., Mensch, A., Bamford, C., Chaplot, D. S., Casas, D. d. l., Bressand, F., Lengyel, G., Lample, G., Saulnier, L., et al. (2023). Mistral 7b. *arXiv preprint arXiv:2310.06825*.

Justesen, N., Bontrager, P., Togelius, J., and Risi, S. (2019). Deep learning for video game playing. *IEEE Transactions on Games*, 12(1):1–20.

Koren, Y., Bell, R., and Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *Computer*, 42(8):30–37.

Lops, P., De Gemmis, M., and Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. *Recommender systems handbook*, pages 73–105.

Lu, J., Wu, D., Mao, M., Wang, W., and Zhang, G. (2015). Recommender system application developments: a survey. *Decision support systems*, 74:12–32.

Manouselis, N., Drachsler, H., Verbert, K., and Duval, E. (2012). *Recommender systems for learning*. Springer Science & Business Media.

Murtaza, M., Ahmed, Y., Shamsi, J. A., Sherwani, F., and Usman, M. (2022). Ai-based personalized e-learning systems: Issues, challenges, and solutions. *IEEE access*, 10:81323–81342.

Pappano, L. (2012). The year of the mooc. *The New York Times, November*, 2.

Pazzani, M. J. and Billsus, D. (2007). Content-based recommendation systems. In *The adaptive web: methods and strategies of web personalization*, pages 325–341. Springer.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., Sutskever, I., Dean, J., and Ghemawat, S. (2019). Language models are unsupervised multitask learners. In *OSDI'04: Sixth Symposium on Operating System Design and Implementation*, pages 137–150.

Ricci, F., Rokach, L., and Shapira, B. (2010). Introduction to recommender systems handbook. In *Recommender systems handbook*, pages 1–35. Springer.

Schafer, J. B., Frankowski, D., Herlocker, J., and Sen, S. (2007). Collaborative filtering recommender systems. In *The adaptive web: methods and strategies of web personalization*, pages 291–324. Springer.

Schein, A. I., Popescul, A., Ungar, L. H., and Pennock, D. M. (2002). Methods and metrics for cold-start recommendations. In *Proceedings of the 25th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 253–260.

Schütze, H., Manning, C. D., and Raghavan, P. (2008). *Introduction to information retrieval*, volume 39. Cambridge University Press Cambridge.

Sun, F., Liu, J., Wu, J., Pei, C., Lin, X., Ou, W., and Jiang, P. (2019). Bert4rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the 28th ACM international conference on information and knowledge management*, pages 1441–1450.

Vaswani, A., Shazeer, N. M., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need. In *Neural Information Processing Systems*.

Wu, C., Wu, F., Huang, Y., and Xie, X. (2023). Personalized news recommendation: Methods and challenges. *ACM Transactions on Information Systems*, 41(1):1–50.

Zhang, Y., Chen, X., et al. (2020). Explainable recommendation: A survey and new perspectives. *Foundations and Trends® in Information Retrieval*, 14(1):1–101.

Zheng, Y. and Wang, D. X. (2022). A survey of recommender systems with multi-objective optimization. *Neurocomputing*, 474:141–153.

Zhou, Y., Huang, C., Hu, Q., Zhu, J., and Tang, Y. (2018). Personalized learning full-path recommendation model based on lstm neural networks. *Information sciences*, 444:135–152.