International Journal of Cognitive Computing in Engineering 5 (2024) 221–236

Contents lists available at ScienceDirect

International Journal of Cognitive Computing in Engineering

journal homepage: http://www.keaipublishing.com/en/journals/international-journal-of-cognitive-computing-in-engineering/

Analyzing emotions in online classes: Unveiling insights through topic modeling, statistical analysis, and random walk techniques

Benyoussef Abdellaoui [a,*], Ahmed Remaida [a], Zineb Sabri [b], Mohammed Abdellaoui [c], Abderrahim El Hafidy [d], Younes El Bouzekri El Idrissi [a], Aniss Moumen [a]

[a] National School of Applied Sciences, Engineering Sciences Laboratory, Ibn Tofaïl University, Kenitra, Morocco
[b] Faculty of Sciences, Laboratory of Computer Science, Ibn Tofaïl University, Kenitra, Morocco
[c] LPHE-modeling and Simulation, Faculty of Sciences, Mohammed V University, Rabat, Morocco
[d] Software Project Management Research Team, ENSIAS, Mohammed V University, Rabat, Morocco

ARTICLE INFO

Keywords:
Deep learning
Emotion recognition
Topic modeling
NMF
Emotion detection
Facial emotion recognition
AHC
Factor analysis
Random walk

ABSTRACT

High dropout rates globally perpetuate educational disparities with various underlying causes. Despite numerous strategies to address this issue, more attention should be given to understanding and addressing student emotions during classes. This lack of focus adversely affects learner engagement and retention rates. While previous studies on online learning have primarily emphasized the effectiveness of technology, infrastructure, cognition, motivation, and economic benefits, there is still a gap in understanding the emotional aspects of distance learning. First, this study addresses this gap by employing thematic modeling and utilizing non-negative matrix factorization (NMF) for emotion recognition through students' deep learning techniques and facial emotion recognition (FER). Second, statistical analysis of these findings further augments the depth of the study. Finally, the research proposes a mathematical model based on the random walk of emotional state transitions. The findings of this study underscore the importance of considering emotions in distance learning environments and their significant impact on student's academic performance and satisfaction. By acknowledging and addressing these emotional factors, educators can enhance learner engagement, promote positive emotions, mitigate negative emotions during online learning, and ultimately improve the effectiveness of online courses.

1. Introduction

Around the world, high dropout rates of schools affect individuals, families, and communities, creating an inter-generational dynamic of poor educational outcomes and leading to unequal opportunities for academic success. According to social capital theory, this situation results in gaps in social promotion. In the United States alone, approximately a third of public school students drop out yearly (Fall & Roberts, 2012). Uneducated individuals face higher rates of unemployment (Sum, Khatiwada, McLaughlin, & Palma, 2009) and an increased likelihood of engaging in criminal behavior and experiencing incarceration (Catterall, 1987). Children of unqualified parents are more likely to repeat the same experience as their parents, creating a cycle of disadvantage. Dropping out of school can be caused by non-academic factors such as low family income and family problems. Academic factors such as lack of study and the student's emotional infrastructure also cause dropout.

Several strategies have been adopted to combat dropout of school: controlling school absences and interruptions, diversifying and enriching financial resources for the development of the education sector, activating decentralized structures such as management councils, involving stakeholders surrounding educational establishments, developing an organizational plan for academic support, enriching educational multimedia resources, intensifying literacy, and emphasizing careerism. Despite these efforts, little attention is given to students' emotions and well-being so they can complete their studies in good conditions. Feelings are essential to learner engagement and retention by influencing their motivation and engagement in learning (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011).

Deep learning, which falls under Artificial Intelligence (AI) and machine learning (ML), employs artificial neural networks to handle complex data such as images, audio, and text. These networks are

* Corresponding author.
E-mail addresses: benyoussef.abdellaoui@uit.ac.ma (B. Abdellaoui), ahmed.remaida@uit.ac.ma (A. Remaida), zineb.sabri@uit.ac.ma (Z. Sabri), abdellaoui.mohammed@um5r.ac.ma (M. Abdellaoui), abderrahim_elhafidy@um5.ac.ma (A.E. Hafidy), y.elbouzekri@uit.ac.ma (Y. El Bouzekri El Idrissi), aniss.oumoumen@uit.ac.ma (A. Moumen).

https://doi.org/10.1016/j.ijcce.2024.05.003
Received 11 September 2023; Received in revised form 13 May 2024; Accepted 15 May 2024
Available online 27 May 2024

structured in layers for progressive feature extraction from raw input, empowering applications such as self-driving automobiles and image recognition (Sarker, 2021). The process involves training vast and intricate neural networks with numerous layers of interconnected nodes, enabling the model to automatically derive hierarchical representations of features from the data. This approach is characterized by various architectures, such as the Deep Boltzmann Machine (DBM), Deep Stacking Networks (DSN), deep belief networks (DBN) (Mary & Begam, 2020), Deep auto-encoders, deep neural networks (DNN), and convolutional neural networks (CNN) (Chahal & Gulia, 2019). Machine learning finds applications across a diverse range of fields, including computer vision, natural language processing, robotics, security and road safety (Balasubramani, Aravindhar, Renjith, & Ramesh, 2024), speech recognition (Stoychev, 2023), medicine, image and audio processing, social media, natural language, emotion detection, and sentiment analysis (Mahalakshmi, Shenbagavalli, Raguvaran, Rajakumareswaran, & Sivaraman, 2024), and handwriting recognition (Alzubaidi et al., 2023; Remaida, Moumen, El Idrissi, & Abdellaoui, 2020).

Facial Emotion Recognition constitutes a subset of computer vision and machine learning to distinguish human emotions from facial expressions. Emotion recognition involves identifying and comprehending emotions experienced by oneself or others, accomplished through computational methods or human recognition. It necessitates distinguishing between various emotions and interpreting the accompanying signs and signals. The analysis encompasses multiple stages, including face detection (Abdellaoui, Moumen, El Idrissi, & Remaida, 2020) and alignment to pinpoint facial landmarks, feature extraction to capture pertinent information from facial images, and the utilization of machine learning models, often deep learning, for emotion classification. The models' refinement and hyperparameters' optimization are pivotal for achieving high accuracy. Real-time applications may pose additional challenges, such as managing variations in lighting, facial occlusions, and non-frontal face perspectives. The depth of analysis can span from detecting the primary emotions, as delineated by Ekman and Friesen (1971), to nuanced emotion analysis, which can entail identifying subtle emotions like surprise, disgust, or a combination of emotions. Emotion recognition encompasses nonverbal indicators such as body language, facial expressions, vocal tone, and other nonverbal cues (Bonner et al., 2008). Nonetheless, this study focuses solely on recognizing emotion from facial expressions.

Convolutional Neural Networks (CNNs) or a combined feature extraction approach and classification techniques are commonly employed in traditional deep facial expression identification architectures. These methods aim to extract information from photos and categorize facial emotions (Sajjad et al., 2023). However, contemporary approaches delve into more intricate techniques, including attention processes and recurrent neural networks.

Topic modeling is a computational method for automatically discovering and extracting underlying topics or subjects in various documents (Silva, Galster, & Gilson, 2021). It finds utility in natural language processing and machine learning (Bonner et al., 2008), seeking to estimate the prevalence of each subject across a corpus of textual sources. It constitutes a form of unsupervised learning aiming to uncover the hidden semantic structure within vast amounts of text data. Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003), a statistical framework, assumes that each document contains a blend of different subjects, representing each subject as a probability distribution over the vocabulary terms.

Non-negative Matrix Factorisation (NMF) (Liu & Wu, 2010) and Hierarchical Dirichlet Process (HDP) (Teh, Jordan, Beal, & Blei, 2004) are two more common subject modeling techniques.

Research on online education has gained significance due to the rapid growth of online learning platforms, particularly in the spread of the COVID-19 pandemic, which forced educational establishments and students to adapt to digital alternatives. Understanding the emotional aspects of online classes is essential because emotions significantly impact student participation, motivation, and overall academic achievement (Di Leo, 2020).

Scientists have devised multiple techniques for examining emotions, such as self-reported assessments, behavioral observations, physiological measures, and neural network architectures such as CNN or ResNet-50 (Li & Lima, 2021). Advanced architectures like VGG19 and ResNet-50 enhance facial emotion recognition, improving student learning outcomes and enhancing e-learning platform quality (Gupta, Kumar, & Tekchandani, 2023). Many challenges face scholars studying emotions, such as the complexity of the subject, difficulty in measuring emotion objectively, and the absence of widespread databases that can be used in research (Straulino, Scarpazza, & Sartori, 2023). Furthermore, discerning emotional cues in online settings poses a considerable challenge owing to the inherent nature of digital communication and the absence of face-to-face interaction, which is pivotal for gauging emotions and crucial for fostering student motivation (Esra & Sevilen, 2021). Under their isolation and limited immediate assistance, distance learners may encounter difficulties regulating their emotions. Unlike conventional classrooms, where facial expressions, body language, and verbal cues are easily perceivable, online courses predominantly depend on written or spoken exchanges, making interpreting emotions more challenging (Abdellaoui, Remaida, Sabri, EL IDRISSI, & Moumen, 2024). Picard (2003) states that measuring and predicting emotions is as challenging as forecasting the weather. In either scenario, attaining absolute reliability remains highly improbable. The presumption that a computer can precisely detect people's emotions with an 80% precision rate is fundamentally flawed. The emotions elicited in online classes can be enthusiasm, frustration, boredom, and anxiety (Russell, 1980). Understanding and classifying these emotions consistently and meaningfully is challenging due to the intricate and complicated nature of emotions. Teachers can observe students' emotional states in traditional classrooms and adjust their teaching accordingly. In summary, evaluating and comprehending students' emotions accurately in distance learning is quite challenging. Utilizing communication technologies may result in depersonalization, potentially dismantling the emotional connections between instructors and students or even amongst the students themselves. Moreover, learners' privacy and data security concerns exacerbate their reluctance to articulate genuine feelings and thoughts. Self-report measures of emotions may only capture a fraction of the entirety of emotions experienced by students. Instructors cannot rapidly assess students' emotional responses and change their instruction accordingly. It takes work to establish a solid teacher-student relationship, which is necessary for emotional support. Research findings have indicated that students' emotions can have a crucial impact on their motivation, involvement, contentment, and accomplishment (Artino Jr, 2012; Wu & Yu, 2022; Zhao & Song, 2022). Emotionally engaged and motivated students are more likely to learn efficiently and persist in their studies (Pekrun, Goetz, Titz, & Perry, 2002). Online classes can exacerbate feelings of isolation and anxiety; hence, it is crucial to pinpoint students who might require extra support. Research in this domain can advance mental health and well-being (Aucejo, French, Araya, & Zafar, 2020). Gaining insights into students' emotions can facilitate the creation of personalized learning experiences, and adapting courses for the online format is imperative. These courses' quality and successful adaptation will profoundly impact students' academic progress (Baltà-Salvador, Olmedo-Torre, Peña, & Renta-Davids, 2021). In the learning process, it is essential to adapt the learning approach to align with the learner's personality traits and present emotional state (Fatahi & Ghasem-Aghaee, 2010). Adaptive educational technology harnesses student emotional data to dynamically adapt materials, pacing, and support, catering to each learner's needs. Delving into emotions within online classes can refine course designs and shape educational strategies. Furthermore, comprehending students' emotional states in online learning holds significance for their emotional well-being (Rezapour & Elmshaeuser, 2022). Employing topic modeling, statistical analysis, and random walk techniques within the realm of emotions during online classes presents a distinctive and challenging avenue of study. This amalgamation of methodologies can facilitate unearthing concealed patterns and provide valuable insights into students' emotional experiences within this distinctive setting. The exploration of this subject holds particular significance against the backdrop of the ever-evolving landscape of education, where digital learning environments persist in garnering increased prominence.

The following gaps have been identified. Existing reviews (Khare, Blanes-Vidal, Nadimi, & Acharya, 2023) on how computers recognize emotions tend to:

- use only one method to recognize emotions, such as facial expressions, instead of combining various techniques, which is not advisable (Zhang, Yin, Chen, & Nichele, 2020).
- use EEG analysis for brain signals and avoid exploring alternative options (Kamble & Sengupta, 2023).
- have limited explanation regarding the challenges of implementing and using emotion-related technologies in the real world (Hasnul, Aziz, Alelyani, Mohana, & Aziz, 2021).
- have a limited explanation regarding proposing ideas for future research, which is poorly explained (Adyapady & Annappa, 2023).

By addressing these gaps, researchers can better understand emotions and craft more potent tools for the future. The existing lacunae in research concerning emotions within online courses possess crucial implications and practical ramifications for educators, students, and educational institutions. Emotions significantly influence students' engagement and retention due to their effect on motivation and involvement in the learning process (Pekrun et al., 2011). A decrease in retention rates may result from failing to recognize and consider students' emotional experiences during online courses. Furthermore, the emotional well-being of students is at risk because feelings of loneliness, anxiety, and frustration can increase stress levels and lead to mental health issues that, if left untreated, can impair students' ability to succeed in their academic endeavors (Yu, Shek, & Zhu, 2018). Emotional intelligence embodies the capacity to comprehend and regulate one's emotions and those of others, thereby enhancing work performance. Maamari and Salloum (2023) highlights that educators within universities who exhibit a heightened emotional intelligence level can notably improve the efficacy of their teaching methods. Consequently, policymakers and educational institutions must conscientiously consider the emotional dynamics experienced by educators and students to make well-informed decisions regarding online learning initiatives. Such comprehension is pivotal in crafting policies and schemes that bolster online learning and elevate student achievement. Ensuring the quality and efficacy of online education is crucial in today's ever-expanding digital landscape; thus, addressing this research gap becomes imperative. The study presented in this article attempts to answer the following questions:

- Q1. What is the emotional state most often observed during the lesson?
- Q2. Which cluster of emotions dominates the student's emotional state, and which emotions are not seen much during the lecture?
- Q3. Is there a mathematical model based on random variables that can approximate the model's results based on CNN?

The proposed study will focus on:

- a literature review about emotions using NMF.
- The study gathers data on students' facial emotions after their consent by utilizing a webcam. Subsequently, the collected data is transmitted and stored in the cloud for analysis.
- the use of a pre-trained facial emotion detection system that identifies facial emotions in online learning during COVID-19.
- an in-depth statistical study of the model output.
- clustering distinct emotions into a group most seen during the experience.
- providing the classroom supervisor insights into the student's emotional state to improve their learning and productivity.
- proposing a mathematical model based on random variables capable of simulating and comparing the computer model.

The applicability of the technique elucidated in this paper relies primarily on several critical factors, including, but not limited to, the specific application domain, the nature of the data, and the underlying assumptions of the technique itself. Concerning limitations, our approach integrates topic modeling, statistical analysis, and random walk techniques to analyze emotions in online classrooms. Nonetheless, it may not comprehensively encapsulate the complexity of human emotions or accommodate the diversity of student populations and online platforms. Implementation challenges include difficulties with data collection and student privacy, as well as model preprocessing and reliability. Ensuring scalability and reliability across various educational contexts and platforms also poses challenges. Furthermore, effective implementation directly correlates with the computing resources, encompassing storage and processing machinery, required for its utilization in an educational setting. By addressing these factors, the authors expect to clarify findings while highlighting the need for more investigation and improvement in this field of study.

In this paper, the authors address feeling recognition to help readers overcome the challenge of increasing search paper findings. Our paper consists of two primary sections: the research methodology, the results, and the discussion.

2. Research methodology

In this research project, three distinct methodologies are employed to extract valuable insights into the study of emotion. First, the power of the Non-Negative Matrix Factorisation (NMF) algorithm is harnessed. This algorithm facilitates the decomposition of the corpus into non-negative components, shedding light on the underlying patterns and structures. Second, convolutional neural networks (CNN) are utilized, adopting a model that automatically capitalizes on intricate convolutional layers to predict emotions in online classes. Third, a mathematical approach was used to model transitions between emotional states, resulting in comprehensive and complementary outcomes that enhance the multifaceted understanding of the subject.

2.1. Topic modeling

Topic modeling is a technique within the realm of machine learning used for identifying latent topics or themes in a corpus of text data. It is a sub-field of natural language processing (NLP) that aims to uncover hidden thematic structures within a collection of textual data. One of the most widely used techniques for topic modeling is Latent Dirichlet Allocation (LDA) (Jelodar et al., 2019). LDA assumes that documents are mixtures of topics containing various words (Bouchard, Clinchant, & Darling, 2014). The depth of analysis can involve exploring various LDA models, optimizing hyperparameters, and assessing the quality of topics generated (Blei et al., 2003). Researchers may delve into probabilistic graphical models, Bayesian inference, and the mathematical foundations of LDA.

The technique used in this article is NMF topic modeling, which typically involves decomposing the document-word representation of texts into two components: a matrix that represents topics within documents and another matrix that illustrates the relationship between words and these topics (Wang & Zhang, 2023). In this paper, the NMF algorithm is applied. NMF divides a given matrix into two non-negative

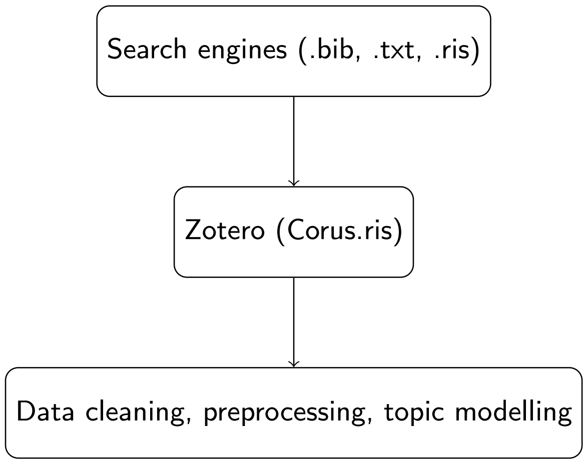

Fig. 1. Diagram illustrating the sequence of the data processing stages.

Table 1
Number of articles in different databases.

Database	Number of articles
Scopus	860
Science Direct	733
Web of Science	423
IEEE Xplore	309
Total	2325

matrices, the product of which approximates the original matrix (He, Lu, Huang, & Shi, 2015). This method frequently uses text mining and topic modeling to extract latent characteristics and themes from a word frequency matrix. There are several primary phases involved in performing topic modeling. Scientific databases available through institutional subscriptions are utilized to collect data. The research question is defined to refine search terms and focus the search. The following search term is "Deep learning in feelings recognition". The relevance and credibility of articles retrieved by the search must be evaluated by applying various filters to limit search results, ensuring they are pertinent to the subject. Then, the corpus data must be preprocessed by eliminating stop words, punctuation, and other special characters, and then stemming or lemmatization must be used to reduce words to their primary form. The data was subsequently arranged into a structured database using reference management software. This step involves extracting relevant metadata from the articles, such as author names, publication dates, journal names, abstracts, keywords, DOI, type of articles, ISSN, scientific database, and publisher. The flowchart in Fig. 1 illustrates the sequence of stages involved in data processing.

The article search was conducted in April 2023, identifying 2325 research papers, as illustrated in Table 1. Scopus provides the highest publication rate of the four databases, followed by Science Direct and Web of Science. IEEE Xplore has the fewest articles published in this period.

Our preprocessing involves several steps. First, we exclude stop words, considering them irrelevant to the search analysis. The next step is stemming, which consists of converting various words to their root form. For example, terms such as 'teacher' and 'teaching' are transformed into 'teach'. The preprocessed data is then analyzed using the NMF technique to extract insights and patterns from the articles. A word cloud is generated, and topic modeling is performed using the proposed algorithm.

2.2. Models primarily used for image classification and analysis

In our second phase, we move into the context of convolutional neural networks (CNNs).

CNN. Convolutional Neural Networks (CNN) are deep-learning neural networks often used to study images and video (Lasri, Solh, & El Belkacemi, 2019). CNNs are intended to learn the spatial hierarchies of characteristics from input photos or videos automatically and adaptively. This learning process is achieved by utilizing convolutional layers (LeCun, Bottou, Bengio, & Haffner, 1998), which apply a collection of learned filters to an input picture or feature map to extract meaningful information. Subsequently, the outcomes from the convolutional layers are directed to a pooling layer, where the dimensions of the features are reduced. This step enhances the model's ability to handle minor spatial variations and increases its robustness (Alzubaidi et al., 2021). CNNs can have multiple convolutional and pooling layers, succeeded by one or multiple fully connected layers for classification or regression. Backpropagation is used to determine the weights of the filters and fully linked layers (Ch et al., 2023), which fine-tunes the weights to reduce the loss function disparity between the expected and actual labels (Sartipi, Torkamani-Azar, & Cetin, 2023). Convolutional neural networks (CNNs) have demonstrated the ability to attain cutting-edge performance on diverse tasks related to image and video processing, encompassing tasks such as categorizing images, identifying objects, segmenting semantics, and more (Guo, Lu, Liu, Cheng, & Hu, 2023a).

VGG16. The Visual Geometry Group at Oxford University launched VGG16 in 2014 (Simonyan & Zisserman, 2014). Its design is based on the structure and idea of neural networks and CNN. It is named "16" due to its 16 layers. The VGG16 architecture is distinguished using tiny 3×3 convolutional filters that are layered for network depth extension. The network also incorporates maximizing pooling layers, which decrease the size of feature maps and diminish their spatial dimensions through down-sampling (Rawat & Wang, 2017). The VGG16 architecture has been widely used for image classification tasks and has demonstrated state-of-the-art performance on various benchmark datasets, including ImageNet. The pre-trained VGG16 model is also commonly employed as a starting point for transfer learning, involving fine-tuning the model on a new dataset for a specific purpose.

AlixNet. was created in 2012 by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton (Krizhevsky, Sutskever, & Hinton, 2017); it is a pioneering architecture in deep convolutional neural networks. It gained the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 (Alammar et al., 2023), solidifying its prominence. In this competition, participants endeavored to discern and classify objects within an image dataset comprising over 1 million pictures, categorized into 1000 classes. The AlexNet architecture comprises eight layers, five of which are convolutional and three are fully connected (Nguyen, Nguyen, Tran, Castagliola, & Frénod, 2019). The convolutional layers use a combination of convolution, pooling, and local response normalization operations, whereas the fully connected layers use standard feed-forward neural network techniques. The architecture also incorporates dropout regularization to prevent overfitting. The input to AlexNet is a 224×224 RGB image, and the output is a probability distribution over the 1000 categories of the ImageNet dataset. Backpropagation and stochastic gradient descent optimization algorithms were used to train the network. On the ILSVRC 2012 dataset, AlexNet attained a top-5 error rate of 15.3% (Simonyan & Zisserman, 2014), a considerable improvement over the prior state-of-the-art. Fig. 2 illustrates the flowchart used to detect emotions and analyze the model's results in depth.

2.3. Statistical analysis

Statistical analysis encompasses collecting and analyzing data to discover patterns and trends. It uses techniques to obtain significant data, and it is used in various fields such as research, industry, government, and healthcare. There are two primary types of statistical analysis: descriptive, which is done by summarizing data, and inferential, which

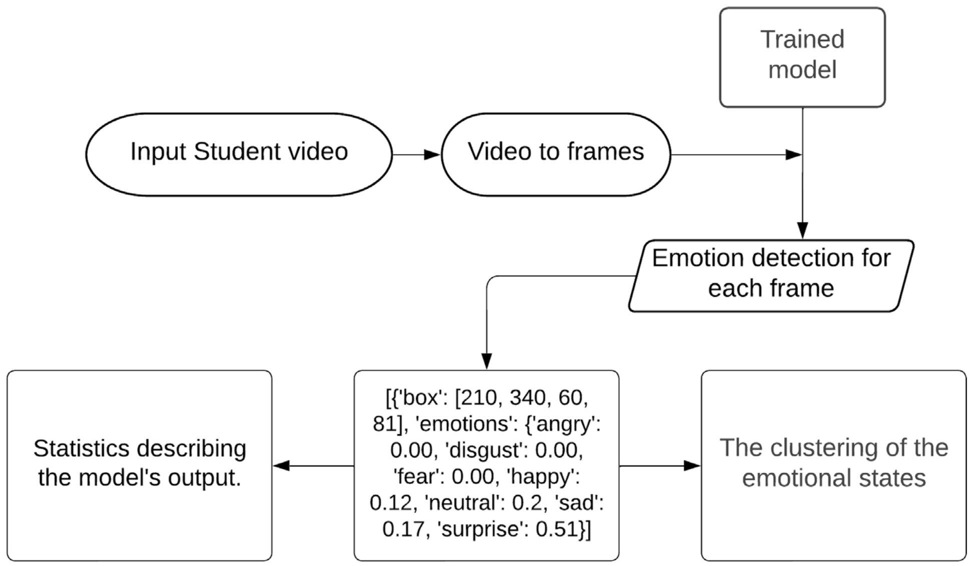

Fig. 2. Emotion Detection Flowchart and Analysis.

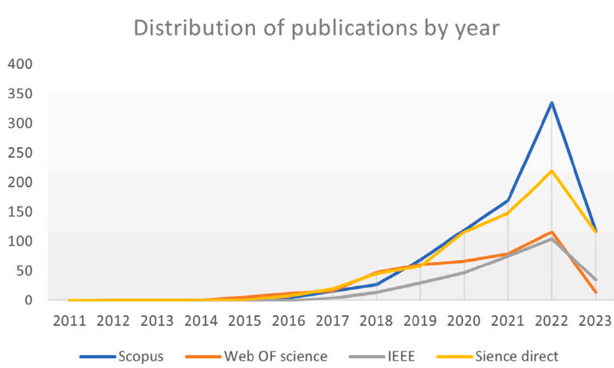

Fig. 3. Numbers of published articles by year.

is done by making population inferences from samples (Mishra, Pandey, Singh, Keshri, & Sabaretnam, 2019). In AI and ML, these analyses are vital scientific tools for transforming vast data into valuable insights by identifying common patterns and trends. Advanced statistical techniques, including multivariate analysis, time series analysis, and non-parametric statistics, further enrich the analytical toolbox. The depth of analysis can vary widely, ranging from fundamental summary statistics to sophisticated modeling. It also encompasses critical processes such as data preprocessing, data visualization, and data cleaning to ensure a comprehensive and insightful examination of data.

2.4. Random walk

Random walks and Markov chains are related but not identical concepts in probability and stochastic processes. The random walks approach is a stochastic or random process that characterizes a trajectory involving a series of unpredictable movements within a mathematical space (Xia et al., 2019). It is a series of discrete probabilistic steps that an object takes in a given direction. The future transition is entirely unrelated to the current step. Random walks represent scenarios where an entity advances through a series of steps in directions wholly chosen randomly (Kalikova, 2021). A Markov chain is a stochastic model describing a succession of possible events, where the probability of each event is dependent only on the state attained in the prior event (Paxinou, Kalles, Panagiotakopoulos, & Verykios, 2021). The system's future state is solely determined by its current state and is not influenced

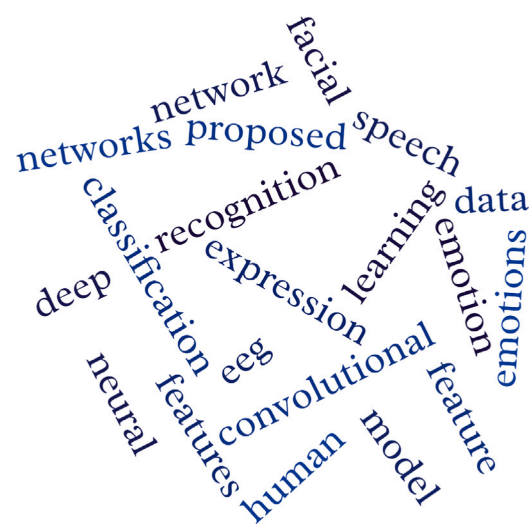

Fig. 4. Display of the top 20 terms in the corpus.

by its past states, known as the Markov property. A random walk can be a model for numerous processes and is used in various fields such as mathematics, computer science, physics, chemistry, biology, economics, and more (Weiss, 1983).

3. RESULTS

3.1. NMF results

The number of published articles has reached its highest point in 2022, as demonstrated in Fig. 3.

Two fundamental steps were taken to carry out this NMF. Firstly, the corpus and the stop-list were loaded into the work environment. Subsequently, the relevance of terms in the document corpus was measured using Term Frequency-Inverse Document Frequency (TF-IDF). It considers how often a term appears in a document(TF) and the frequency of the term across the entire corpus (IDF).

Fig. 4 displays the most frequently appearing words in the research corpus.

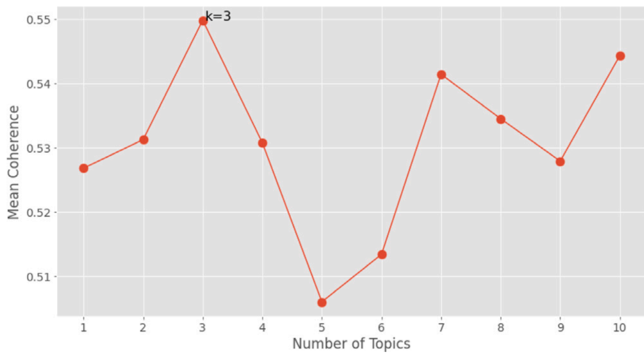

Fig. 5. Mean topic coherence scores.

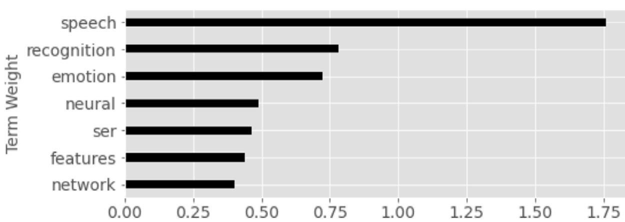

Fig. 6. Terms weight in topic 1.

Next, the TF-IDF normalization is loaded to create NMF models to generate a line plot of the coherence scores. A combination of tools offering lightweight pipelining in Python is employed. Word embedding is constructed, and a set of topics is singled out using an approach of constant selection, which revolves around examining the unity between topics. Therefore, coherence in topic modeling measures how interpretable and meaningful the subjects are. Furthermore, a coherence score is a crucial method to evaluate the quality of topics generated by a topic modeling algorithm. It assesses the degree of semantic relevance among the top words within a topic. Fig. 5 shows mean topic coherence scores.

The coherence score typically ranges from 0 to 1, with higher values indicating stronger thematic cohesion. In this model, coherence scores range from 0.5060 to 0.5498. In summary, these scores suggest that the optimal number of topics for this corpus is three (k = 3); however, other values of k, such as 7 and 10, also yield relatively high coherence scores. Moreover, the model may encounter challenges in generating coherent and meaningful topics, leading to variations or stabilization in the coherence score.

As a result, the authors have delineated five pivotal themes, encapsulating the prevalent words and their respective weights. These findings are underscored in the illustrations presented henceforth:

Topic 1 (see Fig. 6):

– Facial emotion analysis and recognition utilizing a deep convolution neural network.

Topic 2 (see Fig. 7):

— Detection of emotion, stress, attention, and meditation using EEG signals and deep learning technologies.

Topic 3 (see Fig. 8):

– Image sentiment analysis and emotion detection from tweets using deep learning and convolutional neural network (CNN).

Topic 4 (see Fig. 9):

– Human and speech emotion recognition using deep physiological affect network and machine learning techniques.

Topic 5 (see Fig. 10):

– Assess simulation-based learning utilizing emotion recognition and explore the foundational aspects of teaching and learning that students and lecturers contribute to the field.

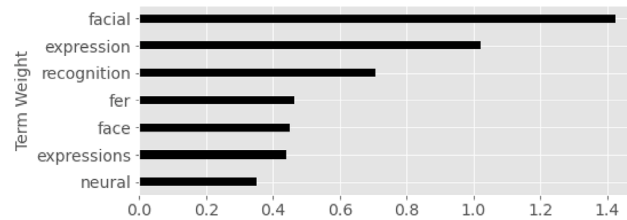

Fig. 7. Terms weight in topic 2.

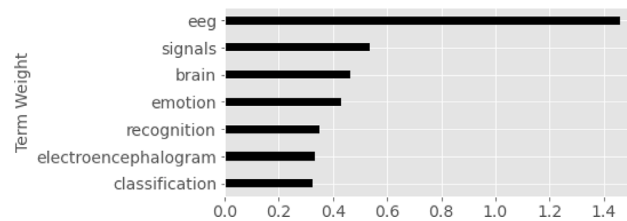

Fig. 8. Terms weight in topic 3.

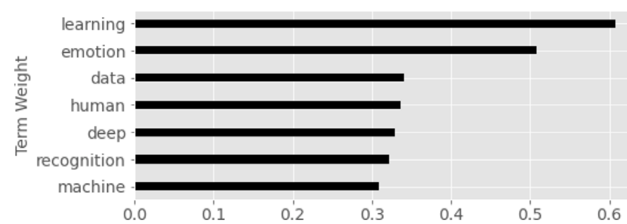

Fig. 9. Terms weight in topic 4.

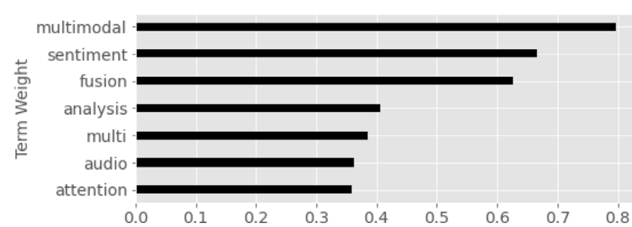

Fig. 10. Terms weight in topic 5.

Table 2 presents the three most relevant papers for each subject area.

The first topic deals with a speech-emotion recognition system that incorporates gender information, the architecture of the gated recurrent unit for automatic emotion classification, and improving model performance. The second topic involves recognizing facial expressions by applying convolutional neural networks, specifically utilizing a double-code LBP layered spatial attention network-based on a multi-data set. The third topic is deep learning models for EEG-based emotion recognition using convolutional neural networks and dense convolutional networks, which aim to learn high-level feature representations from EEG data to identify and classify emotional states accurately. The fourth topic concerns the application of deep learning and transfer learning techniques for emotion recognition from EEG signals and human activity recognition in smart classrooms. This theme aims to develop emotionally aware AI systems for smart classrooms that can enhance students' learning experience. The last topic concerns multimodal advanced deep learning methods for sentiment analysis and fusion networks. This topic aims to develop fusion networks that can exploit the strengths of different modalities, such as EEG signals, vision-based data, and text, to improve the accuracy of sentiment analysis.

Table 2
Top three papers on each topic.

	Paper 1	Paper 2	Paper 3
Topic 1	Prakash, Anuradha, Iqbal, Galety, Singh, and Neelakandan (2023)	Byun and Lee (2021)	Sun (2020)
Topic 2	Bin, Zhenyu, and Enguo (2020)	Lopes, de Aguiar, Souza, and Oliveira-Santos (2017)	Guo, Lu, Wang, Lu, and Zhang (2023b)
Topic 3	Cizmeci and Ozcan (2023)	Chen, Jiang, Zhang, and Zhang (2020)	Gao et al. (2021)
Topic 4	Islam et al. (2021)	Ray, Kolekar, Balasubramanian, and Hafiane (2023)	Kim, Soyata, and Behnagh (2018)
Topic 5	Du, Liu, Peng, and Jin (2022)	Le, Lee, Kim, Kim, and Yang (2023)	Lee, Han, and Ko (2021)

Table 3
Comparison between some articles.

Paper	Problematic	Methodology	Results
Kumar, Kumar, and Sanyal (2017)	The computer modeling and prediction of human emotions	The chosen algorithm was applied to the FERC-2013 database for training and evaluation through the authors' proposed experiments	This method allows for good results, and the highly accurate results encourage the researchers to use future computer modeling and prediction based on emotion recognition systems.
Mohammadpour, Khaliliardali, Hashemi, and AlyanNezhadi (2017)	Application of human–computer interaction	Using CNN to recognize and classify the seven basic categories of facial emotion expression through facial action units (AUs) in which CNN recognizes these units. For evaluation, the Cohn-Kanade database is used.	Compared with direct CNN, which results in 95.75 rate accuracy, this model achieves a higher accuracy rate of 97.01
Liao, Chen, and Liu (2019)	Prediction of users' stress feeling	Authors apply deep learning to predict human stress when listening to music.	To improve human focus and provide psychological treatment, the authors discovered the great effects of music or artistic performance in achieving predefined results.
Tarunika, Pradeeba, and Aruna (2018)	Recognition of emotion from speech	To recognize emotions in speech, especially in a scary state of mind, authors use DNN (Deep Neural Network) and k-NN (knearest neighbor)	The paper's findings make a fruitful contribution. As a result, the palliative care system has benefited from this research.

Table 3 summarizes the paper's methodology, problematics, and results obtained from some articles.

3.2. Empirical part

During the COVID-19 containment period, distance learning was adopted by several institutions. Therefore, an opportunity exists to assess students' emotions and invite them to record and submit their videos during courses. Once they agreed to process their data, the researchers selected the highest-quality videos with optimal light exposure and facing the camera. The treatment method involves splitting the video frame by frame and utilizing a predefined model[1] to predict emotions, with the resulting data used for a quantitative study. For each frame, The extraction of facial features is followed by the classification of facial images to recognize facial emotions. The system predicts the probabilities of basic emotions, as described by Benisha and Mirnalinee (2023). The code excerpt referenced in listing 1 demonstrates a portion of a script employed to analyze facial expressions using facial expression recognition (FER). Fer is a model that uses a convolutional neural network.

Listing 1: Facial expression recognition using FER.

```
from fer import FER
import cv2

image = cv2.imread("test.jpg")
EmotionDetector = FER()
EmotionDetector.detect_emotions(image)
```

[1] https://github.com/justinshenk/fer

The text below shows the system output for an example of a single video image.

```
[{'box': [322, 110, 50, 71], 'emotions': {'angry': 0.00,
'disgust': 0.00, 'fear': 0.00, 'happy': 0.22,
'neutral': 0.3, 'sad': 0.07, 'surprise': 0.41}]
```

The key 'box' represents the bounding box of the detected face with the values coordinates of the top-left corner (x, y) and the bounding box's width and height (w, h). The key 'emotions' details the detected emotions within the detected face. The value associated with 'emotions' is another dictionary in which each emotion is represented as a key, and its corresponding probability score is the value. This study analyzed one thousand frames (n = 1000) and estimated the emotional probabilities within each frame.

The objectives of this work are as follows: First, which predominant emotions do individuals commonly experience in the context of distance learning? Second, how can a multidisciplinary approach combining topic modeling with NMF, statistical analysis of emotions, and random walk modeling be used to comprehensively understand emotional patterns and sentiments? What are the implications of this understanding for empowering educators to create online courses that foster positive emotions and well-being in virtual spaces?

Table 4
Descriptive statistics (Quantitative data).

Mea	A	D	F	H	S	Su	N
N	1000	1000	1000	1000	1000	1000	1000
Min	0.000	0.000	0.000	0.000	0.000	0.000	0.060
Max	0.480	0.010	0.220	0.680	0.820	0.880	0.980
1Q	0.030	0.000	0.010	0.000	0.060	0.010	0.610
Me	0.060	0.000	0.020	0.010	0.100	0.010	0.720
3Q	0.100	0.000	0.040	0.020	0.190	0.030	0.820
Mean	0.075	0.000	0.029	0.025	0.157	0.029	0.685
Var	0.003	0.000	0.001	0.004	0.025	0.003	0.034
Std	0.058	0.000	0.028	0.059	0.158	0.059	0.185

Mea: Measure, A: Angry, D: Disgust, F: Fear, H: Happy, S: Sad, Su: Surprise, N: Neutral, N: Number of observations, Min: Minimum, Max: Maximum, $1Q$: 1st Quartile, Me: Median, $3Q$: 3rd Quartile, Var: Variance (n−1), and Std: Standard deviation (n−1)

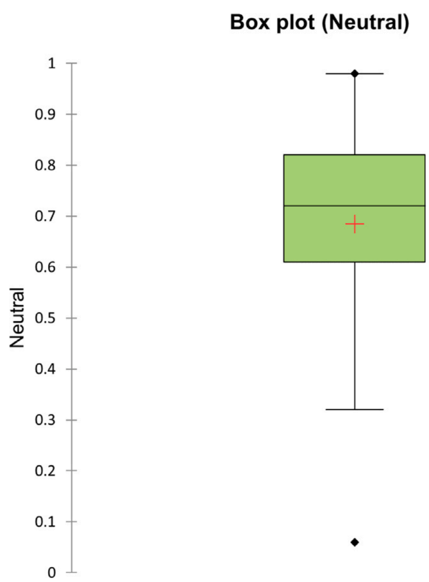

Fig. 11. Boxplot of the neutral emotional state.

3.2.1. Descriptive statistics

Table 4 provides statistical characteristics for the seven fundamental emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. Based on 1000 observed images each, offering a comprehensive overview of the emotional landscape within the data. For each image, the model calculates the probability of each emotional state. Minimum and maximum values range from 0 to specific probabilities corresponding to extreme emotional occurrences. Examination of the quartiles shows that the distribution of emotional expressions differs from one emotion to another. Quartiles serve a useful purpose in identifying the central trends within the distribution. The mean and standard deviation also describe the average and dispersion of each emotion's frequency.

The illustrative Fig. 11 delineating the "neutral" emotion across 1000 frames reveals a spectrum of scores ranging from 0.060 to 0.980, with a mean value of 0.685. The variance, standing at 0.034, and the standard deviation, at 0.185, suggest a dispersion of data points around the mean.

Fig. 12 represents the "Sad" feeling, ranging from mild to intense sadness. Most images exhibited a mild level of sadness, with a mean value of 0.157. The data are relatively consistent, as shown by the variance (n-1) of 0.025 and the standard deviation (n-1) of 0.158.

The boxplot shown in Fig. 13 shows a relatively concentrated distribution, with a median of 0.010 and a mean of 0.029. The data have a moderate dispersion, as seen in the variance (n-1) of 0.003 and the standard deviation (n-1) of 0.059 across 1000 frames. This emotional state is almost nonexistent.

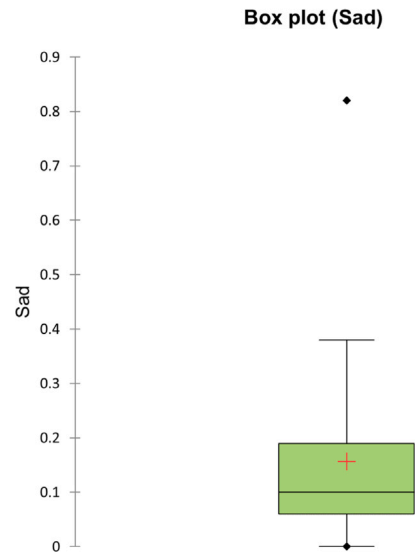

Fig. 12. Boxplot of the sad emotional state.

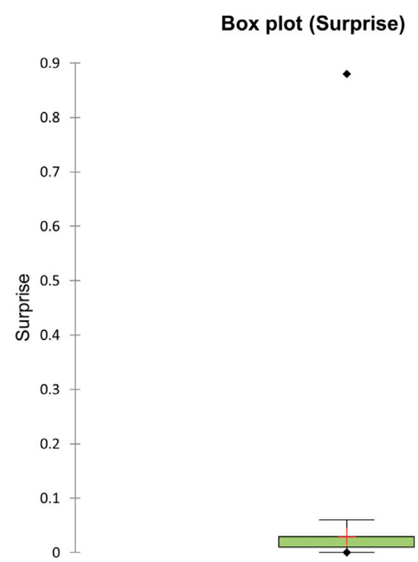

Fig. 13. Boxplot of the surprise emotional state.

The "Happy" emotion, depicted in Fig. 14, presents a spectrum of values, with most observations clustered at lower happiness levels.

The "disgust" state values range from a minimum of 0 to a maximum of 0.01. Interestingly, the first, second (median), and third quartiles are identical at 0, suggesting that most observations fall within this value. The mean, variance (n-1), and standard deviation (n-1) are also 0, indicating a consistent and stable distribution of the Disgust emotion throughout all frames. This emotional state is relatively uncommon, as depicted in Fig. 15.

Fig. 16 displays the concentration of "fear" emotion intensity, as demonstrated by the first quartile at 0.010, the median at 0.020, and the third quartile at 0.040. The mean intensity of fear across the frames was relatively low at 0.029, and the variability of fear's intensity within the sample was relatively small, as indicated by the low variance and standard deviation. These findings suggest that fear was not a dominant emotion in all observations.

Fig. 17 illustrates the data distribution of the emotion "angry", indicating that the first quartile has an anger intensity of 0.030, the median is 0.060, and the third quartile is 0.100. The emotion "Anger"

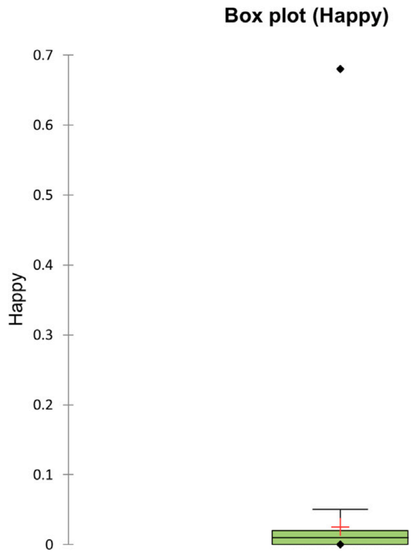

Fig. 14. Boxplot depicting the distribution of happy emotion.

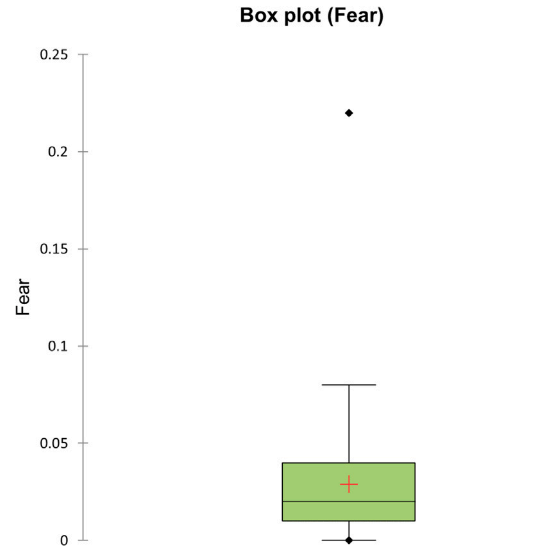

Fig. 16. Boxplot representation of fear emotion.

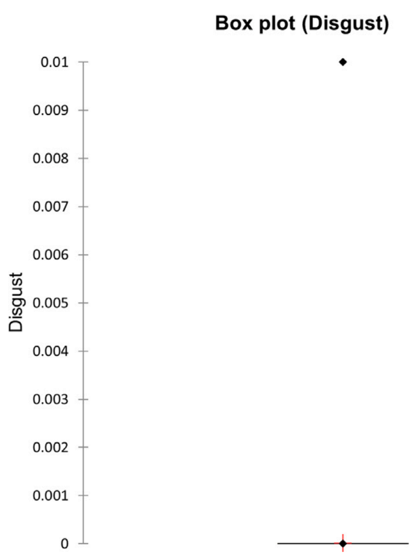

Fig. 15. Boxplot representation of disgust emotion.

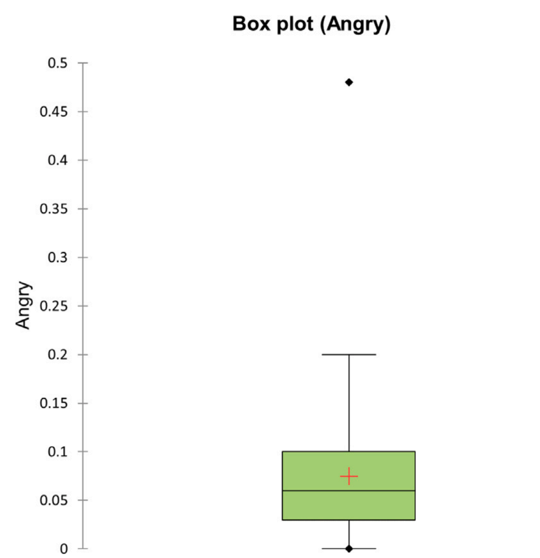

Fig. 17. Boxplot representation of angry emotion.

is expressed with a mean intensity of 0.075, and the variance (n-1) is calculated at 0.003, indicating a relatively consistent range of observations. Additionally, the standard deviation (n-1) is 0.058, reflecting the dispersion of anger intensity around the mean value. The findings imply a notable consistency in the intensity of anger throughout the dataset, with a slight variation around the mean value.

A *p*-value is a statistical indicator used to determine whether to accept or reject the null hypothesis (Vexler, 2021), often indicating the absence of a relationship between the examined variables or no significant difference between them. According to Table 5, there are substantial differences, for example, between anger and disgust, anger and sadness, anger and surprise, disgust and fear, and fear and happiness. Most emotions have considerable discrepancies in the table, indicating their specific relationships. Overall, the table shows that emotions can be distinguished from one another based on the statistical significance of their relationships, highlighting the complexities of human emotional experiences.

3.2.2. Normality tests

Normality tests are statistical procedures that check if a dataset follows a normal distribution. Normal density function $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ defines the normal distribution. Where x is the random variable, μ is the distribution's mean, and σ is the distribution's standard deviation. Shapiro–Wilk, Kolmogorov–Smirnov, and Anderson–Darling tests are common in the literature, according to Lira and Neto (2013).

These tests help ensure that the data meets assumptions for specific statistical analyses. Table 6 shows the results of four different normality tests that were conducted on the output of our model that were used to predict the probabilities of the following basic emotions: Angry, Disgusted, Fearful, Happy, Sad, Surprised, and Neutral. The results of these tests are represented as p-values. Smaller p-values suggest more compelling evidence against the assumption of normality. If the *p*-value exceeds the significance criterion (often set at 0.05), it indicates that the data are probably normally distributed. Conversely, if the *p*-value is less than or equal to the significance level, it suggests that the data deviate significantly from a normal distribution. In our case, all p-values were less than 0.0001, indicating a significant deviation of the data for

Table 5
Matrix of p-values.

Var	A	D	F	H	S	Su	N
Angry	0	<0.0001	0.482	0.297	<0.0001	<0.0001	<0.0001
Disgust	<0.0001	0	0.028	0.673	0.063	0.752	0.001
Fear	0.482	0.028	0	0.766	0.000	<0.0001	<0.0001
Happy	0.297	0.673	0.766	0	0.117	0.445	<0.0001
Sad	<0.0001	0.063	0.000	0.117	0	<0.0001	<0.0001
Surprise	<0.0001	0.752	<0.0001	0.445	<0.0001	0	0.000
Neutral	<0.0001	0.001	<0.0001	<0.0001	<0.0001	0.000	0

Var: Variables, A: Angry, D: Disgust, F: Fear, H: Happy, S: Sad, Su: Surprise, and N: Neutral

Table 6
Statistical tests for emotions.

Variable/Test	Shapiro–Wilk	Anderson–Darling	Lilliefors	Jarque–Bera
Angry	<0.0001	<0.0001	<0.0001	<0.0001
Disgust	<0.0001	<0.0001	<0.0001	<0.0001
Fear	<0.0001	<0.0001	<0.0001	<0.0001
Happy	<0.0001	<0.0001	<0.0001	<0.0001
Sad	<0.0001	<0.0001	<0.0001	<0.0001
Surprise	<0.0001	<0.0001	<0.0001	<0.0001
Neutral	<0.0001	<0.0001	<0.0001	<0.0001

all emotions from a normal distribution. Therefore, the intensities of these emotions do not follow a normal distribution. This information is significant when considering further statistical analyses that assume normality, as these tests indicate that such assumptions might not hold for the given emotional data. It is advisable to explore alternative statistical methods suitable for non-normally distributed data or use transformation to near normality as an alternative. However, according to the central limit theorem, ignoring the violation of the normalcy requirement is possible. Given the presence of 1,000 observations, according to the Central Limit Theorem, for large samples, the sample means distribution approximates a normal distribution, regardless of the shape of the original data (Altman & Bland, 1995; Elliott & Woodward, 2007).

3.2.3. Correlation matrix (pearson) and eigenvalues

The authors in this paper used Pearson's correlation matrix, as shown in Table 7, to determine the connection between the factors within our dataset. This matrix lists the correlation coefficients between several variables, ranging from −1 to 1. As one sentiment increases, the other follows. The correlation coefficients are positive and tend towards 1 in this case. When one sentiment tends to decrease, the other increases. The correlation coefficients are negative and tend towards -1.

The table shows varying degrees of positive and negative correlations between different emotions, but the strength of these correlations can go from very weak to moderately strong. Notably, fear and surprise demonstrate a robust and favorable correlation of 0.296, whereas anger and sadness display a significant positive correlation of 0.250. Conversely, the emotion "Sad" reveals a significant adverse correlation of −0.822 with neutral. Angry has a strong negative correlation of −0.474 with neutral, which shows that the level of sadness or angst tends to decrease as the level of neutrality rises. The poorest correlations – close to zero – between disgust and surprise suggest that these emotions do not exhibit a significant linear relationship in the data. It is important to note that the correlation matrix does not provide information on the causal relationships between these emotions. Fig. 18 graphically illustrates the correlation between emotions.

Table 8 represents the eigenvalues for different emotional states (Angry, Disgusted, Fear, Happy, Sad, Surprised, Neutral) across four factors (F1, F2, F3, F4). Eigenvalues indicate the variance explained by each factor in the data.

Examining the values reveals that the emotional states of anger, disgust, fear, and sadness have negative values for F1 and F2, suggesting that these emotions share similar patterns in response to these factors.

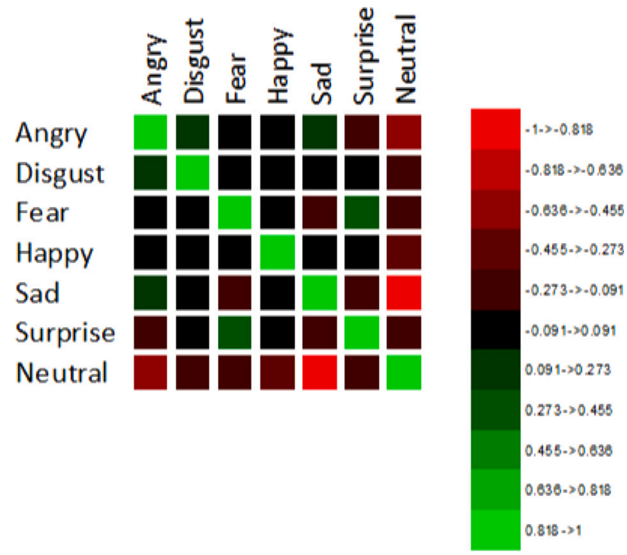

Fig. 18. Illustration depicting the matrix of correlations.

On the other hand, Happy and Surprise have negative Eigenvalues for F2, indicating that they may share some common patterns in response to that factor. F3 appears to distinguish between the emotions of Fear and Surprise, with negative and positive eigenvalues, respectively. Meanwhile, F4 characterizes the emotional states of anger and disgust, which have negative eigenvalues, from the emotions of happiness and sadness, which have positive eigenvalues for this factor. Neutral emotion stands out as it has positive eigenvalues for all factors (F1, F2, F3, F4); this suggests that any specific factor could influence it less or that it responds consistently to all factors.

In summary, the eigenvalues highlight the relationships and patterns between emotional states and the underlying factors, offering insights into how emotions are related and influenced by different aspects captured by these factors.

3.2.4. Factor analysis and agglomerative hierarchical clustering (AHC)

Both factor analysis and agglomerative hierarchical clustering are valuable tools in data analysis and exploration, helping to uncover underlying patterns and relationships within datasets. The research begins by employing factor analysis to identify underlying factors elucidating correlations or covariances between emotions. Then, it performs a hierarchical structure of clusters that reveals the relationships between emotions.

3.2.4.1. Factor analysis. This study explores how to depict an individual's emotion using a limited set of characteristics, and the solution lies in factor analysis. The probabilities of the seven fundamental emotions will be predicted for the 1000 images obtained from segmenting an online course video. These images will be evaluated based on the scores of 0 to 1 assigned to each emotion. For instance, a high score for happiness indicates that the person is happy, whereas a low score means

Table 7
Pearson's correlation matrix.

Var	A	D	F	H	S	Su	N
A	1	0.149	0.022	−0.033	0.250	−0.147	−0.474
D	0.149	1	0.069	−0.013	0.059	−0.010	−0.102
F	0.022	0.069	1	0.009	−0.112	0.296	−0.157
H	−0.033	−0.013	0.009	1	−0.050	0.024	−0.275
S	0.250	0.059	−0.112	−0.050	1	−0.245	−0.822
Su	−0.147	−0.010	0.296	0.024	−0.245	1	−0.114
N	−0.474	−0.102	−0.157	−0.275	−0.822	−0.114	1

Var: Variables, A: Angry, D: Disgust, F: Fear, H: Happy, S: Sad, Su: Surprise, and N: Neutral

Table 8
Eigenvalues for different emotions and factors.

Emotion	F1	F2	F3	F4
Angry	−0.290	0.112	−0.017	−0.624
Disgust	−0.080	0.025	−0.066	−0.467
Fear	−0.024	−0.169	−0.465	−0.283
Happy	−0.171	−0.873	0.421	−0.003
Sad	−0.590	0.292	0.133	0.452
Surprise	0.067	−0.316	−0.724	0.329
Neutral	0.726	0.103	0.244	0.026

Table 9
Factor pattern.

Emotion	F1	F2	F3
Angry	**−0.403**	0.115	−0.015
Disgust	**−0.110**	0.026	−0.058
Fear	−0.034	−0.175	**−0.410**
Happy	−0.236	**−0.898**	0.370
Sad	**−0.819**	0.302	0.117
Surprise	0.093	−0.326	**−0.638**
Neutral	**0.973**	0.103	0.207

The bold values indicate the factor for which the squared cosine is the highest for each variable.

the absence of joy. The simultaneous presence of all seven emotions is improbable, as joy and sadness are contradictory. Emotional variations tend to be grounded in a constrained set of characteristics: each of the seven measured emotions arises from a broader emotional state trait. Factor analysis will unveil these foundational emotional traits, which we will technically refer to as latent factors. The software for this experiment automatically determines the number of factors to be generated in our analysis. Table 9 showcases the outcomes.

The initial two factors elucidate 42% of the mutual variability among the estimated emotions. This tabulated presentation of factorial coordinates, featuring columns labeled f1 to f3 representing the latent factors, is organized in decreasing order of significance, while the rows correspond to the estimated emotions. Prominent absolute scores pinpoint the predominant emotions associated with each factor. For instance, the first factor is characterized by emotions like "angry", "disgust", "sad", and "neutral". The most captivating facet of factor analysis becomes evident through a technique known as varimax rotation, which provides a more tangible portrayal of these latent factors. The initial factor pattern often presents complexity and is difficult to interpret despite showing the correlations between variables and factors. After applying Varimax rotation, the factor pattern becomes more interpretable, with loadings concentrating on specific factors, enhancing high and diminishing low loads. This rotation preserves orthogonality, ensuring that the factors remain uncorrelated and distinct. Table 10 shows the factor pattern after Varimax rotation.

This study aims to encapsulate emotions within two primary traits by consolidating the factors into just two. Fig. 19 translates this into a graph. The horizontal axis captures the essence of the first latent factor, whereas the vertical axis encapsulates the second. The initial factor relates to emotions like "disgust", "anger", and "sad" on the right, contrasting with "neutral" emotions on the left, indicating a representation of negative emotions. The second factor opposes "happy",

Table 10
Factor pattern after Varimax rotation.

Emotion	D1	D2
Angry	0.415	−0.054
Disgust	0.113	−0.009
Fear	0.007	0.178
Happy	0.099	0.924
Sad	0.855	−0.176
Surprise	−0.140	0.308
Neutral	−0.947	−0.247

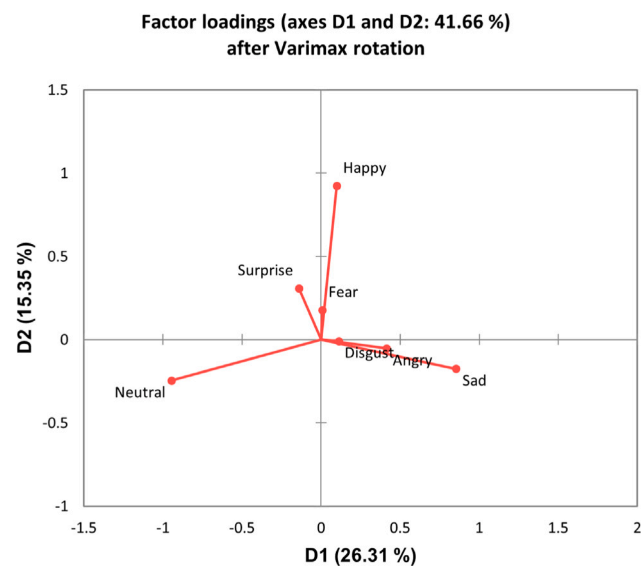

Fig. 19. Factor loading axes D1 and D2 after Varimax rotation.

"fear", and "surprise" at the top, potentially reflecting intense and powerful emotions. It is important to note that factor analysis has challenges, and the results heavily depend on various methodological choices, such as the number of factors to extract and the type of rotation applied. Proper interpretation and validation of the factors are essential to ensure the meaningfulness and accuracy of the results obtained from factor analysis.

3.2.4.2. Hierarchical cluster analysis. is a method used in data analysis and machine learning to examine and identify data points that share similarities and then organize them into groups based on their characteristics (Zhang, Murtagh, Van Poucke, Lin, & Lan, 2017). There are two main types of hierarchical clustering: agglomerative and divisive. Hierarchical clustering analysis is often referred to as hierarchical cluster analysis (HCA); there are two main types of hierarchical clustering: agglomerative (Liu, Xu, Zeng, & Ren, 2021) and divisive (Roux, 2015). Euclidean distance, Manhattan distance, and correlation distance are typical distance metrics used in hierarchical clustering, while standard linking methods include single, average, complete, centroid, and Ward's Linkage (Zhang & An, 2018). Users can select the number of clusters at various degrees of granularity using hierarchical clustering. However,

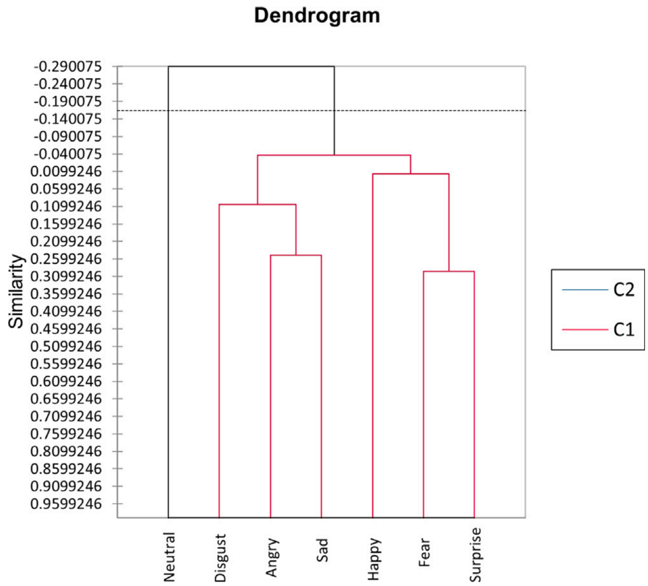

Fig. 20. Agglomerative hierarchical clustering.

Table 11
Distances between the cluster centroids.

Center	C1	C2
C1	0	21.133
C2	21.133	0

it is computationally intensive and may not be appropriate for large datasets. Each cluster is successively merged or divided into other clusters to build a hierarchy of clusters in the data. The AHC method was employed to find similarities in our data. The outputs of this method are illustrated as a dendrogram in Fig. 20.

The analysis was conducted using different numbers of clusters, ranging from two to seven. Clusters were formed based on the similarity of the emotions (Somarathna, Vuilleumier, & Mohammadi, 2023). For example, when there are two clusters, all emotions are in the same cluster except for neutral, which is in a separate cluster. When there are seven clusters, each emotion is in its cluster. At every stage, the two nearest clusters are merged, gradually reducing the cluster count by one. This process continues until it reaches one cluster formed by neutral and all other emotions.

For situations involving two clusters, Table 11 displays the distances separating the centroids of these clusters, namely C1 and C2.

The numerical entry of 21.133 signifies the distance between the centroid of cluster C1 and that of cluster C2.

3.2.5. Evolution of indices

Table 12 presents the evolution of the indices for different clusterings based on the number of clusters considered. The Silhouette index has a value of −0.047 for the two clusters, indicating low cohesion among data points within the clusters. As the number of clusters increased to three, the silhouette index decreased further to −0.373, suggesting a higher degree of dispersion of points within the clusters and poorer separation between the groups. However, with a fourth cluster, the Silhouette index remains almost unchanged at −0.374. Similarly, the Hartigan index (H) shows a slight variation between 1.244 and 1.232 for three and four clusters, respectively, indicating stability in the clustering quality. Nevertheless, with an increase in the number of clusters to five, the Hartigan index decreases to 1.065, indicating enhanced cohesion among the data points within the clusters. The calculation of the difference between the values of the Hartigan index (H(k-1) - H(k)) indicates a trend towards stability or improvement in

Table 12
Evolution of Silhouette, Hartigan (H), H(k−1) − H(k), and Calinski & Harabasz Index.

Number of clusters	2	3	4	5
Silhouette index	−0.047	−0.373	−0.374	−0.378
Hartigan index (H)	1.244	1.255	1.232	1.065
H(k−1) − H(k)	0.233	−0.011	0.023	0.167
Calinski & Harabasz index	1.476	1.396	1.408	1.446

clustering as the number of clusters increases. Regarding the Calinski & Harabasz index, there is a progressive increase as the number of clusters grows, indicating a better separation between the groups and higher internal cohesion within the clusters as their number increases.

3.3. Random walk results

An individual's emotional state at each moment is determined by random fluctuations or influences that can occur independently of their previous emotional state. This study used the random walks approach instead of the Markov chain. The transition from one emotional state to another can be likened to a random walk, as it is unrestricted in its movement across various directions, and the state space is multidimensional. It is a discrete random walk. We can say that if the student is in the emotional state e_i, (the ith emotion), then he can move to the emotional state e_j, (the jth emotion), in the one step, with a probability P_{ij}, called the transition probability, which does not depend on the history before state i: $P_{ij}(n) = P(X = j|X_{n-1} = i)$. The probability of moving in a given direction is the same for all possible directions, equal to 0.14. In reality, this distribution is unfair. For any natural integer n, we denote by N_n, A_n, D_n, F_n, H_n, S_n, Su_n the probabilities that we have the emotional states Neutral, Angry, Disgust, Fear, Happy, Sad, and Surprise at step n, respectively. We note X_n is the row matrix $X_n = \begin{bmatrix} N_n & A_n & D_n & F_n & H_n & S_n & Su_n \end{bmatrix}$, and T is the transition matrix. So, We have $X_{n+1} = X_n$T. If a few conditions are met, P and D matrices are required such that T = P D P^{-1} to simplify the calculation. Therefore, T^n = P D^n P^{-1} where D is a diagonal matrix and P is a passage matrix. If we assume that we will begin with any state, for example, the neutral state, then the probability matrix X_0 is as follows: $X_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$ The authors have introduced a matrix transition approach to represent state transitions based on the findings and outcomes presented in the preceding chapter. Fig. 21 visually depicts the connections associated with the neutral state, while the T matrix encapsulates the details of all other state transitions. In this matrix, the emphasis is on the cluster of strong emotional states.

$$T = \begin{bmatrix} 0.31 & 0.00 & 0.00 & 0.23 & 0.15 & 0.00 & 0.31 \\ 0.27 & 0.00 & 0.00 & 0.24 & 0.26 & 0.00 & 0.23 \\ 0.40 & 0.00 & 0.00 & 0.20 & 0.15 & 0.00 & 0.25 \\ 0.25 & 0.00 & 0.00 & 0.25 & 0.25 & 0.00 & 0.25 \\ 0.24 & 0.00 & 0.00 & 0.31 & 0.25 & 0.00 & 0.20 \\ 0.26 & 0.00 & 0.00 & 0.26 & 0.23 & 0.00 & 0.25 \\ 0.29 & 0.00 & 0.00 & 0.20 & 0.26 & 0.00 & 0.25 \end{bmatrix}$$

Authors have noticed that the emotional state is always intense and powerful. This transition matrix between states depicts 0.92% of the results given by the model based on FER when considering the neutral state and the whole formed by states of intense and powerful emotions. We get $X_1 = \begin{bmatrix} 0 & 0.23 & 0.15 & 0 & 0.31 & 0.31 \end{bmatrix}$, and $X_7 = \begin{bmatrix} 0.125 & 0 & 0 & 0.285 & 0.303 & 0 & 0.285 \end{bmatrix}$. This probability matrix remains unchanged for all steps from the 7th step. From this step, the value of X_n does not depend on the student's initial emotional state but only on the transition matrix. The steady-state behavior of a Markov chain refers to the enduring probabilities associated with each state over an extended period. In other words, regardless of how many transitions occur within the system, it will not alter the current state distribution, and this pattern will persist indefinitely into

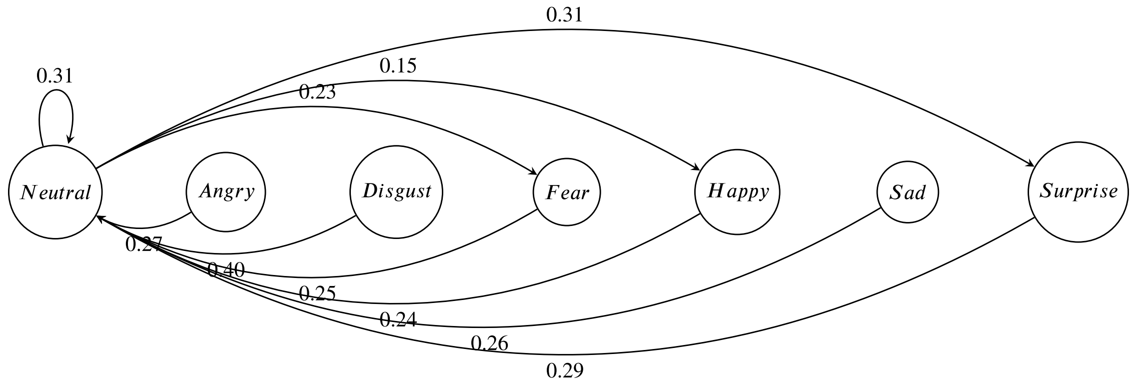

Fig. 21. Random walk transition graph for the neutral state.

the future. Mathematically, we should solve the following equation: $\pi = \pi$ T, where the $\pi(\alpha, \beta, \gamma, \delta, \epsilon, \zeta, \eta)$ row matrix (1x7) represents the steady-state probabilities which correspond to the following system of equations:

$$\begin{aligned}
\alpha &= 0.31\alpha + 0.27\beta + 0.40\gamma + 0.25\delta + 0.24\epsilon + 0.26\zeta + 0.29\eta \\
\beta &= 0 \\
\gamma &= 0 \\
\delta &= 0.23\alpha + 0.24\beta + 0.20\gamma + 0.25\delta + 0.31\epsilon + 0.26\zeta + 0.20\eta \\
\epsilon &= 0.15\alpha + 0.26\beta + 0.15\gamma + 0.25\delta + 0.25\epsilon + 0.23\zeta + 0.26\eta \\
\zeta &= 0 \\
\eta &= 0.31\alpha + 0.23\beta + 0.25\gamma + 0.25\delta + 0.20\epsilon + 0.25\zeta + 0.25\eta \\
\alpha &= 1 - (\alpha + \beta + \gamma + \delta + \epsilon + \zeta + \eta)
\end{aligned} \tag{1}$$

The conclusion is that starting the session with attitudes that evoke positive or negative emotions significantly influences the whole session.

4. Discussion

NMF topic modeling was employed to examine emotions in existing literature, uncovering hidden themes and insights into their conceptualization and study. Numerous methods exist for topic modeling, such as NMF, LDA, Top2Vec, and BERTopic (Umamaheswaran, Dar, Sharma, & Kurian, 2023). NMF demonstrated efficacy in clearly discerning various topics in other content. This study clarifies the effectiveness of applying BERTopic and NMF to examine Twitter data (Egger & Yu, 2022). These topics found in our analysis by NMF offer nuanced interdisciplinary perspectives, revealing both the unity and divergence of ideas in the field. The NMF-based topic modeling literature review on emotions can be compared to prior studies to uncover similarities and differences and compare outcomes within NMF studies and against diverse methods employed for emotion analysis. Our findings highlight the emotional complexity and stress of interdisciplinary teamwork in emotional research. Research into speech emotion recognition, face emotion recognition, multimodal emotion recognition, applications of emotion recognition, and emotion recognition from eye movement, electroencephalogram (EEG) signals, heart rate, and text provides a comprehensive understanding of emotion (Jafari et al., 2023). Recognizing cultural influences on emotional expression demonstrates the need for cultural sensitivity. Practitioners should consider different cross-cultural emotional experiences and adjust interventions accordingly. Moreover, our study points to the potential for enhancing emotional well-being through cognitive strategies (Iovino, Koslouski, & Chafouleas, 2021). However, there are limitations because this study uses a literature review based on abstract and keywords, the need for original data, and the variable quality of the literature. Although limited, our study adds to the emotional discourse and provides a basis for further research in this complex area.

The top three negative emotions expressed by students during online learning were sadness, disgust, and fear. In contrast, the feelings reflecting intense and powerful emotions were happy, fear, and surprise. The study demonstrated that students engaging in online learning exhibited a predominant neutral emotional state, with intense and powerful emotions coming in second. The results are consistent with previous research that emphasizes the importance of positive emotions for promoting engagement and interaction in virtual education. Using FER technology, the authors seek to enhance the credibility of their findings and minimize biases inherent in self-reporting. This novel approach also reinforces prior studies that underscore the valuable insights provided by facial expressions in comprehending emotions.

In the second part of this study, the researchers conducted an in-depth statistical analysis using XLSTAT to examine the emotions experienced by the students and facial emotion recognition (FER) to classify emotions into only six basic emotions in online courses, providing insights that might otherwise be missed through traditional self-report methods. AHC provides valuable insights into the hierarchical organization of data and allows users to determine the optimal number of clusters based on their specific needs by analyzing the dendrogram and selecting an appropriate level of similarity threshold. However, AHC can be computationally expensive, especially for large datasets, as it requires comparing all data points and clusters, making it essential to choose appropriate algorithms and optimization techniques for efficient implementation. Fig. 20 shows that the number of clusters affects the membership of each case. It underscores the dynamics of cluster formation and membership as the number of clusters changes, shedding light on the shifting relationships and similarities among different emotional states within the chosen clustering framework. In this paper (Somarathna et al., 2023), the authors have presented the distribution of feelings in 14 emotion categories. They presented the results of correlation-based hierarchical clustering of discrete emotions. The results of this study overlap with those of the referenced research. However, this study categorizes emotions into six classes while observing similar clusters for disgust, anger, and sadness; the clustering of fear differs from what was identified in the referenced study. Overall, the table provides information on the membership of each case in different clusters, which can be used to identify patterns and similarities within the data. Factor analysis facilitated the recognition of two primary groups of emotions by using data collected from seven emotions out of 1,000 frames.

In the study's third part, the authors introduced a novel approach to emotional analysis by employing a random walk technique. This technique, typically used in behavioral sciences, offers a fresh perspective on understanding the complexities of human and animal behavior. It is a crucial tool for unraveling stochastic processes and uncertainty in various domains and applications, thereby adding a unique dimension to our study.

Our findings offer valuable implications for academics and the wider community. Consider an example illustrating how the study's conclusions might improve online education and learners. Consider a university that has established a sophisticated emotional monitoring system to analyze students' emotional states during online classes. Via statistical analysis, the system finds emotional patterns among learners. For example, if a student's emotional state declines during a session, the system can automatically provide resources or interventions, such as relaxing methods or notifying teachers to offer further support. The more data it collects, the more accurate it becomes in understanding emotional states, making the online learning environment progressively more emotionally supportive. The scenario highlights the practical benefits of online education: it reduces stress and isolation, enhances learning outcomes, provides personalized support for individual emotional needs, and fosters positive emotions such as trust, satisfaction, and challenge while reducing negative emotions such as stress, inadequacy, and boredom. Emotion recognition can also be employed in healthcare, analyze consumer reactions to products, enhance user experiences in gaming and virtual reality, improve the interaction between humans and technology, and be used for security purposes. The study has limitations: it only categorized emotions into six basic types using FER technology, potentially overlooking emotional complexity. It is important to note the study's limitations. Firstly, it categorized emotions into six basic types using FER technology, which may have oversimplified emotional complexity. Secondly, it needed to investigate how students' demographics influenced their online course emotions. Lastly, the study's context-specific nature warrants caution when applying its findings to different scenarios. While data analysis is reliable, it may only partially capture the intricate nature of emotions. In future research, we aim to leverage these findings to deepen our understanding and enhance the effectiveness of online education by fostering engagement and academic success.

5. Conclusion

This study employed a comprehensive approach by combining topic modeling and statistical analysis of emotions to investigate factor analysis, agglomerative hierarchical clustering, and principal component analysis. The authors dissected the intricate landscape of emotions through an extensive literature review. Factor analysis and agglomerative hierarchical clustering provided insights into the underlying structures of emotions, revealing two distinct clusters. Meanwhile, principal component analysis offered a robust dimensionality reduction technique to discern pivotal factors within emotional datasets. This multifaceted exploration enhances our understanding of the nuanced interplay of emotions, laying the groundwork for more profound insights into psychological and computational research. In conclusion, the comprehensive literature review conducted through topic modeling and statistical analysis of emotions has shed light on the intricate landscape of emotional analysis. This paper has gained a deeper understanding of the underlying structures and relationships among various emotional dimensions by employing factor analysis, agglomerative hierarchical clustering, and principal component analysis. These analytical approaches have enabled us to distill complex emotional data into discernible patterns and clusters, offering valuable insights into the multifaceted realm of human emotions. This synthesis of research not only contributes to the enrichment of emotional theory but also paves the way for more targeted and nuanced emotional studies in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We sincerely thank KeAi Communications Co., Ltd. for covering the article processing charges and enabling this publication to have gold open access.

References

Abdellaoui, B., Moumen, A., El Idrissi, Y. E. B., & Remaida, A. (2020). Face detection to recognize students' emotion and their engagement: A systematic review. In *2020 IEEE 2nd international conference on electronics, control, optimization and computer science* (pp. 1–6). IEEE.

Abdellaoui, B., Remaida, A., Sabri, Z., EL IDRISSI, Y. E. B., & Moumen, A. (2024). Emotion detection and student engagement in distance learning during containment due to the covid-19. *Baghdad Science Journal*, *21*(4), 1432–1432.

Adyapady, R. R., & Annappa, B. (2023). A comprehensive review of facial expression recognition techniques. *Multimedia Systems*, *29*(1), 73–103.

Alammar, Z., Alzubaidi, L., Zhang, J., Li, Y., Lafta, W., & Gu, Y. (2023). Deep transfer learning with enhanced feature fusion for detection of abnormalities in X-ray images. *Cancers*, *15*(15), 4007.

Altman, D. G., & Bland, J. M. (1995). Statistics notes: the normal distribution. *Bmj*, *310*(6975), 298. http://dx.doi.org/10.1136/bmj.310.6975.298, URL https://pubmed.ncbi.nlm.nih.gov/7866172/.

Alzubaidi, L., Bai, J., Al-Sabaawi, A., Santamaría, J., Albahri, A. S., Al-dabbagh, B. S. N., et al. (2023). A survey on deep learning tools dealing with data scarcity: definitions, challenges, solutions, tips, and applications. *Journal of Big Data*, *10*(1), http://dx.doi.org/10.1186/s40537-023-00727-2, URL https://journalofbigdata.springeropen.com/articles/10.1186/s40537-023-00727-2#citeas.

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., et al. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, *8*, 1–74.

Artino Jr, A. R. (2012). Emotions in online learning environments: Introduction to the special issue. *The Internet and Higher Education*, *15*(3), 137–140.

Aucejo, E. M., French, J., Araya, M. P. U., & Zafar, B. (2020). The impact of COVID-19 on student experiences and expectations: Evidence from a survey. *Journal of Public Economics*, *191*, Article 104271.

Balasubramani, S., Aravindhar, J., Renjith, P., & Ramesh, K. (2024). DDSS: Driver decision support system based on the driver behaviour prediction to avoid accidents in intelligent transport system. *International Journal of Cognitive Computing in Engineering*, *5*, 1–13.

Baltà-Salvador, R., Olmedo-Torre, N., Peña, M., & Renta-Davids, A.-I. (2021). Academic and emotional effects of online learning during the COVID-19 pandemic on engineering students. *Education and Information Technologies*, *26*(6), 7407–7434.

Benisha, S., & Mirnalinee, T. (2023). Human facial emotion recognition using deep neural networks. *International Arab Journal of Information Technology*, *20*(3), 303–309. http://dx.doi.org/10.34028/iajit/20/3/2, URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85160225028&doi=10.34028%2fiajit%2f20%2f3%2f2&partnerID=40&md5=d1325365bee894d97797d69601163db1.

Bin, Y., Zhenyu, L., & Enguo, C. (2020). Facial expression recognition based on multi-dataset neural network. *Radioengineering*, *29*(1), http://dx.doi.org/10.13164/re.2020.0259, URL https://pdfs.semanticscholar.org/fc57/226be2a0020b1f03a15e2272099e14f1d56d.pdf.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, *3*, 993–1022, URL https://dl.acm.org/doi/10.5555/944919.944937.

Bonner, M. J., Hardy, K. K., Willard, V. W., Anthony, K. K., Hood, M., & Gururangan, S. (2008). Social functioning and facial expression recognition in survivors of pediatric brain tumors. *Journal of Pediatric Psychology*, *33*(10), 1142–1152.

Bouchard, G., Clinchant, S., & Darling, W. (2014). Hot topic sensing, text analysis, and summarization. In *Handbook of research on advanced ICT integration for governance and policy modeling* (pp. 216–247). IGI Global.

Byun, S.-W., & Lee, S.-P. (2021). A study on a speech emotion recognition system with effective acoustic features using deep learning algorithms. *Applied Sciences*, *11*(4), 1890. http://dx.doi.org/10.3390/app11041890.

Catterall, J. S. (1987). On the social costs of dropping out of school. *The High School Journal*, *71*(1), 19–30.

Ch, Y. R., et al. (2023). Anomaly detection in solar modules with infrared imagery. *Vol. 391*, In *E3S web of conferences* (p. 01069). EDP Sciences.

Chahal, A., & Gulia, P. (2019). Machine learning and deep learning. *International Journal of Innovative Technology and Exploring Engineering*, *8*(12), 4910–4914. http://dx.doi.org/10.35940/ijitee.L3550.1081219, URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85074008705&doi=10.35940%2fijitee.L3550.1081219&partnerID=40&md5=69debac8f40a769fe83900f3feee7680.

Chen, J., Jiang, D., Zhang, Y., & Zhang, P. (2020). Emotion recognition from spatiotemporal EEG representations with hybrid convolutional recurrent neural networks via wearable multi-channel headset. *Computer Communications*, *154*, 58–65. http://dx.doi.org/10.1016/j.comcom.2020.02.051, URL https://www.sciencedirect.com/science/article/pii/S0140366420300013.

Cizmeci, H., & Ozcan, C. (2023). Enhanced deep capsule network for EEG-based emotion recognition. *Signal, Image and Video Processing*, *17*(2), 463–469. http://dx.doi.org/10.1007/s11760-022-02251-x.

Di Leo, I. (2020). *The role and sequencing of academic emotions during mathematics problem solving among elementary students*. McGill University (Canada).

Du, Y., Liu, Y., Peng, Z., & Jin, X. (2022). Gated attention fusion network for multimodal sentiment classification. *Knowledge-Based Systems*, *240*, Article 108107. http://dx.doi.org/10.1016/j.knosys.2021.108107, URL https://www.sciencedirect.com/science/article/pii/S0950705121011679.

Egger, R., & Yu, J. (2022). A topic modeling comparison between lda, nmf, top2vec, and bertopic to demystify twitter posts. *Frontiers in Sociology*, *7*, Article 886498.

Ekman, P., & Friesen, W. V. (1971). Constants across cultures in the face and emotion. *Journal of Personality and Social Psychology*, *17*(2), 124.

Elliott, A. C., & Woodward, W. A. (2007). *Statistical analysis quick reference guidebook: With SPSS examples*. Sage.

Esra, M., & Sevilen, Ç. (2021). Factors influencing EFL students' motivation in online learning: A qualitative case study. *Journal of Educational Technology and Online Learning*, *4*(1), 11–22.

Fall, A.-M., & Roberts, G. (2012). High school dropouts: Interactions between social context, self-perceptions, school engagement, and student dropout. *Journal of Adolescence*, *35*(4), 787–798.

Fatahi, S., & Ghasem-Aghaee, N. (2010). Design and implementation of an intelligent educational model based on personality and Learner's emotion. arXiv preprint arXiv:1004.1224.

Gao, Z., Wang, X., Yang, Y., Li, Y., Ma, K., & Chen, G. (2021). A channel-fused dense convolutional network for EEG-based emotion recognition. *IEEE Transactions on Cognitive and Developmental Systems*, *13*(4), 945–954. http://dx.doi.org/10.1109/TCDS.2020.2976112, URL https://ieeexplore.ieee.org/document/9011570.

Guo, M.-H., Lu, C.-Z., Liu, Z.-N., Cheng, M.-M., & Hu, S.-M. (2023a). Visual attention network. *Computational Visual Media*, 1–20.

Guo, X., Lu, S., Wang, S., Lu, Z., & Zhang, Y. (2023b). DLSANet: Facial expression recognition with double-code LBP-layer spatial-attention network. *IET Image Processing*.

Gupta, S., Kumar, P., & Tekchandani, R. (2023). EDFA: Ensemble deep CNN for assessing student's cognitive state in adaptive online learning environments. *International Journal of Cognitive Computing in Engineering*, *4*, 373–387.

Hasnul, M. A., Aziz, N. A. A., Alelyani, S., Mohana, M., & Aziz, A. A. (2021). Electrocardiogram-based emotion recognition systems and their applications in healthcare—A review. *Sensors*, *21*(15), 5015.

He, Y.-C., Lu, H.-T., Huang, L., & Shi, X.-H. (2015). Non-negative matrix factorization with pairwise constraints and graph laplacian. *Neural Processing Letters*, *42*, 167–185.

Iovino, E. A., Koslouski, J. B., & Chafouleas, S. M. (2021). Teaching simple strategies to foster emotional well-being. *Frontiers in Psychology*, 5239.

Islam, M. R., Moni, M. A., Islam, M. M., Rashed-Al-Mahfuz, M., Islam, M. S., Hasan, M. K., et al. (2021). Emotion recognition from EEG signal focusing on deep learning and shallow learning techniques. *IEEE Access*, *9*, 94601–94624. http://dx.doi.org/10.1109/ACCESS.2021.3091487, URL https://ieeexplore.ieee.org/document/9462089.

Jafari, M., Shoeibi, A., Khodatars, M., Bagherzadeh, S., Shalbaf, A., García, D. L., et al. (2023). Emotion recognition in EEG signals using deep learning methods: A review. *Computers in Biology and Medicine*, Article 107450.

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., et al. (2019). Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimedia Tools and Applications*, *78*, 15169–15211.

Kalikova, A. (2021). Statistical analysis of random walks on network. *Scientific Journal of Astana IT University*, (5), 77–83.

Kamble, K., & Sengupta, J. (2023). A comprehensive survey on emotion recognition based on electroencephalograph (EEG) signals. *Multimedia Tools and Applications*, 1–36.

Khare, S. K., Blanes-Vidal, V., Nadimi, E. S., & Acharya, U. R. (2023). Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations. *Information Fusion*, Article 102019.

Kim, Y., Soyata, T., & Behnagh, R. F. (2018). Towards emotionally aware AI smart classroom: Current issues and directions for engineering and education. *IEEE Access*, *6*, 5308–5331. http://dx.doi.org/10.1109/ACCESS.2018.2791861, URL https://ieeexplore.ieee.org/document/8253436.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, *60*(6), 84–90.

Kumar, G. A. R., Kumar, R. K., & Sanyal, G. (2017). Facial emotion analysis using deep convolution neural network. In *2017 international conference on signal processing and communication* (pp. 369–374). http://dx.doi.org/10.1109/CSPC.2017.8305872, URL https://ieeexplore.ieee.org/document/8305872.

Lasri, I., Solh, A. R., & El Belkacemi, M. (2019). Facial emotion recognition of students using convolutional neural network. In *2019 third international conference on intelligent computing in data sciences* (pp. 1–6). IEEE.

Le, H.-D., Lee, G.-S., Kim, S.-H., Kim, S., & Yang, H.-J. (2023). Multi-label multimodal emotion recognition with transformer-based fusion and emotion-level representation learning. *IEEE Access*, *11*, 14742–14751. http://dx.doi.org/10.1109/ACCESS.2023.3244390, URL https://ieeexplore.ieee.org/document/10042438.

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278–2324.

Lee, S., Han, D. K., & Ko, H. (2021). Multimodal emotion recognition fusion analysis adapting BERT with heterogeneous feature unification. *IEEE Access*, *9*, 94557–94572. http://dx.doi.org/10.1109/ACCESS.2021.3092735.

Li, B., & Lima, D. (2021). Facial expression recognition via ResNet-50. *International Journal of Cognitive Computing in Engineering*, *2*, 57–64.

Liao, C.-Y., Chen, R.-C., & Liu, Q.-E. (2019). Detecting attention and meditation EEG utilized deep learning. In J.-S. Pan, A. Ito, P.-W. Tsai, & L. C. Jain (Eds.), *Recent advances in intelligent information hiding and multimedia signal processing* (pp. 204–211). Cham: Springer International Publishing, http://dx.doi.org/10.1007/978-3-030-03748-2_25, URL https://link.springer.com/chapter/10.1007/978-3-030-03748-2_25.

Lira, S. A., & Neto, A. C. (2013). Assessing the efficiency of data normality verification tests. *International Journal of Mathematics and Computers in Simulation*, *7*(2), 106–115, URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-84878000253&partnerID=40&md5=35171c38abe2c85d4a4e47cd11ad462b.

Liu, H., & Wu, Z. (2010). Non-negative matrix factorization with constraints. *Vol. 24*, In *Proceedings of the AAAI conference on artificial intelligence* (1), (pp. 506–511). http://dx.doi.org/10.1609/aaai.v24i1.7681, URL https://ojs.aaai.org/index.php/AAAI/article/view/7681.

Liu, N., Xu, Z., Zeng, X.-J., & Ren, P. (2021). An agglomerative hierarchical clustering algorithm for linear ordinal rankings. *Information Sciences*, *557*, 170–193.

Lopes, A. T., de Aguiar, E., Souza, A. F. D., & Oliveira-Santos, T. (2017). Facial expression recognition with convolutional neural networks: Coping with few data and the training sample order. *Pattern Recognition*, *61*, 610–628. http://dx.doi.org/10.1016/j.patcog.2016.07.026, URL https://www.sciencedirect.com/science/article/pii/S0031320316301753.

Maamari, B. E., & Salloum, Y. N. (2023). The effect of high emotionally intelligent teachers on their teaching effectiveness at universities: the moderating effect of personality traits. *International Journal of Educational Management*, *37*(3), 575–590.

Mahalakshmi, V., Shenbagavalli, P., Raguvaran, S., Rajakumareswaran, V., & Sivaraman, E. (2024). Twitter sentiment analysis using conditional generative adversarial network. *International Journal of Cognitive Computing in Engineering*, *5*, 161–169.

Mary, A. R., & Begam, M. F. (2020). A comprehensive survey on deep learning based automated diabetic retinopathy detection. *Journal of Xidian University ISSN*, 1001–2400.

Mishra, P., Pandey, C. M., Singh, U., Keshri, A., & Sabaretnam, M. (2019). Selection of appropriate statistical methods for data analysis. *Annals of Cardiac Anaesthesia*, *22*(3), 297.

Mohammadpour, M., Khaliliardali, H., Hashemi, S. M. R., & AlyanNezhadi, M. M. (2017). Facial emotion recognition using deep convolutional networks. In *2017 IEEE 4th international conference on knowledge-based engineering and innovation* (pp. 0017–0021). http://dx.doi.org/10.1109/KBEI.2017.8324974, URL https://ieeexplore.ieee.org/document/8324974.

Nguyen, Q., Nguyen, H., Tran, K. P., Castagliola, P., & Frénod, E. (2019). Real-time production monitoring approach for smart manufacturing with artificial intelligence techniques. In *ISSAT international conference on data science in business, finance and industry* (pp. 100–103).

Paxinou, E., Kalles, D., Panagiotakopoulos, C. T., & Verykios, V. S. (2021). Analyzing sequence data with Markov chain models in scientific experiments. *SN Computer Science*, *2*, 1–14.

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The achievement emotions questionnaire (AEQ). *Contemporary Educational Psychology*, *36*(1), 36–48.

Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research. *Educational Psychologist*, *37*(2), 91–105.

Picard, R. W. (2003). Affective computing: challenges. *International Journal of Human-Computer Studies*, *59*(1–2), 55–64.

Prakash, P. R., Anuradha, D., Iqbal, J., Galety, M. G., Singh, R., & Neelakandan, S. (2023). A novel convolutional neural network with gated recurrent unit for automated speech emotion recognition and classification. *Journal of Control and Decision*, *10*(1), 54–63. http://dx.doi.org/10.1080/23307706.2022.2085198.

Rawat, W., & Wang, Z. (2017). Deep convolutional neural networks for image classification: A comprehensive review. *Neural Computation*, *29*(9), 2352–2449.

Ray, A., Kolekar, M. H., Balasubramanian, R., & Hafiane, A. (2023). Transfer learning enhanced vision-based human activity recognition: A decade-long analysis. *International Journal of Information Management Data Insights*, *3*(1), Article 100142. http://dx.doi.org/10.1016/j.jjimei.2022.100142, URL https://www.sciencedirect.com/science/article/pii/S2667096822000854.

Remaida, A., Moumen, A., El Idrissi, Y. E. B., & Abdellaoui, B. (2020). Handwriting personality recognition with machine learning: a comparative study. In *2020 IEEE 2nd international conference on electronics, control, optimization and computer science* (pp. 1–6). IEEE.

Rezapour, M., & Elmshaeuser, S. K. (2022). Artificial intelligence-based analytics for impacts of COVID-19 and online learning on college students' mental health. *PLoS One*, *17*(11), Article e0276767.

Roux, M. (2015). A comparative study of divisive hierarchical clustering algorithms. arXiv:1506.08977.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161.

Sajjad, M., Ullah, F. U. M., Ullah, M., Christodoulou, G., Alaya Cheikh, F., Hijji, M., et al. (2023). A comprehensive survey on deep facial expression recognition: challenges, applications, and future guidelines. *Alexandria Engineering Journal*, *68*, 817–840. http://dx.doi.org/10.1016/j.aej.2023.01.017, URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85147953411&doi=10.1016%2fj.aej.2023.01.017&partnerID=40&md5=26c99178a6a082bae48299efc523e8b0.

Sarker, I. H. (2021). Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science*, *2*(6), 420.

Sartipi, S., Torkamani-Azar, M., & Cetin, M. (2023). A hybrid end-to-end spatio-temporal attention neural network with graph-smooth signals for EEG emotion recognition. *IEEE Transactions on Cognitive and Developmental Systems*.

Silva, C. C., Galster, M., & Gilson, F. (2021). Topic modeling in software engineering research. *Empirical Software Engineering*, *26*(6), 120. http://dx.doi.org/10.1007/s10664-021-10026-0.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

Somarathna, R., Vuilleumier, P., & Mohammadi, G. (2023). EmoStim: A database of emotional film clips with discrete and componential assessment. arXiv preprint arXiv:2306.08196.

Stoychev, V. (2023). *The potential benefits of implementing machine learning in supply chain management* (Ph.D. thesis), Technische Hochschule Ingolstadt.

Straulino, E., Scarpazza, C., & Sartori, L. (2023). What is missing in the study of emotion expression? *Frontiers in Psychology*, *14*, Article 1158136.

Sum, A., Khatiwada, I., McLaughlin, J., & Palma, S. (2009). The consequences of dropping out of high school. *Center for Labor Market Studies Publications*, *23*.

Sun, T.-W. (2020). End-to-end speech emotion recognition with gender information. *IEEE Access*, *8*, 152423–152438. http://dx.doi.org/10.1109/ACCESS.2020.3017462, URL https://ieeexplore.ieee.org/abstract/document/9170617.

Tarunika, K., Pradeeba, R., & Aruna, P. (2018). Applying machine learning techniques for speech emotion recognition. In *2018 9th international conference on computing, communication and networking technologies* (pp. 1–5). http://dx.doi.org/10.1109/ICCCNT.2018.8494104, URL https://ieeexplore.ieee.org/document/8494104.

Teh, Y. W., Jordan, M. I., Beal, M. J., & Blei, D. M. (2004). Sharing clusters among related groups: Hierarchical Dirichlet processes. In *Proceedings of the 17th international conference on neural information processing systems* (pp. 1385–1392). Cambridge, MA, USA: MIT Press, URL https://proceedings.neurips.cc/paper_files/paper/2004/file/fb4ab556bc42d6f0ee0f9e24ec4d1af0-Paper.pdf.

Umamaheswaran, S., Dar, V., Sharma, E., & Kurian, J. S. (2023). Mapping climate themes from 2008–2021—An analysis of business news using topic models. *IEEE Access*, *11*, 26554–26565.

Vexler, A. (2021). Valid p-values and expectations of p-values revisited. *Annals of the Institute of Statistical Mathematics*, *73*(2), 227–248.

Wang, J., & Zhang, X.-L. (2023). Deep NMF topic modeling. *Neurocomputing*, *515*, 157–173.

Weiss, G. H. (1983). Random walks and their applications: Widely used as mathematical models, random walks play an important role in several areas of physics, chemistry, and biology. *American Scientist*, *71*(1), 65–71.

Wu, R., & Yu, Z. (2022). Exploring the effects of achievement emotions on online learning outcomes: A systematic review. *Frontiers in Psychology*, *13*, Article 977931.

Xia, F., Liu, J., Nie, H., Fu, Y., Wan, L., & Kong, X. (2019). Random walks: A review of algorithms and applications. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *4*(2), 95–107.

Yu, L., Shek, D. T., & Zhu, X. (2018). The influence of personal well-being on learning achievement in university students over time: Mediating or moderating effects of internal and external university engagement. *Frontiers in Psychology*, *8*, 2287.

Zhang, B., & An, B. (2018). Clustering time series based on dependence structure. *PLoS One*, *13*(11), Article e0206753.

Zhang, Z., Murtagh, F., Van Poucke, S., Lin, S., & Lan, P. (2017). Hierarchical cluster analysis in clinical research with heterogeneous study population: highlighting its visualization with R. *Annals of Translational Medicine*, *5*(4).

Zhang, J., Yin, Z., Chen, P., & Nichele, S. (2020). Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review. *Information Fusion*, *59*, 103–126.

Zhao, S., & Song, J. (2022). Unpacking the emotional experiences of learners in a blended learning context. *Frontiers in Psychology*, *13*, Article 879696.