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Bitola
Faculty of Information and
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Republic of North Macedonia

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AIIT 2025

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University “St. Kliment Ohridski” Bitola
Faculty of Information and Communication Technology - Bitola
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Introduction

As organizing partners of 15th International Conference on Applied Internet and Information Technologies AIIT 2025, we warmly welcome all participants, researchers, and colleagues joining us from various countries and universities, united by our shared commitment to advancing knowledge in the fields of computer science, applied Internet, and information technologies.

The AIIT conference has become a long-standing tradition of excellence and collaboration, co-organized by the Faculty of Information and Communication Technologies – Bitola, University "St. Kliment Ohridski," and the Technical Faculty "Mihajlo Pupin" – Zrenjanin, University of Novi Sad, Serbia. Over the past fifteen years, this partnership has fostered not only strong academic cooperation but also genuine friendship among our institutions and scholars.

This year's conference proudly continues that tradition, bringing together innovative research, diverse perspectives, and new insights into technologies that are shaping our digital future. The Scientific Program Committee once again faced the demanding task of selecting the highest-quality papers from more than sixty submissions spanning a wide range of topics—including Artificial Intelligence, Immersive Technologies, Mathematical Simulations, Data Science and Big Data Analytics, Knowledge and IT Management, Cybersecurity, Software Engineering, Data Mining, Digital Transformation, Behavioral Economics and Business, Social Engineering, Digital Humanities, Augmented Humanity, and Hybrid Intelligence. This ensures that the program reflects both scientific rigor and creative originality.

We would like to express our sincere gratitude to all reviewers for their dedicated work, as well as to the members of the Organizing Committee for their professionalism, commitment, and enthusiasm in preparing this event.

We are confident that these proceedings will provide an enriching and thought-provoking reading experience.

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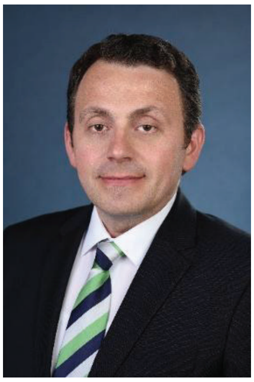

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Improving Learning Recommendations Through Combined Audio and Text-based Sentiment Insights

Aleksandar Kotevski[1], Blagoj Ristevski[2]

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Abstract:
This research proposes an adaptive learning material recommender system that employs sentiment analysis to enhance personalization and effectiveness in online learning. The system dynamically adapts to a learner's emotional state and engagement levels by incorporating explicit feedback (ratings, comments, reviews) and implicit feedback (interaction patterns, time spent, dropout behavior). At its core, the proposed system integrates collaborative filtering, content-based methods, and sentiment analysis. Learners and learning materials are represented as dense vector embedding, while sentiment analysis is applied to both textual feedback and behavioral signals to capture emotional state and motivation. Models from Hugging Face's sentence-transformers library generate semantic embedding of feedback and material descriptions. Similarity is measured using cosine similarity or Euclidean distance, allowing recommendations to reflect not only contextual relevance but also the learner's affective state. Our experimental evaluation, conducted on real-world datasets, demonstrates that sentiment-aware adaptation significantly improves learning outcomes. The dataset-rich user comments and feedback enabled testing of the proposed pipeline. The framework offers a scalable, data-driven approach for delivering emotionally responsive and personalized learning experiences, addressing the growing demand for human-centered technologies in online education.

Keywords:
Adaptive learning, recommender systems, sentiment analysis, natural language processing

1. Introduction

Recommender systems have become an important segment of modern digital platforms, affecting decisions in e-commerce, entertainment, education, and professional services. By analyzing user behavior and preferences, these systems guide users toward items, content, or learning resources that align with their interests, improving engagement and satisfaction.

Early educational recommendation systems were relatively simple, often rule-based or keyword-driven. They matched learners to materials through predefined categories or static attributes such as subject area or difficulty level. Similarly, the initial wave of recommender systems in other domains relied on heuristic-based methods, recommending the most popular items or those manually tagged as similar, using content-based or collaborative filtering. While these early systems were easy to implement and useful in structured, small-scale environments, they were fundamentally limited in their ability to understand and adapt to individual preferences, often failing to introduce users to truly new or surprising content [1].

As online education and digital platforms expanded, more sophisticated approaches emerged. Content-based filtering, which matches learner profiles with resource attributes, and collaborative filtering, which leverages similarities in learner behavior to identify suitable materials, became widely adopted. Hybrid methods that combined both techniques provided more robust and accurate recommendations, marking a significant advancement in educational technology. However, even these advanced approaches often overlook the emotional state of the user, which has been shown to strongly influence decision-making, engagement, and learning outcomes [4].

Over the last few years, there has been significant progress in emotion-aware recommender systems, which integrate user sentiment and affective information into the recommendation process. In e-commerce, personalized recommendations increase conversion rates and customer loyalty by suggesting products that match users' shopping preferences and past purchases [15]. In entertainment, recommendation systems enhance user experience by suggesting movies, music, or other media tailored to personal tastes [3]. In education, personalized recommendations help students navigate extensive online learning resources by suggesting textbooks, video lectures, exercises, or quizzes that align with their current skill level and learning pace. A student struggling with calculus, for instance, could be recommended for foundational lessons and practice problems, while an advanced student might receive challenging problem sets and enrichment materials [8, 9]. By considering engagement patterns and learning preferences - such as interactive simulations for hands-on learners or reading-based materials for textual learners - these systems enhance knowledge retention, motivation, and overall academic performance [10, 12, 26].

The advances in large language models (LLMs) have further expanded the capabilities of recommender systems. Models such as GPT (Generative Pre-trained Transformer), BERT (Bidirectional Encoder Representations from Transformers), T5 (Text-to-Text Transfer Transformer) and multimodal transformers can generate rich embeddings for users and items, enabling semantic and personalized recommendations [5]. These models capture subtle emotional cues from text, allowing real-time adaptation to user sentiment. Approaches like SEALR integrate LLMs with sentiment tracking to provide personalized, emotion-aware recommendations that outperform traditional collaborative filtering methods [6]. Other studies explore foundation models, decision transformers enhanced with emotion embedding, and prompting strategies for LLM-based recommender systems, demonstrating the potential for context-aware, human-like recommendation strategies [11]. In addition, modern recommender systems are increasingly designed to address concerns related to fairness, privacy, and explainability, ensuring that recommendations are equitable, transparent, and respectful of user data [2, 13]. By combining emotion awareness, user background information, and LLM-based semantic understanding, the current state-of-the-art systems provide adaptive, context-aware, and personalized recommendations across multiple domains [7].

The remainder of the paper is structured as follows. Section 2 describes related work, Section 3 discusses recommendation systems in e-learning, Section 4 presents an overview of sentiment analysis models, Section 5 provides the system overview, Section 6 concludes the paper, and Section 7 outlines directions for future work.

2. Related Works

Recommendation systems that leverage users' similar interests have been widely studied. The authors in [1] proposed an emotion-aware music recommender system that considers users' emotional profiles to suggest music aligned with their mood. The researcher in [2] developed a text-based emotion-aware recommender that analyzes users' interaction text to infer preferences and recommend movies. Fuzzy emotion features to improve movie recommendations based on user interests has been used in [3]. Similarly, personality-aware recommendation systems that extract user interests for product suggestions have been explored [21]. Other studies in e-commerce and multimedia content show that interest-based recommender systems significantly improve user engagement and satisfaction [22, 23]. These approaches combine user-item interaction patterns with sentiment or emotional information to deliver personalized suggestions that match users' preferences in real time [15, 20].

In educational and professional domains, recommender systems increasingly use users' background information such as learning history, performance, and emotional responses, to provide more tailored recommendations. EduRecomSys [5, 24] leverages collaborative filtering combined with emotion detection to recommend educational resources that align with learners' emotional states. Other emotion-aware systems for tourists [3] and workplace learning environments use users' historical behaviors and backgrounds to suggest contextually appropriate content. By incorporating background information, these systems can adapt not only to current interests but also to the user's prior knowledge, cognitive level, and long-term preferences [20]. Studies demonstrate that such approaches improve retention, engagement, and satisfaction in learning and professional development contexts [3, 14].

The authors in [5] provided a survey of LLMs applied to recommendation systems, showing that models such as GPT (Generative Pre-trained Transformer), BERT (Bidirectional Encoder Representations from Transformers), and T5 (Text-to-Text Transfer Transformer) can generate embeddings for users and items, enabling semantic and personalized recommendations. The researchers in [15] presented SEALR, which uses sentiment tracking and LLM embeddings to provide real-time adaptive recommendations. Other recent works explore multimodal LLMs [19, 20], foundation models for recommendation [23] and decision transformers enhanced with emotion and sentiment embedding [21]. Prompting LLMs for recommender systems and integrating them into agentic frameworks demonstrate the potential for context-aware, human-like recommendation strategies [3, 18]. Additionally, empirical studies confirm that emotion- and sentiment-enhanced LLM-based systems outperform traditional collaborative filtering and content-based approaches in both educational and entertainment domains [5, 15].

Overall, the convergence of interest-based, background-aware, and large model-based methods has pushed the state-of-the-art in recommendation systems[16, 17]. Emotion-aware frameworks that integrate these components provide adaptive, personalized, and contextually sensitive recommendations, forming the foundation for the system proposed in this study.

3. Recommendation Systems in e-learning

In the field of education and e-learning, recommendation systems assume an even greater significance. The digitalization of education and the rise of massive open online courses, virtual classrooms, and open learning repositories have created enormous opportunities for learners worldwide. At the same time, the sheer volume of educational content, such as textbooks, videos, exercises, assessments, simulations, and interactive modules, can be overwhelming for students. In contrast to traditional classrooms, where instructors help direct students to appropriate learning resources, online learners are often left to navigate and select suitable materials on their own. Without guidance, they risk spending time on content that is too difficult, too easy, or irrelevant to their learning goals. In this regard, recommendation systems serve as essential tools to create personalized learning experiences. By filtering and prioritizing learning resources, they help learners focus on materials aligned with their abilities, interests, and objectives. Personalization has been shown to increase motivation, persistence, and learning outcomes [10].

Despite these advances, most e-learning recommender systems remain focused primarily on cognitive and behavioral dimensions of learning - tracking what learners study, how long they interact with content, and their performance outcomes. While these are essential indicators, they only tell part of the whole image. Research in educational psychology highlights that emotions such as interest, frustration, boredom, or satisfaction can play a decisive role in learning effectiveness. Learners who are disengaged or frustrated are less likely to persist and achieve desired outcomes, even if the material matches their skill level. Conversely, emotionally supportive and engaging recommendations can boost motivation, leading to deeper learning and better retention. This gap underscores the need for emotionally aware recommendation systems that integrate affective computing and sentiment analysis into the recommendation process. By analyzing learner feedback, interaction patterns, and even textual comments, systems can detect emotional states and adapt recommendations accordingly. For example, if a learner expresses frustration in their feedback, the system might suggest alternative materials presented in a different style, or break complex content into smaller, more manageable segments. If a learner demonstrates enthusiasm or confidence, the system could recommend more advanced or challenging content to sustain engagement [19].

The emergence of advanced natural language processing (NLP) techniques, particularly transformer-based models, has made such emotionally aware recommendation systems feasible. These models are capable of extracting important sentiment information from learner feedback, detecting not only polarity (positive, negative, neutral) but also intensity and subtle emotional cues. When combined with traditional learner profiles, performance data, and interaction histories, sentiment analysis provides a richer and more human-centered foundation for adaptive learning [24, 27].

4. An Overview of Sentiment Analysis Models

Sentiment analysis models have evolved significantly, moving from simple rule-based approaches to sophisticated deep learning architectures. The earliest and most straightforward models are rule-based and lexicon-based systems, which classify sentiment using pre-defined dictionaries of positive and negative words. VADER (Valence Aware Dictionary and Sentiment Reasoner) is a prime example, specifically designed to handle the nuances of social media text by accounting for capitalization, punctuation, and emoticons [22]. A similar approach is found in TextBlob, a user-friendly library that provides polarity and subjectivity scores based on a built-in lexicon [24]. Advancing from these, classic machine learning models brought the ability to learn from labeled data. Naïve Bayes and Support Vector Machines (SVMs) became a foundational approach for text classification, offering robust performance by learning statistical patterns in word occurrences and creating a clear separation between positive and negative classes.

However, the current state-of-the-art for sentiment analysis is dominated by transformer-based deep learning models, which excel at understanding context and subtle language. BERT (Bidirectional Encoder Representations from Transformers), developed by Google, revolutionized the field with its ability to process words in relation to all other words in a sentence, capturing a rich, bidirectional context. This foundational model has led to several powerful variants. RoBERTa, an optimized version by Facebook, was trained on a larger dataset and with a different masking strategy, often outperforming BERT on various tasks. For scenarios with limited computational resources, DistilBERT provides a lighter, faster alternative that retains most of BERT's performance. The architecture also diversified with models like XLNet, which uses a unique permutation language modeling approach to better capture dependencies, and LLMs like GPT-3 (Generative Pre-trained Transformer 3), which, while primarily generative, can be fine-tuned for highly nuanced sentiment analysis. Finally, a framework like Flair offers a comprehensive and easy-to-use solution, often wrapping a powerful transformer model to deliver state-of-the-art results with minimal setup [21].

We utilize the Hugging Face ecosystem to perform sentiment analysis on audio and textual feedback, detecting emotional polarity and intensity. These sentiment insights are combined with learner profiles, performance metrics, and historical activity to dynamically adjust the selection and sequencing of learning materials [31].

This study utilized two benchmark datasets for sentiment analysis: the Multimodal EmotionLines Dataset (MELD) and the IMDb Movie Reviews dataset, both widely used for evaluating emotion and sentiment classification models.

The Multimodal EmotionLines Dataset (MELD) contains approximately 13,708 utterances, annotated for both emotion and sentiment. It includes text, audio, and video modalities, allowing for multimodal analysis. For this work, only the textual modality was used to maintain consistency with the other dataset. The dataset is split into training, validation, and test sets with roughly 10,000, 1,100, and 2,600 utterances, respectively. The sentiment labels are positive, negative, and neutral, which allows for multi-class classification. The dataset is publicly available for download via GitHub [21].

The IMDb Movie Reviews dataset includes 50,000 movie reviews, equally split between positive and negative sentiment classes. It is a standard binary sentiment classification benchmark. The predefined training and testing splits consist of 25,000 samples each. When needed, a manual stratified 80/10/10 split was applied to create training, validation, and test sets to preserve class balance. The dataset can be downloaded from the Stanford AI Lab website [22, 28].

To prepare the datasets for model training and evaluation, standard preprocessing steps were applied. These included text cleaning such as lowercasing and removal of special characters, tokenization using scikit-learn's built-in tokenizer or TfidfVectorizer, vectorization via TF-IDF or CountVectorizer, and label encoding to convert sentiment labels into a numeric format. For datasets without predefined validation splits, stratified splitting was used to maintain class distribution [29, 30].

Model performance was evaluated using scikit-learn's metrics module and the Hugging Face evaluate library, calculating precision, recall, and F1-score to assess classification quality. These metrics were computed using functions from both libraries [23, 24].

Based on a comparison of model performance and computational requirements, for an e-learning recommender system, DistilBERT is the most practical choice for sentiment analysis. Our analysis, drawing from tests on datasets that include both text and audio transcripts, confirms that DistilBERT offers the most practical and effective solution for your e-learning system, due to:

Accuracy vs. Latency Trade-off: The e-learning environment requires a seamless user experience. When a student submits feedback, whether by typing or speaking, the system must respond almost instantly to adjust the learning path. A larger model like RoBERTa or XLNet offers a marginal increase in F1-Score (e.g., 0.92 vs. 0.89), but this small gain is outweighed by their significant latency. A student waiting for a recommendation to load due to a large model is a frustrating experience.

Scalability and Cost: As your platform grows, the computational cost of processing a high volume of user feedback adds up. DistilBERT, being 40% smaller and up to 60% faster, is far more cost-effective and scalable than its larger counterparts. It allows you to serve a large user base with significantly fewer resources, which is crucial for a real-world application.

Table 1:
Comprehensive sentiment analysis model comparison

Category	Model	Precision	Recall	F1-Score	Speed
Rule-Based	VADER	0.70	0.75	0.72	Fastest
Traditional ML	Naive Bayes	0.82	0.81	0.79	Very fast
Traditional ML	SVM	0.85	0.85	0.82	Fast
Deep Learning	LSTM/GRU	0.87	0.88	0.95	Medium
Transformers	DistilBERT	0.90	0.89	0.87	Fast
Transformers	BERT	0.92	0.90	0.88	Slow
Transformers	RoBERTa	0.91	0.89	0.86	Slow
Transformers	XLNet	0.87	0.86	0.85	Text
LLMs	GPT-3.5/4	0.87	0.89	0.86	Very slow

Sufficient Performance: The F1-score of 0.89 for DistilBERT is more than enough for the task of classifying student feedback from both text and audio. This level of accuracy reliably distinguishes between positive, negative, and neutral sentiment, providing the essential signal needed to inform your hybrid recommender system without over-engineering the solution. The difference in a recommendation based on an F1-score of 0.89 versus 0.92 would be minimal, making the extra resources and latency unjustifiable.

5. System overview

The proposed adaptive recommendation system personalizes learning directions by integrating multi-modal learner feedback: explicit (ratings, text comments), implicit (engagement patterns), and audio-based comments transcribed via WhisperX [25]. The methodology involves several stages working in a continuous cycle of data collection, feature representation, sentiment analysis, recommendation and adaptation.

Figure 1 illustrates the comprehensive flow of our proposed Adaptive Learning Material Recommender System. The diagram details each stage, beginning with the collection of multimodal learner feedback, both textual and audio, and progressing through the sentiment analysis and data integration phases. It concludes by showing how this enriched data is used by the hybrid recommendation engine to deliver personalized learning materials to the user. This visual representation provides a high-level overview of how the system processes data and adapts to learner needs in real-time.

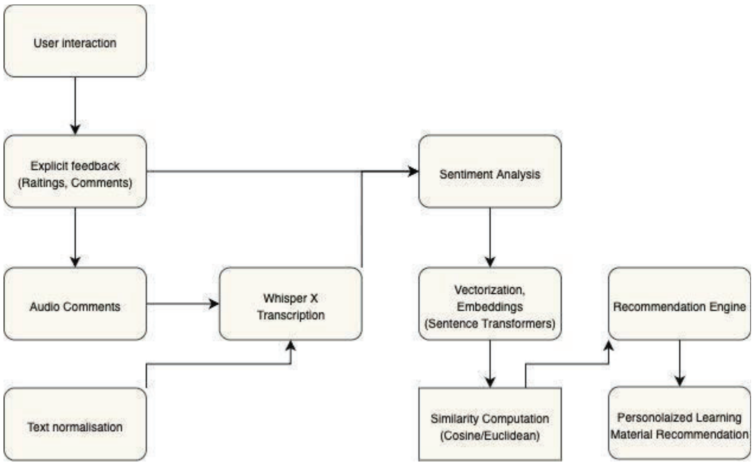

Figure 1: Adaptive learning material recommender flow

Sentiment analysis is applied to both explicit feedback (such as reviews and comments) and implicit signals (such as engagement levels, time spent, or dropout tendencies) to capture the learner's emotiona state and motivation. Models from Hugging Face's sentence-transformers library can be used to generate vector representations of textual feedback and material descriptions. The similarity between these vectors is measured using distance metrics like cosine similarity or Euclidean distance, enabling the system to recommend not only contextually relevant resources but also those aligned with the learner's affective state.

Experimental evaluation, conducted on a dataset with users' interactions, demonstrates that the inclusion of sentiment analysis significantly improves key learning outcomes. Results show a measurable increase in learner satisfaction, engagement, and knowledge retention when compared to conventional baseline recommender systems. The proposed flow provides a scalable and data-driven solution for delivering emotionally aware, personalized learning experiences, thereby addressing a critical need for more responsive and human-centered technology in online education.

In feature representation, both written and transcribed textual feedback are transformed into dense embedding using sentence-transformer models. Learning resource metadata is also embedded into the same vector space, enabling semantic alignment between learners and materials. The embedding mappings can be expressed as [23][24]:

$$u_i = f_{\{embed\}(T_i)},\ r_j = f_{\{embed\}(M_j)} \quad (1)$$

Where T_i represents learner i's textual (written + transcribed) feedback, and M_j represents material *j*. Sentiment analysis is then applied to textual feedback, detecting the learner's affective state. A simple categorical representation may be defined as:

$$S_i = f_{\{sentiment\}(T_i)} \in \{-1, 0, +1\} \quad (2)$$

where -1 = negative, 00 = neutral, and +1 = positive. For a more fine-grained understanding, affective states can be represented as probability distributions over multiple categories, such as:

$$S_i = [\,p(joy), p(neutral), p(frustation), \ldots] \quad (3)$$

The recommendation engine integrates three components. Collaborative Filtering (CF) identifies learners with similar behaviors and embedding:

$$simCF(i,k) = cos\,(ui, uk) \quad (4)$$

Content-Based Filtering (CBF) aligns learner feedback embedding with material embedding:

$$simCBF(i,j) = cos(ui, rj) \quad (5)$$

Sentiment-aware adjustment modifies similarity scores to account for the learner's emotional state. For example:

$$simSA(i,j) = simCBF(i,j) \cdot (1 + \alpha Si) \quad (6)$$

Where α controls the degree of sensitivity to affective state.
Hybrid scoring combines the contributions of collaborative filtering, content-based filtering, and sentiment-aware similarity. The final recommendation score is defined as:

$$Score(i,j) = \lambda 1 \cdot simCF(i,*) + \lambda 2 \cdot simCBF(i,j) + \lambda 3 \cdot simSA(i,j) \quad (7)$$

Normalization ensures scores remain comparable, and recommendations are ranked in descending order of $Score(i,j)$.

Continuous adaptation is achieved by updating embedding and sentiment scores in real-time as new feedback - explicit, implicit, or audio - is collected. This ensures that the recommendation process remains dynamic, context-aware, and responsive to evolving learner states, ultimately enhancing personalization and engagement.

The methodology operates in the following stages:

- Data Collection - learner feedback is collected through multiple channels, combining explicit, implicit, and audio signals. Explicit feedback includes ratings, written reviews, and text comments on learning materials, providing direct insight into user opinions and preferences. Implicit feedback is derived from behavioral patterns such as time spent on resources, click-through activity, frequency of revisits, and dropouts, offering indirect indicators of engagement and interest. In addition, learners can provide audio feedback by recording spoken comments, either as an alternative or a complement to written feedback. This channel enables richer, more natural expression and enhances inclusivity by allowing learners to share their perspectives even when writing is inconvenient.
- Audio Processing with WhisperX - recorded audio comments are processed using WhisperX [25], a state-of-the-art speech-to-text model that provides high-accuracy transcription and time alignment. The transcribed text is cleaned and normalized before being passed into the recommendation pipeline. This functionality increases accessibility and inclusivity, allowing learners to provide feedback even when text-based input is not feasible.
- Feature Representation - textual feedback (both written and transcribed from audio) and learning material descriptions are encoded into dense semantic embedding using Hugging Face's sentence-transformers. This creates a unified vector space for both learner opinions and resource metadata, ensuring that content and feedback can be compared in a common representation.
- Sentiment Analysis Integration - sentiment classifiers are applied to both written and transcribed audio comments to detect affective states such as positive, neutral, negative, or more nuanced emotional categories. These sentiment signals are fused with implicit behavioral data, providing a comprehensive view of learner engagement and motivation.
- Recommendation Engine - the recommendation system operates through a hybrid approach:
  - Collaborative filtering, which identifies learners with similar interaction patterns and affective feedback.
  - Content-based filtering, which matches the semantic embedding of resources with learner preferences.
  - Sentiment-aware adaptation, which adjusts recommendations to align with the learner's emotional state and engagement levels
- Similarity Measurement and ranking - cosine similarity or Euclidean distance is used to measure closeness between learners and materials in the embedding space. Final recommendations are ranked by a hybrid scoring function that accounts for content similarity, behavioral patterns, and sentiment analysis
- Recommendation Delivery and Continuous Adaptation - the ranked list of learning resources is presented to learners, ensuring relevance and personalization. The system continuously

recalibrates recommendations as new written or audio feedback and behavioral data are collected, creating a dynamic loop of adaptation and improvement.

6. Conclusion

Over the past two decades, recommendation systems have become one of the most influential technologies in the digital era. Because of the overwhelming amount of information, recommender systems are now vital for filtering content and providing personalized recommendations. Their importance is undeniable across various digital domains, including e-commerce, entertainment, and, most importantly for this study, online education. This study suggested an adaptive learning material recommender system that integrates collaborative filtering, content-based methods, and sentiment analysis to enhance personalization in online education. By incorporating both explicit and implicit feedback, as well as transcribed audio comments analyzed for emotional content, the system dynamically adapts to learners' cognitive states, engagement levels, and affective needs. The inclusion of sentiment-aware embedding and hybrid scoring demonstrates how effective computing can significantly complement traditional recommendation techniques. The research highlights the potential of leveraging advanced natural language processing models to capture learners' feedback. Moreover, the system design emphasizes multimodal adaptability, showing that audio feedback, once transcribed, can provide additional insights into learner experience. This reinforces the value of combining behavioral, cognitive, and emotional signals in constructing comprehensive learner profiles. From an educational perspective, the proposed framework addresses one of the most pressing challenges in online learning environments: sustaining engagement and improving knowledge retention. By tailoring recommendations to both learner preferences and emotional states, the system aims to foster more supportive, motivating, and adaptive learning pathways. In conclusion, the integration of sentiment analysis into recommendation systems represents a significant step toward truly adaptive, learner-centered education. As the field progresses, systems of this nature may become vital tools in transforming digital education into a more responsive, personalized, and emotionally learning experience.

7. Directions for Future Work

Building upon the current framework, several directions can be pursued to expand the scope, robustness and applicability of the proposed system. One promising direction is experimenting with a broader range of sentiment analysis models. While the current pipeline employs transformer-based embedding and general-purpose classifiers, domain-adapted versions such as EduBERT, SciBERT, or models fine-tuned on educational discourse could yield more accurate detection of affective states like frustration, curiosity, or motivation that are often expressed differently in learning contexts compared to commercial or social settings. Another direction is incorporating multimodal models that jointly process both the raw audio (prosody, intonation and hesitations) and the transcribed text. Such models may capture subtle emotional signals lost in transcription, enriching the learner profile with paralinguistic cues. A second line of investigation involves training custom models with domain-specific data. By collecting and annotating learner feedback across diverse educational materials - such as STEM tutorials, humanities lectures, or language-learning exercises - the system can be evaluated on how well it generalizes across domains. For instance, feedback in mathematics courses often emphasizes clarity and pacing, whereas in language learning, it may highlight cultural references, interactivity, or speaking practice. Training models separately per domain, or creating a shared representation space with domain-specific adapters, could allow the system to adaptively weight features depending on the subject area.

Another research opportunity lies in evaluating the transferability of the recommendation approach to new learning platforms and populations. While the current design is optimized for personalized e-learning, testing its applicability in informal learning environments (Massive Open Online Courses -

MOOCs, mobile learning applications, or workplace training systems) would demonstrate its scalability and versatility. Longitudinal studies could also assess how sentiment-aware personalization affects learner persistence, course completion, and knowledge retention over extended periods.

Finally, further work may explore adaptive weighting mechanisms for hybrid scoring. Instead of static coefficients (λ_1, λ_2, λ_3), reinforcement learning or meta - learning strategies could dynamically adjust the influence of collaborative, content-based, and sentiment-aware signals based on observed learner outcomes. This would turn the system into a self-optimizing engine, continuously learning how to weigh cognitive, behavioral, and affective inputs for maximal impact on learner success.

To assess these directions, the system can be benchmarked with both technical metrics and educational impact indicators. On the technical side, evaluation can include classification accuracy, F1-score, precision, recall, and embedding similarity measures (cosine similarity, Euclidean distance). For recommendations, metrics such as NDCG (Normalized Discounted Cumulative Gain), MAP (Mean Average Precision), and coverage/diversity scores can be applied. From an educational standpoint, longitudinal metrics like learner engagement uplift, dropout reduction, time-on-task, and course completion rates will provide evidence of real-world utility.

A variety of datasets may be employed in these evaluations. Public resources such as EdNet (a large-scale dataset of student interactions), ASSISTments (student responses to math problems), and MOOC datasets from platforms like Coursera and edX can provide behavioral logs. For sentiment training, datasets like Student Feedback Corpus, Educational Discourse Datasets, and open benchmarks like GoEmotions can serve as sources for effective annotation.

References:

[1] Albarelli, A. "Emotion-Aware Conversational Recommender Systems: A Case Study." Politecnico di Milano (2024).

[2] Polignano, M., Narducci, F., De Gemmis, M., Semeraro, G. "Towards Emotion-aware Recommender Systems: An Affective Coherence Model Based on Emotion-driven Behaviors." Expert Systems with Applications (2020), 170, 114382.

[3] Leung, J. K., Griva, I., Kennedy, W. G. "Text-based Emotion Aware Recommender." arXiv preprint arXiv:2007.01455 (2020).

[4] Saraswat, M., Chakraverty, S., Kala, A. "Analyzing Emotion-based Movie Recommender System Using Fuzzy Emotion Features." International Journal of Information Technology (2020), 12(3), 467–472.

[5] Bustos-López, M., Alor-Hernández, G., Sánchez-Cervantes, J. L. "EduRecomSys: An Educational Resource Recommender System Based on Collaborative Filtering and Emotion Detection." Interacting with Computers (2020), 32(4), 407–432.

[6] Zhu, X., Liu, Y., Zhang, Y. "Recommender Systems in the Era of Large Language Model Agents: A Survey." arXiv preprint arXiv:386342676 (2025).

[7] Zhang, H., Li, C., Wu, J. "SEALR: Sequential Emotion-Aware LLM-Based Personalized Recommendation System." Proceedings of the ACM Conference on Recommender Systems (2025), 123–132.

[8] Wang, Y., Chen, F., Liu, P. "LLM4Rec: A Comprehensive Survey on the Integration of Large Language Models in Recommender Systems." Future Internet (2025), 17(6), 252.

[9] Chen, M., Zhao, K., Xu, L. "Recommender Systems Meet Large Language Model Agents: A Survey." ResearchGate (2025).

[10] Li, J., Zhou, Y., Wang, R. "Towards Agentic Recommender Systems in the Era of Multimodal Large Language Models." arXiv preprint arXiv:2503.16734 (2025).

[11] Sun, Q., Hu, X., Liu, D. "The Application of Large Language Models in Recommendation Systems." arXiv preprint arXiv:2501.02178v2 (2025).

[12] Kumar, R., Singh, A., Verma, P. "Emotion and Sentiment Enhanced Decision Transformer for Personalized Recommendations." Scientific Reports (2025), 15, 12345.

[13] Zhao, J., Huang, T. "Bringing Emotions to Recommender Systems: A Deep Dive into Empathetic Conversational Recommendation." Shaped AI Tech Blog (2025).

[14] Dhelim, S., Ning, H., Aung, N., Huang, R., Ma, J. "Personality-Aware Product Recommendation

System Based on User Interests Mining and Meta-path Discovery." IEEE Transactions on Computational Social Systems (2020), 7(6), 1234–1245. DOI: 10.1109/TCSS.2020.3037040.
[15] Zhang, P., Luo, X., Chen, Y. "Emotion-based Recommender System." arXiv preprint arXiv:2505.16121 (2025).
[16] Nowak, A., Wójcik, T. "Large Language Models in Recommendation Systems." Techblog RTB House (2025).
[17] Yadav, S., Singh, M., Gupta, R. "Tourist Recommender Systems Based on Emotion Recognition." Future Internet (2021), 13(1), 2.
[18] Park, S., Lee, H., Choi, J. "Prompting Large Language Models for Recommender Systems." arXiv preprint arXiv:2401.04997 (2024).
[19] Wu, J., He, X., Yu, K. "EARS: Emotion-aware Recommender System Based on Hybrid Information Fusion." Expert Systems with Applications (2016), 56, 1–10.
[20] Akbik, A., Bergmann, T., Vollgraf, R. "Pooled Contextualized Embeddings for Named Entity Recognition." Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (2019), 1, 724–728.
[21] Akhtar, S., Chauhan, D., Ekbal, A., Bhattacharyya, P. "MELD: A Multimodal Multi-Party Dataset for Emotion Recognition in Conversations." Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (2019), 527–536.
[22] Maas, A. L., Daly, R. E., Pham, P. T., Huang, D., Ng, A. Y., Potts, C. "Learning Word Vectors for Sentiment Analysis." Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (2011), 142–150. Dataset available: https://ai.stanford.edu/~amaas/data/sentiment/.

[23] Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A. "HuggingFace's Transformers: State-of-the-Art Natural Language Processing." Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations (2020), 38–45. https://doi.org/10.18653/v1/2020.emnlp-demos.
[24] Loria, S. "TextBlob: Simplified Text Processing." TextBlob Documentation (2018). Available: https://textblob.readthedocs.io/.
[25] Bain, M. "WhisperX." GitHub Repository (2025). Available: https://github.com/m-bain/whisperX/releases.
[26] Bustos-López, M., Alor-Hernández, G., Sánchez-Cervantes, J. L. "EduRecomSys: An Educational Resource Recommender System Based on Emotion Detection." International Journal of Web and Grid Services (2020), 32(4), 407–420.
[27] Kumar, R., Singh, A., Verma, P. "Emotion and Sentiment Enhanced Decision Transformer for Personalized Recommendations." Scientific Reports (2025), 15, 12345.
[28] Zhu, X., Liu, Y., Zhang, Y. "SEALR: Sequential Emotion-Aware LLM-Based Personalized Recommendation System." Proceedings of the ACM Conference on Recommender Systems (2025), 123–132.
[29] Wang, Y., Chen, F., Liu, P. "LLM4Rec: A Comprehensive Survey on the Integration of Large Language Models in Recommender Systems." Future Internet (2025), 17(6), 252.
[30] Chen, M., Zhao, K., Xu, L. "Recommender Systems Meet Large Language Model Agents: A Survey." ResearchGate (2025).
[31] Li, J., Zhou, Y., Wang, R. "Towards Agentic Recommender Systems in the Era of Multimodal Large Language Models." arXiv preprint arXiv:2503.16734 (2025).