

A Multimodal Sentiment Analysis Framework for Personalized Mentoring in Learning Management Systems.

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Abstract

The proliferation of online learning in today's digital world necessitates advanced techniques for personalized mentoring. Online learning has transformed education, but its success hinges on maintaining learner engagement and motivation. A learner's emotional state plays a crucial role in online learning, influencing motivation, engagement, and comprehension. Unlike traditional classrooms, digital environments often lack real-time emotional cues, making it harder to detect struggles or disengagement. Understanding and responding to a learner's emotions enables personalized interventions to create an effective learning experience that enhances both academic performance and well-being. Learning Management Systems (LMS) must recognize learners' preferences, needs, and learning styles to adapt themselves and provide the necessary recommendations and personalized content. Our objective in this paper is a discussion on personalized mentoring-based learning management systems (LMSs) that will enhance the learning motivation of an e-learner through multimodal sentiment analysis (MSA). The emotional state of a learner is a major contributing factor to his or her learning quality. This research states how emotional states could be identified by MSA techniques from their reactions and feedback on different social media platforms like Facebook, Instagram, and Twitter by applying Natural Language Processing (NLP), Computer Vision (CV), Prompt Engineering using Generative AI, and Agentic AI....

Keywords: Online learning, learner's emotions, Learning Management Systems (LMS), multimodal sentiment analysis (MSA). Natural Language Processing (NLP), Computer Vision (CV), Agentic AI, Generative AI, Prompt Engineering.

Introduction

The advancement in the use of Information and Communication Technology (ICT) especially social networking is greatly improving and changing social relations and sharing of knowledge. Social networking sites have now become an important part of the current society as it has made it possible to be connected 24/7 no matter the time differences across the world. This trend has also shifted organizational and institutional communication from the conventional approach of reaching out to a consumer at a given time and extending it to reach out when the consumer is convenient to use social media platforms. This cultural shift is defined by the recent upgrade of Learning Management Systems (LMS) that took education from a traditional physical classroom to an online education platform that could be accessed anywhere at any time. Our subject of interest in this paper is a discussion on personalized mentoring-based learning management systems (LMSs) that will enhance the learning motivation of an e-learner through multimodal sentiment analysis (MSA), which is shown in Figure 1, 2, 6. Along with all the other sectors, the teaching-learning process is also shifting its paradigm from a physical classroom and tutor with a prescheduled time slot to anywhere anytime teaching learning without any physical classroom or tutor. The fundamental reason behind the rapidly growing popularity of these (LMSs) is the evolution of personalized learning environments (PLE). The e-learning processes are now able to educate learners according to their personalized features. This is an attempt to replicate the physical teaching-learning process virtually. Due to the enormous development in the machine learning (ML) sphere, these LMSs can classify learners according to their different personalized features like learning style, attentiveness, cognitive ability, specialized requirements, etc. The learners belonging to different classes are recommended different learning objects (LO), learning content (LC), tutors, etc. after discovering the most appropriate one for them by applying different ML algorithms. In our

observation what is still not taken into consideration is the sentiment or emotion of the learners. The emotional state of a learner is a major contributing factor to his or her learning quality. Firstly, learners' emotional states could be identified by MSA techniques from their reactions and feedback on different social media platforms like Facebook, Instagram, and Twitter, or by using Prompt engineering followed by applying Generative AI and Large Language Models LLMs. Then according to the proposal of this work, the learners identified with interactive/non-interactive patterns could be assisted or recommended with LOs and LCss to alter his or her emotional state to a more positive sentiment. The recommended LOs and LCs could be built from the interactive feedback of the learner or sentiment/emotion analysis of the learner using Natural Language Processing (NLP), Computer Vision (CV), Prompt Engineering using Generative AI, and Agentic AI. The final target is to enhance the learner's learning motivation based on their sentiment or emotions. According to our observation, we surveyed 78 previous research works broadly from two sections. One is recommender systems, and another is MSA. We have focused especially on the systems that are related to the teaching-learning process including some works from other domains like social networking sites, YouTube, music, Travel, movies, etc. We have summarised some related survey works in Table 2. This shows that previously no research work has been conducted including both the topic of recommender systems and MSA in the context of e-learning using Generative AI and Agentic AI as per our findings. We have discussed some of the previous work related to this topic. However, we were unable to discover any single previous work in our thorough inquisition which contains both the topic MSA as well as recommender systems based on e-learning. The objective of this survey is to motivate more research works on how to improve learning motivation in online learning platforms that are capable of providing recommendations to the learners. As motivation is directly related to a person's sentiment we included an extended survey of both the topics of recommender systems and multi-modal sentiment analysis. So the development of new frameworks of intelligent tutoring systems with personal mentoring to improve the motivation of a learner could be encouraged. We justify the novelty of this work through the above exposition. One of the fundamental factors that have informed the implementation of these systems is known as personalized learning and it entails delivering learning content based on characteristics of the learners. Due to Machine Learning innovations of recent days, LMS can now sort the learners based on distinct criteria like learning styles, intelligence levels, and learning requirements. Despite the effectiveness of these capabilities, there remains an untapped area for enhancing learning outcomes: managing engagement and passion from learners. Besides mood's important influence on learning outcomes, the current LMSs rather ignore this point. While prior work proffers an approach to measuring learners' emotions, it fails to present integrated indices for sentiment detection. Hence, given this knowledge, appropriate education systems can positively influence the emotional response and promote effective learning. This survey aggregates knowledge obtained from the analysis of 78 research papers published in the last five years covering recommender systems and MSA. More importantly, the literature reveals that few studies have integrated these fields in the context of e-learning which places this research within a unique and promising research territory and opens up the possibilities of knowledge integration in this area.

Article Selection Process

The procedure of the article inclusion in this survey aimed at specifying the works in which authors used MSA to examine the learners' emotional state for delivering individual learning in the context of e-learning platforms. A total of 78 articles were chosen based on their alignment with two primary clusters: recommender systems in PLE and MSA and using and developing positive feedback loops in the former and partnering and network analysis in the latter.

Clusters and related references

Cluster	Cluster Name	No of Articles		
1.	Recommender Systems	37		
2.	Multimodal Sentiment Analysis	41		

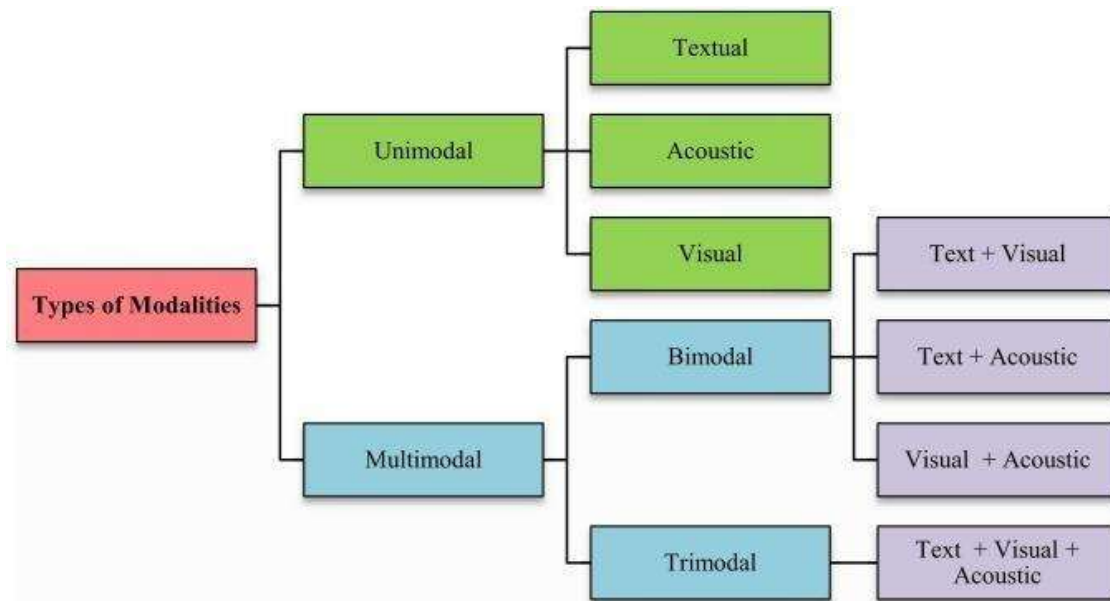
Year-Wise Publication Count

Year	Publication Count
2024	37
2023	12
2022	4
2021	7
2020	1
2019	5
2018	2
2017	0
2016	0
2015	1
2014	0
2013	0
2012	2
2011	1

The first of them, which includes 37 articles, relates to recommender systems specific to e-learning platforms. The intent here is to create systems that favor learning experiences with the capacity to deliver content following the learner's desire and requirements. Focus was made on the papers that describe how sentiment analysis is incorporated to capture the emotions of learners to make educational content more dynamically responsive. The second cluster is devoted to the analysis of multimodal sentiment, which includes 41 articles. These researches focus on the multimodal approaches that are text, image, and speech for the analysis and recognition of learners' emotions. The selected articles describe new approaches in algorithms and architectures that have been designed for the increased precision of class recognition together with a greater level of detail. In filter criteria, the focus was made on the latest works to the year 2024, which allowed addressing the contemporary research findings and methods. Studies were chosen to match the special focus on MSA and applying personalized systems for learners considering both the online and face-to-face learning environments. The selection procedure was designed to offer a general perspective of the current tendencies, opportunities, weaknesses, and innovations associated with the use of MSA to increase learners' engagement and educational processes in various e-learning contexts. The main objective is to enhance the learning motivation of an e-learner based on their sentiment or emotion. For this, a recommender system has to be designed and developed which will personalize the learning experience. Now the Recommender system category is divided into the following subcategories. The block diagram of these categories is also shown in Figure 3.

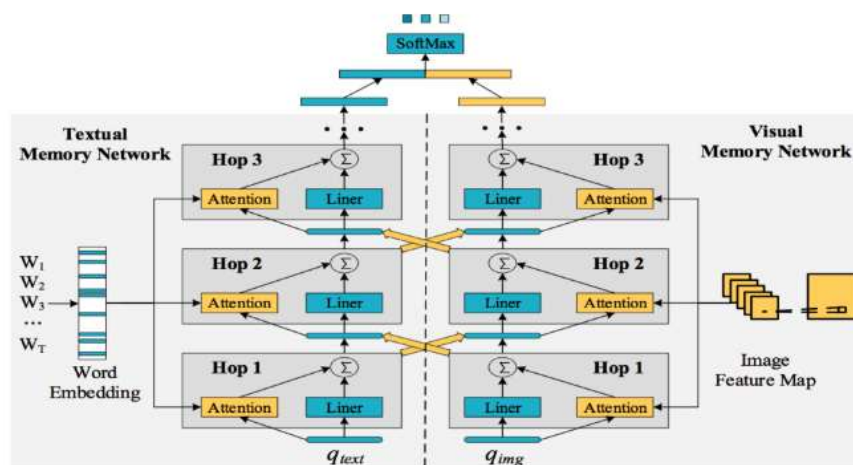
Learning-Based Recommender System- In this section, we studied articles that have used recommendation systems as a part of an e-learning process. We reviewed a total of 9 articles which are further classified into the following two categories.

Recommendation according to learning style - In this category we have selected those articles that have considered the learner's learning style to recommend learning content accordingly. A total of three articles have been chosen and their objective, limitations, and scope of future works are discussed Nafea et al. [1] [2] Jyothi et al.[3]. E-learning framework systems are central to the processes of availing educational experiences tailored towards learner attributes. The three articles reveal various strategies for utilizing recommendation algorithms to boost the performance of learning environments. Thus, categorizing these studies, the survey tries to identify the trends in the approaches and instruments used to provide material that is sensitive to the learners' needs and preferences and to adjust the learning material in real time. Such categorization emphasizes the importance of recommendation systems for educational efficiency achieved through the effective use of individual learning methods.



Recommendation according to learners' needs and preferences - A total of six articles are taken into consideration in this section to scrutinize their objectives, limitation and possible extensions. Authors of these articles considered learners specific preferences and requirements for offering recommendations to them Hidayet et al [4] Soulef et al [5] Wan et al [6] Cardenas et al [7] Cagliero et al [8] Montuschi et al [9] Mathew et al [10]. Educational research indicates that aspects such as age, education, rate of learning, and lecture processing should be determined by learner characteristics. It is believed that such factors are likely to influence the recommendations to improve the engagement and effectiveness of the strategies offered. Recent studies deploy highly complex algorithms to capture learners' behaviors and preferences from data resulting from learning management systems, user interactions, and feedback instruments. These systems make the learning process more effective by categorizing the recommendations based on the learners' sentiments, which is supported by the MSA.

Recommendation Based on Learning Style - This recommendation system utilizes customization to meet various learning needs based on the nature of the learner, especially through the personalization of learning content and procedures. Extending the idea of different practical learner types: visual, auditory, kinetic, and reading/writing ones, recent studies underline the role of machine learning and data analysis methods for identifying and working with these learning profiles. It seeks to improve learning achievements by identifying the learning styles that are suited to the learners as well as the learning environments.



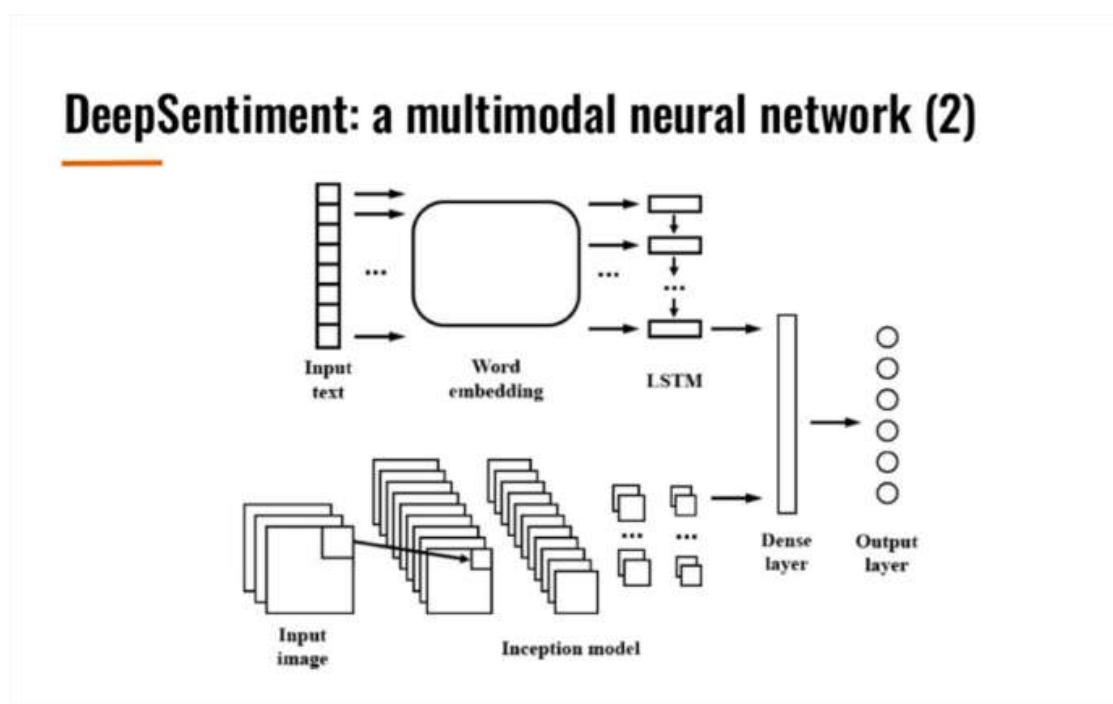
Recommendation with contextual information: The only article selected in this category is where contextual information of a learner is also used as an attribute for creating recommendations as discussed by Verbert et al [11]

Recommendation based on sentiment analysis: Sentiment analysis recommendation intends to utilize the learners' emotions and preferences derived from the analysis of multi-modal data for online learning and face-to-face learning scenarios. Previous works have used text, speech, and facial features to capture emotional state information for improving the accuracy of which movies are recommended to which patron. Some issues are still with the blending of several modes, protection of data, Yazdi et al [12] and other moral issues in using emotional data for learning. However, despite these challenges, there is still a lot of work being done to develop a sentiment-aware recommendation system and there are possibilities for enhancing the effectiveness of personalized e-learning environments and Personal Learning Environments (PLEs) through the help of the offered recommendations as stated by Kousika et al [13] Xiong et al [14] and Shah et al [15]

Recommendation with AR-VR virtual reality and Augmented Reality: AR and VR technologies are being applied in learning institutions as methods of providing students with innovative means of learning through a virtual environment reserved special token 264 These technologies present new opportunities to share and teach multimedia content in face-to-face as well as distance learning environments. These are the stability and synchronization of modalities, problematic identification of the real-time context, optimization of analysis performers, the question of how reliable sentiment analysis is in immersive situations, and ethical questions concerning data privacy and user's emotions. it is observed that the complexities of recommendation systems based on AR-VR remain persistent due to the progress of technology along with applications of multimodal interactions in learning systems, as pointed out in Lian et al [16] , Rahman et al [17] & Shah et al [18]

Previous survey works on Recommender systems

Prior reviews of recommender systems in learning environments have captured more developments in the area of personalized learning clearly. Such surveys have discovered trends in recommendation generation based on learning approaches and context, polarity detection, and incorporation of AR-VR support. it offers coverage and summary of the methodologies and results that shape the current existing research regarding the improvement of future recommendations in education.



Text-Based Sentiment Analysis- The group of studies called “Text-Based Sentiment Analysis” focuses on methods and approaches associated with sentiment assessment from text. These studies seek to categorize sentiment types and also learn about the existence of positive or negative sentiment polarity

Image-Based Sentiment Analysis- Image-based Sentiment Analysis refers to the assessment of sentiments depicted in images. In the past, scientists relied on facial recognition, scene analysis, and image description methods to come up with accurate estimates of emotions depicted by pictures. The deep learning approaches used in this field have been getting better with changes in facial expressions and understanding as discussed by Zhu et al [19] , Nesterenko et al [20] & Chen et al [21]

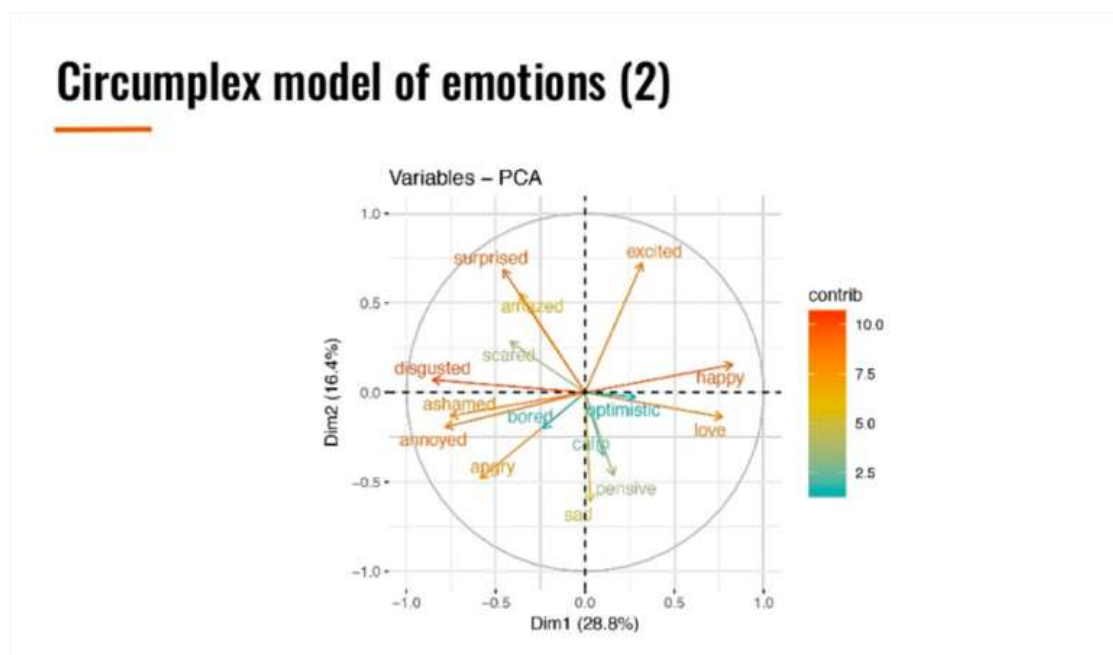
Multi-Mode Based Sentiment Analysis- Multi-Mode Based Sentiment Analysis involves using different data types that include text, images, audio, as well as videos to carry out sentiment analysis. To a certain extent, they are able to capture contextual information well, as this structured framework enables an analysis of emotions across multiple types of data. Deep learning networks applied to sentiment analysis have improved through fused schemes highlighted by Kapoor et al [22], Arumugam et al [23]

Previous Survey Works on MSA- The earlier chapters in MSA are concerned with the ability to employ multiple data streams to measure sentiments in various contexts. These surveys offer a systematic review of the development of techniques for using text, image, audio, and sometimes physiological information to determine affective states accurately. MSA has been applied in educational contexts that have helped improve learners' emotional comprehension, especially in online courses, collaborative platforms, and virtual learning environments. This allows concluding the history and development of the MSA for the individual Learning Space as mentioned Lee et al [24], Om et al [25].

Brief Survey of Selected Articles

Recommender Systems

Recommender systems have advanced with the improvement and development of machine learning and artificial intelligence more so in learning and education systems. Current research reinforces the use of custom learning that entails advanced mathematical models to interpret the user's activity. Educational material recommending and course-finding methods including but not limited to collaborative filtering, content-based filtering, and hybrid approaches are widely used for creating educational materials, courses, and learning paths based on students' requirements.



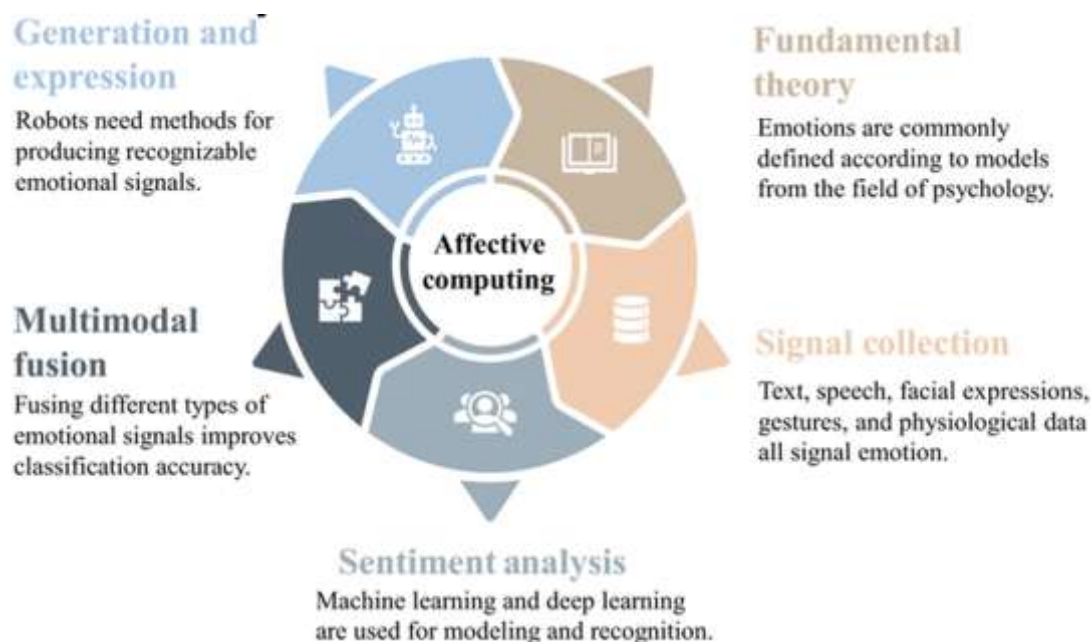
The development of new deep learning models has also helped the recommender system to advance due to the increased capacities for data interactions and feedback from the users. These systems incorporate big data to enhance the effectiveness of recommendations and enhance the utility of recommendation procedures to K to 12 education, college, and professional learning forums. New avenues in recommender systems focus on both the efficiency of and interpretability of the models, clients' and users' privacy, and the provision of reliable evaluation methods for application in the sphere of education.

Learning-Based Recommendation Systems

The professorate of recommender system studies has evolved dramatically to incorporate learning-based models for improving the recommendation function in education. These systems incorporate mechanisms such as machine learning to begin, to dissect users' preferences and behaviors in efforts to bring forth personalization in learning processes, to increase the user engagement, as well as, the learning achievements. Recommendation models that involve learning include collaborative filters, content-based filters, and the hybrid model to recommend other learning materials, courses, and learning activities to students in a special learning environment. The use of multimodal learning systems has expanded the possibilities of the use of recommender systems in educational environments. As for the future research prospects in learning-based recommendation systems, the focus is made on the further developments of large-scale and comprehensible models, more effective and privacy-preserving

approaches, and effective evaluation schemes. Furthermore, the same reforms will act as a stepping-stone to the enhancement of the integration of the advanced recommender systems to the education technology for the improvement of both online and offline learning procedures Pei et al [26], Zheng et al [27], Khan et al [28].

Recommendation according to learning style- Moving to the category of learning-based recommendation systems, the strategy of using personalization as far as the learning styles of learners is concerned has attracted a lot of interest. Scholars have developed models to categorize learners according to learning style models like Felder-Silverman, thus creating better recommendations for LOs. Such systems often have to use clustering algorithms such as K Means and a mix of filtering techniques to estimate learners' preferences; deploying properties such as LO profiles and learner ratings where necessary.



Recommendations Based on Learners- Learning-based recommendation systems are increasingly incorporating personalized attributes of learners. Recent research highlights improvements through the use of MSA (MOS) to enhance the effectiveness of these systems in both online and offline learning environments. These methods utilize deep learning and AI techniques to evaluate various forms of data, including speech, text, and facial expressions, to identify a learner's sentiment and engagement status. Such advancements indicate the emergence of post-ELIAS learning paradigms that leverage learners' affective states and preferences to tailor learning materials and interactions, optimizing outcomes and experiences Peng et al [29], Laak et al [30], Wang et al [31], Goel et al [32].

Recommendations with Contextual Information- Innovations in recommender systems have incorporated contextual information to enhance the accuracy of recommendations in both web-based and face-to-face education. Current research focuses on integrating MSA and deep learning to extract contextual features from text, speech, and facial expressions Jun et al [33]. These developments suggest that learning content and communications should align with a learner's emotional status Figure 4, preferred learning mode, and surrounding conditions. The goal of these systems is to boost learner engagement, achievement, resource utilization, and user satisfaction across diverse learning environments as mentioned by Elbourhamy et al [34], Hazmoune et al [35], Wu et al [36], Moshawrab et al [37]

Recommendations Based on Sentiment Analysis- In recent years, recommender systems have advanced by incorporating sentiment analysis to provide learning environment suggestions for both online and offline settings. New deep learning methods enable these systems to process learners' multimodal data, including text, voice, and facial expressions, to deduce emotional states. This approach addresses varying learner emotions, recommending adaptive learning strategies based on mood, preferences, and emotional responses during the learning Alsality et al [38], Kapoor et al [22], Lee et al [24].

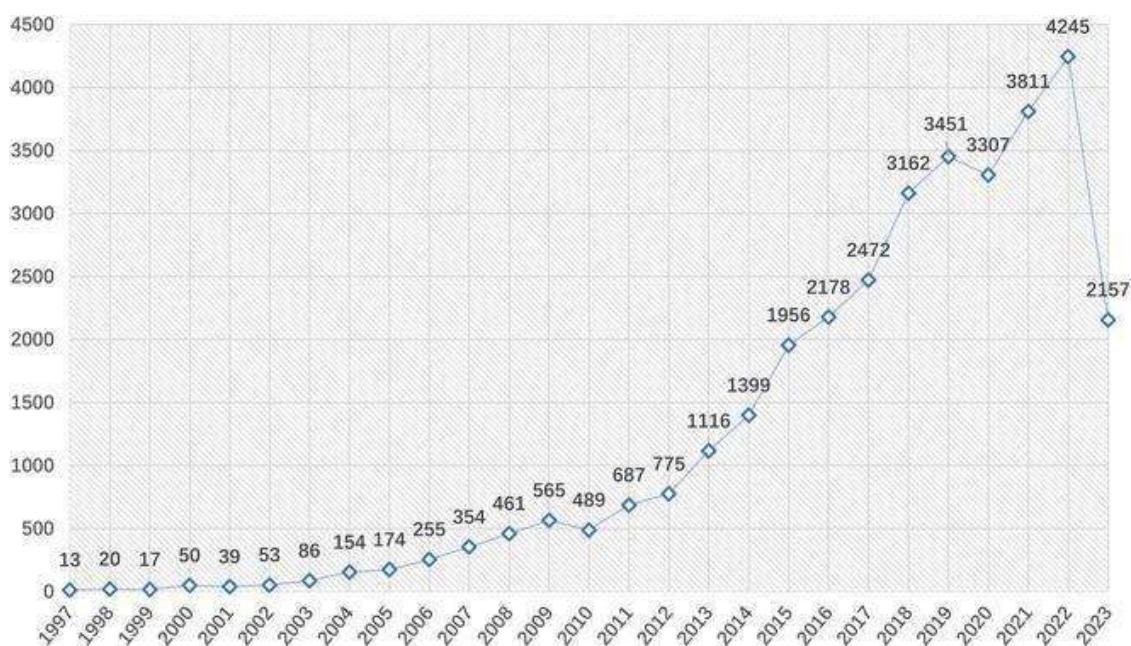
Recommendations with AR-VR- Recommender systems have evolved to integrate augmented reality AR and virtual reality VR technologies, enhancing user experiences in both online and offline learning. AR and VR enable educational content to be integrated into physical reality or create fully simulated environments for educational purposes. The incorporation of AR-VR in recommender systems makes learning platforms more engaging and tailored to users' abilities, thereby improving engagement, retention rates, and learning achievements. This

strategy employs multiple sensory modalities to design engaging, context-aware learning experiences that enhance learning outcomes and knowledge acquisition Verbert et al [11].

Similar Survey Works on E-Learning Recommender Systems- Recent literature reflects a growing interest in enhancing e-learning through advanced recommender systems. These efforts emphasize adaptive learning environments that utilize diverse modalities such as speech, text, and facial expressions to customize educational content and interactions based on individual preferences and emotional responses. This approach aims to optimize learning outcomes in modern educational settings Wang et al [39] [40] , Lee et al [24]

MSA

New directions in MSA have extended the use of additional modalities including speech, text, and facial information for improving emotion recognition in online and offline learning. The future scopes are thus focused on enhancing the model's robustness, developing advanced cross-modal integration methods, and solving the privacy issues related to the massive multimodal datasets. Such efforts tend to individualize learning processes and develop ways of improving the results based on emotional intelligence Cardenas et al [7] , Salur et al [41].



This is advantageous to the system that is used in the analysis and it is also advantageous to the users of the system. Users get ready-made recommendations of content depending on their preferences but they are dependent on the earlier sentimental responses regarding similar topics thus saving a lot of time on the search for similar materials. While as where the system gets the views, opinions, or feedback about a particular related topic by analyzing them they can build a prediction, an insight into a particular product, or incident. This helps the organization that uses the system to develop better products and forecast better outcomes, which in the long run, improves its performance. The above-discussed situation is quite explanatory in making us understand the significance of sentiment analysis in the contemporary world of existence. The underlying technology behind this sentiment analysis is artificial intelligence and machine learning.

Text Based Sentiment Analysis

The state-of-the-art sentiment analysis in multimodal scenarios, with an emphasis on text-based approaches, has been bolstered by the application of deep learning techniques for decoding emotions in text. Recent developments will continue to work on refining the paradigms in natural language processing (NLP), with the focus being placed on the increasingly complex classification of sentiment analysis and developing a composite approach for processing multiple modes of data to better understand the emotional aspect in both online and traditional learning contexts Chen et al [21] , Mahendhiran et al [42] Geetha et al [43]. Other related research includes sentiment classification of e-learning blogs and forums based on textual information by Kechaou et al [44]. MI, IG features, and CHI statistics are applied for this analysis as well as hybridized HMM and SVM classifiers. They might consider using emotional reactions for sentiment analysis and including suggestions to recommend how the e-learning platforms and blogs could be improved Annapareddy et al [45].

Image-Based Sentiment Analysis

Textual sentiment using a deep learning approach has been commonly applied in the multimodal platform for affective information processing. In addressing this research question, this learning approach employs

convolutional neural networks (CNNs) and transfer learning to detect emotionally related aspects in images from education contexts. Some of the major issues are semantic analysis of visual pleasantness, combining text and speech material, and learning from different groups of learners. In future works, the specification of CNN structures for emotion recognition, optimal multimodal fusion through ensemble learning, and explainability in AI frameworks remain as promising areas. The advancements here are used to expand the scope of emotional intelligence, enhancing the empathy assessment of face-to-face, or face-to-face and online learning environments. The process of image analysis to determine the attentiveness of a student is done. This platform known as Smartcoach is used to suggest students' right tutors who are nearer to them best suited to them concerning previous records regarding attributes like proximity, track records, etc. Tutors on their part can avail of this platform to post learning materials, assignments, and quizzes, and monitor student's attendance and attentiveness to the sessions. Eye movements of the student in the student image are used to keep track of attentiveness. However, it has not been implemented in the real-time live classes. For example, attention monitoring could be made more precise, if other parameters like head positions, face angles, and body postures, etc. are taken into account. Ratings could be provided much more accurately if the results of students, the grades of tutors, etc. are taken into account.

Multi-Mode Based Sentiment Analysis

Multi-modal sentiment analysis comprises textual data speech and other significant emotional signifiers to improve educational strategies. Further developments aim at using deep learning architectures and ensemble learning to incorporate several data sources to develop learning activities that take into account distinct emotional states in online and offline learning environments proposed by Wu et al [36], Shah et al [18];

Previous Survey Works on MSA

Previous studies on modality integration for sentiment analysis have provided a useful groundwork for using text, speech, and visuals across different contexts in emotion detection. These surveys explain the current techniques for emotion detection utilizing deep learning approaches with significant issues like data variation, model interpretability, and practical difficulties in real-world application at a large scale. For future work, it is suggested to construct more efficient and thorough multimodal learning architectures that utilize numerous data inputs significantly improving learners' engagement in both, online and on-campus learning environments Zheng et al [27], Salazar et al [46]. According to Hussien et al [47] there are different methods of fusion as well as the features of different modes for categorizing the sentiments of information existing in these modes. The following section includes an overview of the related studies in other languages and English for the MSA Figure 5. A review of the datasets commonly employed in studies of MSA is presented by the authors in the subsequent sections. Finally, the authors discussed various uses of MSA and associated issues. As mentioned by the authors, one of the potential drawbacks and constraints of available works identified in this study is the fact that there are only a handful of frameworks available to the present day for sentiment analysis of information in languages other than English. Sharma et al [48] Shatin et al [49] reviewed the literature on the extraction of sentiments and emotions from text data and feature extraction from images. Their primary goal was to investigate the impact of utilizing deep learning algorithms for sentiments within image and textual data. They posited that through experiments with assorted types of datasets and models, which they have employed, they have determined that CNN models are better than RNN models in connection with textual data. Other features of textual data are also enhanced by pre-trained word embeddings. However, experiments conducted on other modes and languages are not considered in this work. Also, the authors did not describe the specific models they employed or any other technical details of the experiment.

Comparative Analysis of Previous Survey Works

This section provides a brief literature review of prior survey studies examining MMSA in both virtual- and face-to-face communication. Of the surveyed studies, the majority focus on isolated aspects of learning management systems (LMS) such as PPS-RL or MMSA; only a scant few address both at once. Most of the previous research is focused on the technological aspect and applications with significant emphasis on deep learning for emotion recognition and sentiment analysis in the learning context. This review emphasizes the benefits of integrating a personalized learning strategy with MSA to improve social computing systems and provides important implications for future research and application for effective solutions in enhancing the education experience through an intelligent learning approach and personalized sentiment analysis proposed by Kousika et al [13].

Limitations

These points reveal the direction of further technological development, the lack of coverage of new surveys, and the elaboration of actual studies based on the identified approaches in the field of MSA in online and offline learning contexts.

The review describes the technological aspects of the previous studies of MSA and points out the lack of such a survey to understand methodologies and applications in detail.

Another section could be incorporated to specify the history of the advancements of machine learning and deep learning techniques in the field of multimodal sentiment and its relation to e-learning.

Other surveys conducted on similar topics might reveal the new trends in the research that has been carried out in this rather rapidly developing field and stress the need for systematic reviews.

It would be clearer to classify current trends concerning research in terms of technological characteristics such as the use of deep learning structures or multimodal integration methodologies.

Discussion and Future Work

The following section focuses on the possible areas of work on personalized learning concerning MSA by conducting a literature review up to the year 2024. The survey identified several key areas for future research and development in enhancing educational practices through advanced sentiment analysis techniques and personalized learning strategies: The survey identified several key areas for future research and development in enhancing educational practices through advanced sentiment analysis techniques and personalized learning strategies:

Adaptive Teaching Strategies: Perhaps the next related studies could explore how to manage individual learners' moods to learn whether the presence of such a parameter affects the adaptation of teaching methods in various interactive e-learning environments. In this case, personalized adaptivity is intended to maximize the learner's experience depending on current emotional conditions. Ifenthaler et al [50]

Emotion-Driven Recommendations: As one of the potential areas of improvement, it is possible to highlight the further increase in the effectiveness of the teaching-learning process with the help of suggestions made based on learners' affective states. MSA can be complemented with recommender systems and thus, personal education content can be suggested depending on the emotional context Luna-Jimenez et al [51] , Kumar et al [52] , Thao et al [53].

Advanced Recommender Systems: To address still more complex requirements of recommender systems, multichannel sentiment analysis is requisite. it should be able to analyze the emotional signals from different modalities ranging from the textual, spoken, to the video for richer advisement Mohammad Et al [54] , Wang et al [40] , Swalha et al [55].

Social Media Sentiment Analysis: Recognizing facts such as memes, stickers, micro videos, hashtags, and other social media data, it becomes imperative for organizations to employ proper sentiment analysis methodologies Machova et al [56]. This effort shall seek to capture the quantitative measures of negative, positive, and mixed feelings in forms of communication that are ascribed to non-conventional classes in e-learning environments Rasappan et al [57] , Wang et al [40].

Non-Cognitive Skill Development: Subsequent research should attempt to identify strategies that need to be incorporated into e-learning systems to address the non-cognitive aspects of learning including motivation, persistence, attitude, etc. Building up these attributes can decrease the dropout rates and at the same time the general learning gains Amiriparian et al[49] , Wang et al [40].

Enhancing Learning Motivation: Finding ways on how the supervision in learners' learning motivation can be enhanced in e-learning environments may well replicate the role of the class tutor. It also carries the advantage of greatly decreasing the incidence of learners' dropout and improving engagement Jim et al [58] Jimenez et al [51].

Challenges in Recommender Systems: Concerning technical problems like cold start issues, data sparsity, scalability, and over-specialization in recommender systems, the effort persists. There is no way to deny that these characteristics are inherent; researchers have to find ways to offer relevant recommendations.

Privacy Concerns: The recommendation to the learner should employ methods that ensure the learners' private information used in the recommendation is safeguarded especially location and time information. As future work, It recommends the enhancement of privacy-preserving methods in edX and other educational recommender systems.

Multilingual Data Challenges: One challenge that can be noted is that there is a lack of datasets related to the MSA in languages other than English. Overcoming this issue requires the generation of more diverse datasets for sentiment analysis that will support applications in education across the world Pranavneet et al [59].

Video Data Quality: There is a need to enhance the manner of decoding and extraction of emotion from video information. Special approaches towards filtering noises as well as towards improving the clarity are called for if learner emotions are to be quantified from videos Figueroa et al [60].

Cross-Lingual Sentiment Analysis: A rather promising and today's still emerging area of concern is the construction of models capable of specific SA in different languages. It targets overcoming the problem of limited datasets in languages other than English that are usually considered in sentiment analysis.

These areas will enable the subsequent research studies to progress the field of personalized learning using MSA in serving meaningful solutions to improve learning system performance as well as foster learners' development in the online and offline settings Fu et al [61] Fadiweiva et al [62].

Conclusion

The detailed analysis provided by the survey aims to study research trends in HL in association with TEL and also improve the quality of personalized learning by performing MSA through understanding the learner's emotional state through his/her way of interaction in different social media platforms like Facebook, Instagram, Twitter by applying Natural Language Processing (NLP), Computer Vision (CV), Prompt Engineering using Generative AI, and Agentic AI. The survey categorizes the research into two main areas: recommenders and polycontextuality sentiment analysis. This discussion includes different frameworks, methodologies, limitations, and further directions in these areas. The survey reveals that existing work focuses mainly on TEL with suggestions using either recommendation and/or MSA, but seldom both in combination. This survey plays an important role in the scholarly research for proposing the current status and future directions of personalized learning in TEL. Therefore, by identifying the relationship between the recommender systems and MSA, this work paves the way for further research that will attempt to boost the learning experiences by applying advanced technology

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