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Predicting Emotional Impact on Peer Review, Peer Assessment, and Self Assessments Using Deep Learning and NLP in STEM Education

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Abstract: Digitalization has transformed academic environments with an increased volume of scientific articles, projects, reports, and workplace events overload. Applications like NLP, ML, DL, AI, and Cloud computing have ushered in more tools for researchers to automate scientific tasks which has led to a skyrocket in duty overlord and pressure on peer review. Due to huge task overloads, emotional expressions on academic assessments, have outweighed factual justifications consistency. This study highlights the present and future changes associated with academic assessment work overload and how this impacts future scientific lifecycles. Aim: The study investigated the impact of the increasing pressure and burden on academic assessment overload, academic assessment feedback, and increased emotional sentiments on peer reviews. The study applied DL and NLP to investigate the impact of emotional sentiments on academic assessments. A total of 90 reviews and feedback from conferences, journals, and patent comments were utilized to predict 4 years' future sentiment level in academic evaluation. Based on the selected reviewers' comments, our model with an accuracy of 72% predicts a fall in reviewers' emotional sentiments throughout the next four years. The study concluded that Peer Review, Peer Assessment, and Self-Assessment as integral parts of AI-driven sustainable education, are fast integrating with technological evolution to better serve the interest of scientific communities.

Keywords: Deep learning, Natural language processing, Emotional sentiments, Peer Review-Peer Assessment & Self-Assessment, STEM Education.

1. Introduction

Present-day education systems have evolved significantly, integrating advanced technologies into learning, assessments, and evaluations (Gupta et al., 2024). Emotional sentiments are also generated in the educational process, creating emotionally charged datasets. The use of deep learning (DL) and natural language processing (NLP) has become crucial in managing data, ensuring that education remains free from emotional bias. NLP, in particular, has been explored as a tool to foster belonging and connectedness, improving students' psychological well-being (Alqahtani et al., 2023). DL and NLP are increasingly being used to predict the future emotional impact of assessments, addressing work overload, and maintaining sustainable education systems. For example, NLP has been applied as a self-assessment tool in civil law education (Knight et al., 2018). Additionally, research on kindergarten students revealed that negative emotions, both inside and outside of the classroom, negatively impacted school engagement through increased teacher-student conflict (Hernández et al., 2016).

Emotional expressions in assessment feedback can compromise the integrity of academic evaluations, which should be fair, transparent, and consistent. In education, three common assessment techniques are peer review, peer assessment, and self-assessment. Peer feedback is most effective when supported by faculty (Offiah et al., 2024) and drives self-assessment and autonomous learning. Peer feedback processes also promote diversity of thought and a deeper understanding of the subject matter. Research on gender and training in peer feedback suggests that multifaceted training programs are necessary to bridge gender-based differences, with women tending to verify feedback while men elaborate on suggestions (Ocampo et al., 2024).

In the wake of COVID-19, peer review in online learning was investigated, emphasizing the importance of inclusive learning, student engagement, and effective instructional design for dynamic online peer interaction. Although peer review, peer assessment, and self-assessment offer numerous benefits, they also present challenges, particularly when emotional expressions interfere with fair and accurate evaluations. Overall, these practices support lifelong learning and uphold the integrity of the educational process.

2. Literature Review

Over the past decades, research outputs on peer review, peer assessment, and self-assessment across various academic disciplines have significantly advanced our understanding of the shared approach, self-awareness, and reflections. Peer assessment of MOOCs through matrix factorization was examined (Luaces et al., 2017). The matrix factorization technique is a content-based grading evaluation that emphasizes fairness and accuracy. A system review on peer review technology support was examined (Van den Bos and Tan, 2019). The study emphasizes anonymity in the peer review process. Peer review process effectiveness was reaffirmed by (Serrano-Aguilera et al., 2021), in an imperial study that examined six (6) STEM courses. University tutor assessment training authentication was investigated through a single-group pre-test and post-test design (Villarroel et al., 2024). Findings reveal that training authenticity assessment facilitates a change. Learning analytics dashboards for students by (Gujju et al., 2024, August) were examined with a focus on student engagement, motivation, and academic performance. The findings showed that learning analytics dashboards greatly improve student engagement, motivation, and academic performance.

The peer review process allows scientific community experts to critique the work of their peers. The process of peer review fosters critical thinking and deepens understanding of the quality standards required to maintain and uphold academic integrity. Peer assessment on the other hand enables teachers, editors, editorial boards, scientific commissions, and ministries to assign grades respectively enhancing a grasp of assessment criteria to promote collaborative learning. Peer assessment promotes essential skills to teach and learn (Yu, 2024). Active involvement in peer assessment of others' work promotes a writing sociocultural educational context. The excess ability to think in and out of scope comes with increased peer assessment. The role played in peer assessment in the scientific world is very important. This body constitutes policies that promote educational integrity and should be void of political resonance. Self-assessment is a process in the academic world that encourages self-reflection on one's work. Self-assessment reflects practical theories and does not necessarily match with how a person thinks they should be taught or learned (Musolino, 2024). According to the authors, appropriate skill levels and proper techniques are prerequisite elements of a fine professional practice. This shows that self-assessment institutes the zeal for practical reflection that is very important for our professionalism. Self-assessment enhances cultivating self-regulation and personal growth. This process allows the academic community to reflect on its growth, activities, and policies.

Emotional sentiments conveyed in multimedia content affect the sound structure of knowledge insights (Borth et al., 2013, October). An investigation on emotional sentiments in the scholarly peer review process was conducted by (Mah, 2023, October) to measure the effect of sentiments by (Mohammad, 2016) on scholarly peer review feedback. The experiment aims at identifying and measuring the negative impact of sentiments on scholarly work during peer review. This experiment identified a large substantial number of sentiments released in each peer review process. Sentiment analysis is a topic for studying subjective feelings (Zhao et al., 2016; Gordon, 2017). Opinion mining has become very significant in our daily life and most people, especially in academia, have become aware of sentiment analysis. From our investigations, most reviews are very much aware of the consequences of emotional expressions and tone. Social media and its platforms are central areas for emotional expressions (Nandwani and Verma, 2021; Aslam et al., 2020; Yadollahi et al., 2017). Text mining releases human aspects of a text that fall short of objectivity. It is essential to highlight the significance of sentiments as it significantly reduces information quality. Most social media releases most of their success stories, failures, and issues on social media nowadays. These platforms are becoming vital points for understanding communication and community views.

2.1 Bad Emotional Aspects for Peer Review, Peer Assessment, and Self-Assessment

This section lists some selected item this study believe are not good for a peer review, peer assessment, and self-assessment. An investigation on motivation and emotion was conducted with a focus on guilt, shame, pride, social anxiety, and embarrassment (Leary, 2007). The study revealed that the motives to self-enhance, self-verify, and self-expand. Self-enhance, self-verify, and self-expand come from people's concerns with social approval and acceptance. The selected 10 items identified for each assessment method are very bad and can lead to emotional comments. This study suggests that once an author, student, scholar, student, and teacher face this aspect, should immediately notify the editorial board.

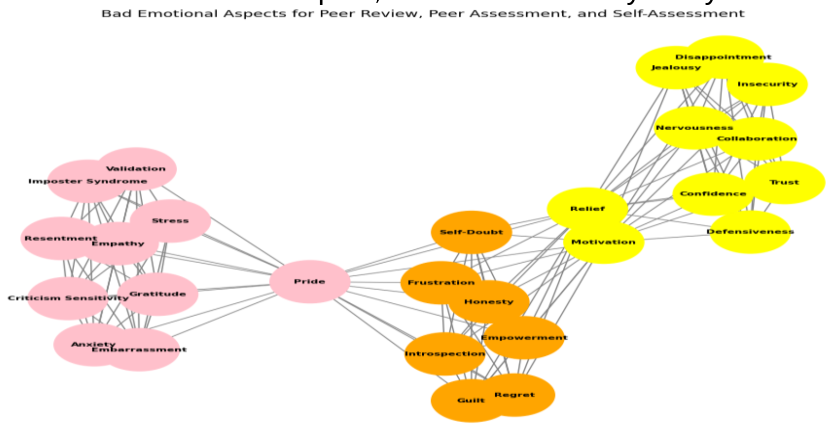


Figure 1. Bad Emotional Aspects for Peer Review, Peer Assessment, and Self-Assessment.

Figure 1 represents aspects of emotions not good for assessment in education. The items in pink colour are not good for peer review reports, yellow colour represents aspects of emotions not good for peer assessment while orange colour represents aspects of emotions not good for self-assessment. When a reviewer has Self-enhance, self-verify, and self-expand he or she will not exhibit own-self validation, resentment, anxiety, criticism, sensitivity, stress, gratitude, and imposter altitude during peer review. People with emotional intelligence, expertise, and higher-level qualifications earn this from people's concerns with social approval and acceptance. When are reviewer exercises any of the ten listed emotional sentiment aspects, it shows he or she might be limited with emotional intelligence, and expertise has low-level qualifications, and has not earned other people's concerns with social approval and acceptance.

Peer Review: Peer review is a process whereby advanced career disciplinarians, and experienced, and expert scientists evaluate the work of their peers. This technique of assessment is very common in the academic and professional sectors. Peer review as a tool of performance enhancement was investigated as part of Malaga, Spain's studying approach (Serrano-Aguilera et al., 2021). Peer review is used in Malaga Spain to foster the spirit of crosswise skills of critical thinking, and autonomous responsibility in students. In the education sector, peer review helps students, researchers, teachers, and academic administrators learn from each other's views, gain different thinking perspectives, and develop critical thinking skills. Although emotional expressions are becoming a problem, there are still opportunities to fix this growing challenge. English as a foreign language was utilized as a learning assessment instrument (He and Wang, 2024). Reviewing the work of other peers helps in a better understanding of the standards and criteria used to assess good quality work. Peer review also fosters a sense of responsibility, as peers learn to provide constructive assessments and feedback free from emotional expressions.

Peer Assessment: Peer assessment is a broader assessment technique than peer review and self-assessment. Peer assessment ensures and enables students, teachers, researchers, scientists, editors, editorial boards, and scientific commissions to provide feedback and assign grades or scores to their peers' work. Peer assessment is effectively being used in most schools and higher education (Magaly, 2020). The effectiveness of peer assessment is culturally diverse, fosters collaboration, advanced knowledge sharing, and improves academic performance. Peer assessment is another minor form of classroom gamification that assists students in learning by practicing themselves with their peers' knowledge. Peer assessment encourages peers to engage deeply with the assessment regulations, standards, policies, and criteria that help authors better understand what is expected in their work. A study aimed at evaluating the impact of online peer-generated citation assessments during student test construction was performed (Yu and Wei, 2024). Cognitive and emotional issues were examined. Findings reveal that students in the citing group scored higher marks than those in the no-citing group. Also, the citing group did not induce a higher cognitive load compared to the no-citing group. Peer assessment should advance collaboration and discourage emotional expressions as a justification that leads evaluations to richer learning experiences. Delivering effective studies feedback in higher education was conducted [8]. The study also examined the key challenges issues teachers faced in delivering student results. The best policy is to permit students to participate in peer assessment, use technological applications like AI, and deliberate on key issues openly with peers.

Self-Assessment: Self-assessment involves a process whereby students, teachers, researchers, authors, and scientists evaluate their work. Self-assessment should be free from emotional sentiments and should foster growth and learned reflection. Peer assist learning (Molgaard[1] and Read, 2024). Peer assist learning provides tutors with training and evaluation. Work overload, Self-assessment, shared assessment, self-marking, and dialogical marking processes were investigated (Herrero-González et al., 2024). This study examines several categories of classroom participation. Amongst the categories, the physical classroom is the best as it provides a place where students can exchange ideas with peers. Self-assessment stands as a strong pillar of personal integrity that allows the peer to cognize their strengths and weaknesses and take responsibility for their growth. Self-assessment helps foster self-regulation and critical self-reflection. A system review examined the impact of peer review in online learning for Higher rates of education in Taiwan (Craig and Kay, 2021). Findings reveal that for every five (5) students, one (1) believes divergent feedback from peer-assessment activities is because of cognitive overload. When peers assess their work, they learn to set strict goals, monitor their progress, and identify areas for improvement. The study revealed that online learning systems have a well-structured environment that can guide students through peer review, peer assessment, and self-assessment. The online learning platform has document editors for teachers monitoring chat rooms for students writing, and worksheets for students' self-reflection.

2.1.1 Significance of Assessment Techniques to Educational Integrity

Utilizing peep learning (DL) and natural language processing (NLP) to predict the future of human emotional responses on the academic assessment overload is both timely and relevant, especially in the context of growing academic and professional workloads. Here's why it's a strong topic

Interdisciplinary Appeal: Thinking beyond oneself is an important aspect that comes with reviewing reflection and in-depth thought on others' views. The combination of peer review, peer assessment, and self-assessment intersects multiple interdisciplinary appraisals that foster academic community. When Peer is involved in the process of assessment, they are forced to think beyond the scope and match the expectations of their fellow peers. In many cases, reviewers gain knowledge and insight into their peer's works that foster an interdisciplinary approach. Peer review, peer assessment, and self-assessment ensure personal growth and hands-on activities to the benefit of peers, the system, and the education community. Peer review, peer assessment, and Self-assessment is an interdisciplinary appeal that ensures psychology and education advance integrity appeal to a broad audience.

Academic Relevance: Peer review, peer assessment, and self-assessment institute practice for academic relevance and integrity that leads to better academic strategies that is improving both the well-being of reviewers and the quality of the peer review process. Currently, the Web of Science recognizes peer review efforts, some publishers issue certificates of peer review and recognition of excellence peer review. This aspect encourages academic relevance and builds up integrity in educational service rendering.

Innovative Outsourcing Approach: Engaging in peer review, peer assessment, and self-assessment is a cutting-edge outsourcing of expertise experience. Peer review, peer assessment, and self-assessment ensure that experts detect subtle patterns in their peers' work that might reveal important or less actionable insights. Innovative outsourcing techniques through peer review, peer assessment, and self-assessment have remained one of the best and still effective academic assessment methods today.

Practical Developments: Peer review, peer assessment, and self-assessment in research could be used to capture important facts on the manuscripts required to develop tools or systems or warning systems against harmful knowledge. Peer review, peer assessment, and self-assessment ensure that new development stands out and doesn't fall short of any expectations of the readers. Practical Development upholds academic integrity. The reason is that all developments come through knowledge creation.

Oriented Skills: Peer review, peer assessment, and self-assessment an important aspect in the lives of students, teachers, researcher authors, commissions, and ministries to address existing issues and anticipate future challenges in the education sector. There is a reward that comes alongside peer review, peer assessment, and self-assessment. As the saying goes "knowledge is the key to open all doors". When you become actively involved in peer review, peer assessment, and self-assessment activities, you gain wider knowledge and perspectives of fellow peers.

3. Applied Method

This research paper highlights, analyses, and predicts the emotional sentiment expressed by some selected review comments from conferences, journals, and datasets from Harvard Dataverse. Conferences, Journals, and patents public comments for the past years were utilized to build, test, and predict emotional sentiments on peer review feedback for over next four years.

Our study uses the following analysis steps:

- ✓ Emotional sentiments extraction from text dataset.
- ✓ Emotional sentiment data aggregating by year.
- ✓ Forecast future emotional sentiment trends based on linear regression model filtering.
- ✓ Visualization based on past emotional history and forecasted sentiment levels in a bar chart.

3.1 Data Collection

The dataset used analyzed in this study was loaded from an Excel file (Emotional Impact on Peer Review, Peer Assessment and Self-Assessments in Education Data.xls). The file is made up of textual data, peer review comments from conferences, and journals, patent peer review comments, and metadata year of submission. The data is made up of about 91 comments from a variety of organizations, institutions, establishments, companies, and other forms of business.

3.2 *Methodology Outlined Steps*

This section outlined steps we used to combine natural language processing (NLP) and deep learning techniques for sentiment analysis with statistical modeling for peer review trend forecasting.

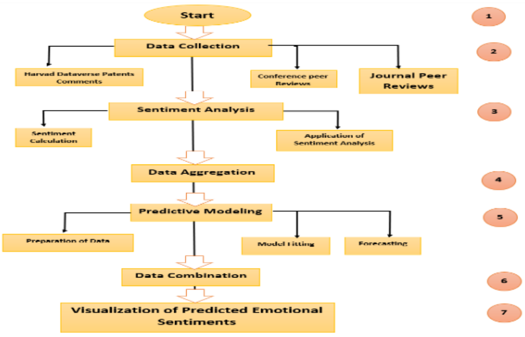


Figure 2. Outlined methodology Analysis.

Figure 2 represents all the eight steps we utilized to predict emotional sentiment for the next four years. The following steps help us to realize our objective and to predict emotional sentiments on the reviewer's feedback. Step 1 Sentiment Calculation, step 2 Application of Sentiment Analysis, step 3 Data Aggregation, step 4 Predictive modelling the preparation of Data, step 5 Model Fitting, step 6 Forecasting, step 7 Data Combination, and step 8 Visualization.

We provide a [link to the emotional analysis implementation]. In the attached file we put together a steps implementation that reflects these four emotional sentiments extraction from text dataset. emotional sentiment data aggregating by year, forecast future emotional sentiment trends based on linear regression model filtering and Visualization based on past emotional history, and forecasted sentiment levels in a bar chart.

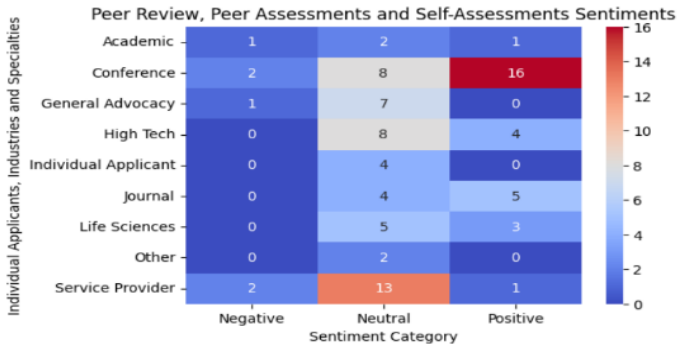
4. Results

To achieve our aim in this study, we make use of the following steps Emotional Sentiment Analysis, Yearly Sentiment Aggregation, Linear Regression Model, and Forecasting and Visualization of the Sentiments.

4.1 *Step 1: Emotional Sentiments Analysis*

Step one of the sentiment analyses begins with the assessment of the emotional tone for the peer review feedback from conference papers, journals, and patent eligibility of some selected public comments. We used the x-axis to represent the years, and the y-axis represents the categorical sentiment levels. We used a bar chart to represent the emotional sentiment levels for each year. Sentiment analysis was calculated utilizing the TextBlob library from the dataset to obtain a sentiment score. This sentiment score ranges from -1 (showing a very negative sentiment attribute), +1 (showing a very positive sentiment attribute), and 0 (showing a neutral sentiment attribute). Positive if polarity > 0.1, Negative if polarity < -0.10, and Neutral if polarity is exactly 0.

A detailed heatmap was generated showing sentiment classification score, historical and predicted data for all sentiment categories ranging from (Positive, Neutral, Negative) for consistency.

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Accuracy: 0.7222222222222222
Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.92      0.83        13
           1       0.50      0.20      0.29         5

    accuracy                           0.72        18
   macro avg       0.62      0.56      0.56        18
weighted avg       0.68      0.72      0.68        18
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Figure 3. Classification analysis.

Figure 3 represents the classification results for our emotional sentiment analysis. The codes were all correctly categorized with a score of 72% accuracy for all sentiments based on the adjusted conditions and generated heatmaps for both historical and predicted sentiment data.

4.2 Step 2: Yearly Sentiment Aggregation

To understand the trend in peer review feedback, and patents public comments, a sentiment analysis over the past four years was examined. To simplify our analysis, all average sentiment score for each category over the years was calculated by grouping the data by the Year column and then computing sentiment mean scores.

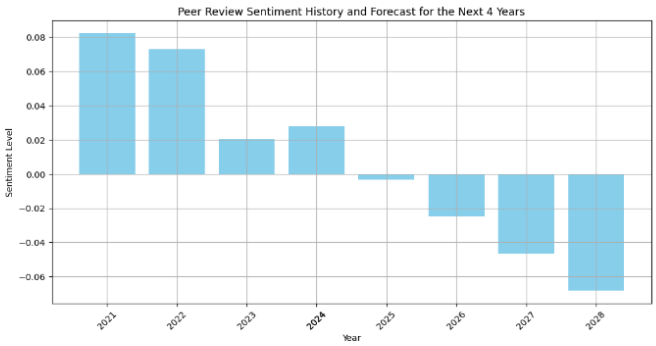

Figure 4. Bar chart sentiment history and forecast.

Figure 4 represents columns, Sentiments, and predicted emotional sentiments for the next four years. We used the sentiment analysis from the peer review feedback and patents public comments to created next four years predictions based on the dataset obtained.

4.3 Step 3: Linear Regression Model

To predict future sentiment levels based on the peer review feedback, and patent public comments on historical trends for the next coming years we apply these two approaches below.
We took the yrs the sentiment was registered, and their corresponding average sentiment scores to train a linear regression Model.

The linear model was trained to understand and interpret the relationship between the year (as the independent variable) and the average sentiment score (as the dependent variable).

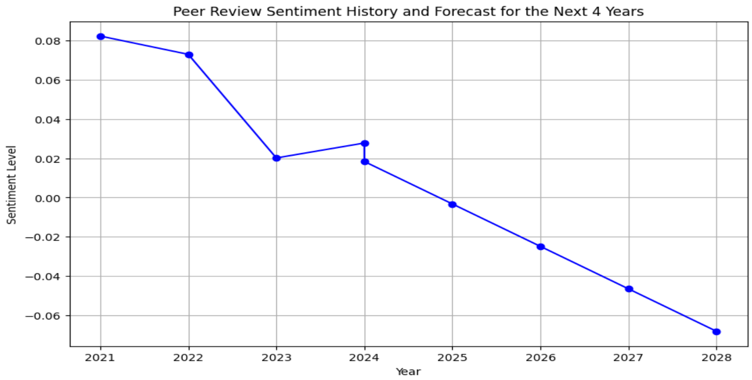

Figure 5. Linear graph sentiment history and forecast.

Figure 5 represents a linear graph for the four years of sentiment history and forecast. The linear regression model, which was successfully trained and modelled to predict, was able to capture the trend in sentiment over the next four years (2024-2028).

4.4 Step 4: Forecasting and Visualization of the Past and Future Sentiments

To forecast and determine the sentiment levels for the next four (4) years that is from (2024 to 2028) the following approaches were utilized. We used a trained linear regression model of peer review feedback and patent public comments to predict emotional sentiment levels for the coming years that is (2025-2028). We predicted sentiment scores using heatmap and bar chart based on historical data.

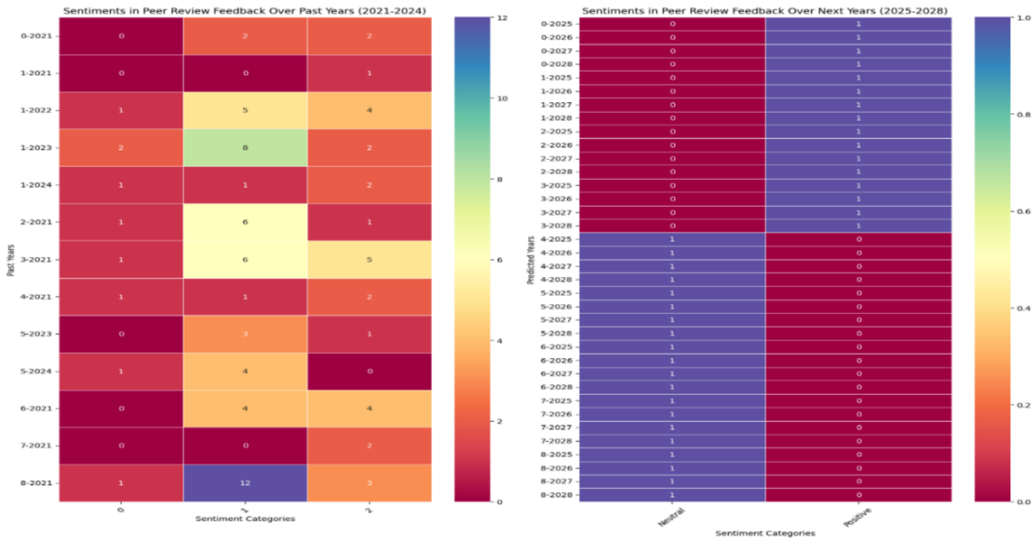

Figure 6. Forecast and visualization sentiments.

Figure 6 represents the sum of sentiments for the past years and forecast sentiments for the next four years. Figure 6 shows our model providing a visualized forecast of sentiment level categories for the years 2024 through 2028, based on the historical observed trend we obtained for this study. To visualize our model in a more accurate approach, we used both the sentiment review feedback and comments historical data to predict the next four years' sentiment levels.

5. Discussion on the Factors to Limit Emotional Sentiments on Peer Assessment Process.

Tackling the challenges associated with peer review, peer assessments, and self-assessment requires a practical multifaceted approach that addresses both efficiency and fairness. The following paragraph represents some of the factors that could be integrated into the education sector into emotional expressions in the assessment process.

The following paragraphs are strategies to enhance the peer review process using AI and technology. Firstly, AI-based filtering tools should be implemented to pre-screen review and editorial comments, removing low-quality feedback with excessive emotional expression. Secondly, leading indexers like Web of Science, Scopus, and PubMed should manage reviewer workloads by recruiting doctoral students as preliminary reviewers to alleviate the strain on the scientific community, which is burdened with excessive manuscripts. Thirdly, providing incentives and recognition for reviewers, particularly junior reviewers, can encourage participation and improve review quality. Financial rewards and career benefits are suggested.

Additionally, training and guidelines on peer review should be introduced as a formal subject for PhD students, coordinated by journals and academic institutions, ensuring ethical and effective reviews. A collaborative review model where teams of reviewers discuss and consolidate feedback is also proposed. Improved reviewer matching** using AI tools can ensure reviewers are selected based on subject expertise, while technological solutions like natural language processing (NLP) could assist in summarizing papers and highlighting key points, making the review process more efficient and focused. These initiatives aim to improve the quality, transparency, and efficiency of the peer review process.

5.1 Limitations and Future Work

The linear regression model applied in this study provides a straightforward approach to forecasting emotional sentiments in the peer review feedback and patent comments. Tin our study, linear relationship between time and sentiment capture, but this approach may be limited to capturing more complex patterns. Future research should endeavour to explore more sophisticated time series models like ARIMA, and more machine learning models that can capture non-linear trends and seasonality in the data.

Additionally, expanding the analysis of emotional sentiment peer review feedback to include other features such as the content of the comments, educational level, academic discipline, and demographic information will further enhance the model's predictive power.

6. Conclusion

Our investigation into peer review, peer assessment, and self-assessment helps us to understand the importance and positive contribution technology is making to our humanity. Our study utilizes a heatmap, linear model graph, and bar chart to visually display the trend in the pear review sentiment for the past to the predicted future, making it easy for readers to observe how generally sentiment has changed and is expected to change over time. Applying NLP (TextBlob), deep learning for emotional sentiment analysis, and linear regression for prediction in the research reveals insights into how researchers, students, teachers, scientific commissioners, scholars, and patent authors' eligibility have evolved in recent years. The study is deeply concerned about the dramatic shift indicated by the predictive model regarding the comments patterning to educational activities. The visualization encapsulates emotional sentiments insights, offering a clear depiction of sentiment from peer review feedback trends and helping stakeholders understand potential future shifts in public opinion due to technological evolution.

Conflict of Interest

No conflict of interest

Data Statement

Data available on request.

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