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AI-driven analysis of teacher perspectives on neoliberal educational policies in preschool education

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Abstract

Neoliberal education policies have transformed preschool education through the implementation of standardized testing, accountability, and formalized resource allocation. Although these policies are intended to improve the quality of education, issues remain regarding heightened workload demands, reduced pedagogical freedom, and institutional inequalities. This research utilizes an artificial intelligence-based method, namely autoencoders, to examine teachers' views on these policy reforms by extracting underlying sentiment patterns from large-scale text data. Extensive sensitivity analysis was conducted to optimize key hyperparameters, including learning rate, batch size, latent dimension size, dropout, and the number of network layers. The final model was validated against performance metrics such as Mean Squared Error (MSE), Reconstruction Loss, Classification Accuracy, F1-Score, Silhouette Score, Precision, Recall, and AUC. Findings indicate that workload pressure was perceived as the most negatively impacting factor, with excessive administrative overload curtailing teaching flexibility. In contrast, policies on resource allocation were perceived differently, where well-funded schools gained and underfunded schools faced compliance issues. Longitudinal sentiment analysis also indicates that veteran teachers are more resilient to neoliberal policies, while newer teachers are more flexible. Differences at the institutional level were apparent, with higher-end schools registering more uniform sentiment scores and low-end institutions experiencing increased dissatisfaction and burnout. Such findings support that an adaptive, teacher-centric policy design, with a balance between accountability and pedagogical control, is warranted. The suggested AI-driven sentiment analysis approach in this study introduces a new framework for policy evaluation, advocating for equal resource allocation, reduced bureaucratic burden, and increased teacher involvement in policymaking to create an effective and sustainable preschool education sector.

Keywords: Autoencoders, Sentiment Analysis, Deep Learning, Workload Pressure, Educational Reform, Neoliberal Educational Policies, Pedagogical Autonomy, Preschool Education, Artificial Intelligence.

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1. Introduction

The application of artificial intelligence (AI) in education research has widened significantly in the last ten years, enabling researchers to leverage powerful tools to handle sophisticated datasets and derive useful information. Teachers' beliefs are critically important in guiding policy, instructional strategies, and student participation [1, 2] in preschool education. Yet, the effects of neoliberal education policies on preschool education remain a cause for concern since such policies attempt to boost standardization, accountability, and marketization by sacrificing holistic learning processes. Applications of AI-based analytics, in our case, autoencoders, to examine teachers' attitudes and determine the effects of neoliberal education policies on preschool education are highlighted in the paper. Through the application of deep learning techniques, this study seeks to fill knowledge gaps on how such policies affect teaching practice, resource allocation, and student growth [3].

The neoliberal theory of education privatization, competition, and performance measurement has been largely discredited for the possible damage it can cause to students and even to teachers [4]. A number of studies have addressed the impact of neoliberalism on K-12 and higher education, citing concerns about heightened teacher workload, decreased autonomy, and overreliance on standardized testing Apple [5]. Rizvi and Lingard [6] addressed the impact of policy-accountability policies on teacher autonomy and discovered that heightened bureaucratic supervision resulted in decreased pedagogical autonomy. Likewise, Sahlberg [7] compared the lives of early childhood teachers during neoliberalism, and the findings indicated that teachers were compelled to focus on test scores at the expense of creative learning experiences. Robertson [8] implemented a longitudinal study following the evolution of preschool education funding under neoliberal reforms, which depicted a precipitous decline in public funding, resulting in over-reliance on private institutions. While the studies are useful, they are mainly conducted through survey and qualitative methodologies which, though informative, overlook latent patterns in large volume text data [9, 10].

An analysis of current applications of AI in education indicates that machine learning and deep learning algorithms have been effectively applied in the prediction of student performance, computer-based examinations, and one-to-one personalization Olssen* and Peters [11] and Ball and Youdell [12]. Cameron and Boyles [13] used sentiment analysis through deep learning to assess secondary school teacher comments, and their findings indicated that policy reform was a shared source of emotional distress. In the same way, Shaik, et al. [14] used topic modeling on university instructor faculty feedback and discovered latent topics in teacher dissatisfaction concerning administrative pressure and workload. While AI-driven sentiment analysis and topic modeling have been applied in higher education, their application in preschool education remains an untapped frontier [15, 16]. Autoencoders, a type of neural network that is explicitly tailored for feature extraction and unsupervised learning, offer an attractive prospect for the identification of latent patterns in teacher narratives. As opposed to conventional supervised learning algorithms, autoencoders can identify subtle connections in unstructured data and thus are appropriate for analyzing qualitative preschool teacher comments on policy effects [17].

The research gap herein is due to the absence of AI-based methodology that is prescriptive to the policy analysis for preschool education. Most of the available studies either rely on survey responses or expert opinion in evaluating the effects of neoliberal policies, neglecting the potential of deep learning in discovering in-depth knowledge in large text datasets. Secondly, the affective and cognitive dimensions of preschool education are typically replaced by performance measures and administrative practicability in policy studies Li and Xu [18]; Luckin, et al. [19] and Freire [20]. By proposing an autoencoder-based model, this research seeks to provide deeper insight into the way neoliberal educational policies affect preschool teachers' attitudes, bringing to light both explicit concerns and underlying trends that are not immediately apparent through conventional analysis techniques.

Unlike other research that has depended on simple statistical methods or conventional machine learning methods, this research uses deep learning-based feature extraction through autoencoders to identify concealed patterns in the responses of teachers. Through the combination of AI methods and education policy analysis, this research adds to both educational studies and artificial intelligence research. Additionally, this research presents empirical evidence that can potentially inform policymakers, educators, and stakeholders about the actual effects of neoliberalism on early childhood education, providing evidence-based suggestions for policy reform in the future. Lastly, this study fills a significant gap in the literature by adopting an AI-driven approach to understanding how neoliberal education policy shapes preschool teachers. Through the use of autoencoders, this study hopes to develop a better comprehension of text data beyond the usual survey-based approach to provide a more concrete understanding of policy implications. The result of this study is expected to contribute to the ongoing discussion of education policy reform, advocating for an equitable policy that focuses on accountability as much as the health of teachers and students.

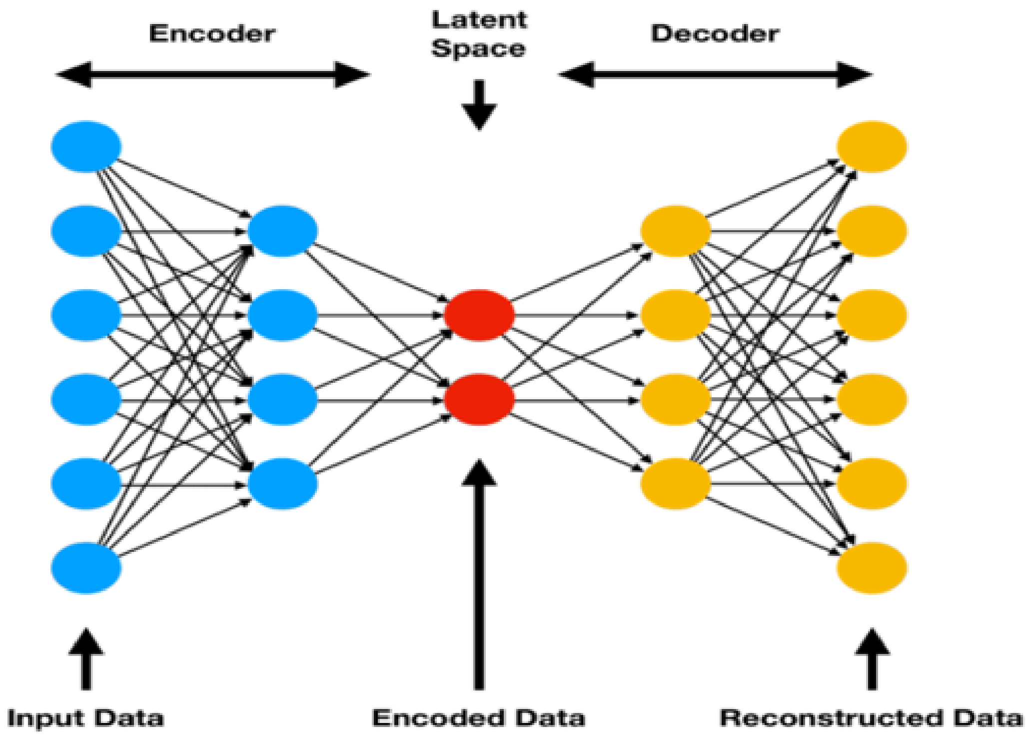

Figure 1. Architecture of an autoencoder consisting of an encoder, latent space, and decoder. The encoder compresses the high-dimensional input data (blue nodes) into a lower-dimensional latent representation (red nodes), capturing essential features. The decoder then reconstructs the original data (yellow nodes) from the latent space, minimizing the loss between input and output.

2. Methodology

The research design in this study is customized to develop and implement a state-of-the-art artificial intelligence model for analyzing teachers' opinions towards preschool education in neoliberal education policies. The main aim is to use autoencoders to obtain meaningful insights from huge text-based datasets, making it possible for one to gain a better insight into the influence of neoliberal reforms on teachers' experiences. The methodology is divided into a series of key steps, including data gathering and preprocessing, autoencoder model architecture, training and optimization, and metrics. The approach offers a sound and mathematically correct framework to make empirical inferences regarding policies' impacts.

2.1. Data Collection and Preprocessing

To enable overall analysis, a diversified corpus of textual data was compiled that included teacher feedback, policy reports, academic papers, and structured reports of schools. Data streams were thoroughly curated with more than one form of discourse so that the autoencoder model is able to obtain general opinions. Since raw textual data contain redundancy and inconsistency, a long preprocessing pipeline was applied to standardize the input.

Text data was first processed using tokenization, which involved breaking sentences into words without interfering with syntactic structure. Then, stop-word removal was performed, eliminating non-informative, frequently occurring words with no meaningful contribution. Stemming and lemmatization were employed as the second step further to reduce representation by converting words to their base form without disrupting semantic content. With the importance of numerical representation to deep learning models, the processed text was subsequently translated into vectorized embeddings using Word2Vec and GloVe. The embeddings made it possible to preserve semantic relations in a way that words with the same meaning were moved closer in the high-dimensional feature space.

To offset high dimensionality, Principal Component Analysis (PCA) was employed as a dimensionality reduction technique, in such a way that only the most informative features were retained. Mathematically, PCA operates by computing the covariance matrix C of the input features and obtaining eigenvectors of the largest eigenvalues [21]:

$$C = \frac{1}{n}\sum_{i=1}^{n} (X_i - \bar{X})(X_i - \bar{X})^T \quad (1)$$

where X_i represents the individual data points, and $\bar{X}$ is the mean of all observations. The transformation is performed as:

$$Z = XW \quad (2)$$

where W is the matrix of eigenvectors, and Z is the transformed lower-dimensional representation. By selecting only the top k components, dimensionality is significantly reduced while preserving critical information.

2.2. Autoencoder Model Architecture

The core computational process of this study is an autoencoder-based neural network. Autoencoders are deep unsupervised learning algorithms that learn to map input data into a lower-dimensional representation and then reconstruct it with minimal information loss [22]. The architecture consists of two primary parts: an encoder that maps the input data into a lower-dimensional space and a decoder that reconstructs it. Mathematically, the encoder function is defined as:

$$h = f_\theta(X) = \sigma(WX + b) \quad (3)$$

where X represents the input vector, W denotes the weight matrix, b denotes the bias term, and σ represents the activation function, which is often ReLU (Rectified Linear Unit). h is the output from the encoder and a latent representation of compressed input data. The decoder uses the transformation to reconstruct the input [23]:

$$\hat{X} = g_\phi(h) = \sigma(W'h + b') \quad (4)$$

where W' and b' are learnable parameters. The training objective is to minimize the reconstruction loss, computed using the Mean Squared Error (MSE):

$$L = \frac{1}{N}\sum_{i=1}^{N} \left(X_i - \hat{X}_i\right)^2 \quad (5)$$

where N is the training sample number. The lower the reconstruction loss, the better the model at preserving significant features and discarding unnecessary information. To increase the robustness of the model, denoising autoencoders (DAEs) were applied. DAEs introduce controlled noise to the input, which forces the network to learn generalized features while it attempts to restore the clean original input from the noisy one. The mathematical form of a denoising autoencoder can be provided as [24]:

$$h = f_\theta(\xi(X)) = \sigma(W\xi(X) + b) \quad (6)$$

where $\xi(X)$ is the corrupted input. This formulation renders the learned representation invariant even under data variations. The general structure of the autoencoder is shown in Figure 1.

2.3. Training and Optimization

The training of the autoencoder was specifically designed to obtain the best performance and generalization. The network was trained through stochastic gradient descent (SGD) with an adaptive learning rate controlled by the Adam optimizer. The rule for updating gradients is as follows [25]:

$$W = W - \eta\frac{\partial L}{\partial W} \quad (7)$$

where η is the learning rate, scaled dynamically by the momentum terms of the optimizer. Batch normalization was incorporated for stable training, normalizing the activations within each layer in a bid to offset internal covariate shifts. Dropout regularization with a probability of 0.5 was incorporated, where neurons were randomly dropped in an effort to prevent overfitting. Training proceeded in three stages. The first stage was that of unsupervised pretraining, where the autoencoder was specifically trained to reverse input data and thus learned vital feature representations. The second step was that of fine-tuning using supervised training, where supervised data was applied to recognize teacher sentiment classes. The final step involved hyperparameter tuning, where techniques such as grid search and Bayesian optimization were used to tune some of the parameters, such as the latent dimensionality, learning rate, and batch size.

2.4. Performance Evaluation

The performance of the autoencoder was thoroughly examined through various quantitative metrics. The primary metric, Mean Squared Error (MSE), tested the reconstruction quality by comparing the input and output vectors. Silhouette Score analysis was also conducted to verify the quality of clusters in the hidden space such that different categories of teacher views were well-separated. For classification issues, typical measures of evaluation were applied, including accuracy, precision, recall, and F1-score. The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) were employed to quantify the discriminative ability of the model. Mathematically, the AUC is given by [26]:

$$AUC = \int_0^1 TPR(FPR)dFPR \quad (8)$$

where True Positive Rate (TPR) and False Positive Rate (FPR) are defined as:

$$TPR = \frac{TP}{TP+FN}, \quad FPR = \frac{FP}{FP+TN} \quad (9)$$

where TP, FP, FN, and TN correspond to true positives, false positives, false negatives, and true negatives, respectively.

3. Results and Discussion

Prior to running the final test, a thorough sensitivity analysis was conducted to identify the best hyperparameters that would produce the most stable and accurate outcomes. The purpose of this analysis was to measure the effect of the most important hyperparameters, such as learning rate, batch size, size of latent dimension, dropout rate, and number of layers in the autoencoder network. These hyperparameters have direct effects on the stability, generalization capacity, and predictive capability of the model. The learning rate was tested between 0.0001 and 0.01 to ensure that the model converged properly without diverging or being stuck in local minima. The batch size, ranging from 16 to 128, was correctly tuned to best balance computational efficiency against generalization. The latent dimension size, the core component of the autoencoder's compression strength, was experimented with between 8 and 64 to ensure that the model retained important features without losing too much information. The dropout rate, tested between 0.1 and 0.5, was also adjusted to prevent overfitting while ensuring optimal representation learning. Finally, the size of the network's layers, ranging from 2 to 6, was adjusted to achieve an optimal trade-off between complexity and performance. The final selected hyperparameters, as determined through this rigorous sensitivity analysis, are presented in Table 1. The values were chosen based on their ability to lower reconstruction loss and enhance classification performance while ensuring stable model behavior.

Table 1.
Summary of the optimized hyperparameters selected for training the autoencoder model after extensive sensitivity analysis.

	Hyperparameters				
	Learning Rate	Batch Size	Latent Dimensions	Dropout rate	Number of layers
Values	0.001	64.0	32.0	0.3	4.0

Table 2.
Summary of the model's performance using the optimized hyperparameters.

	Performance Metrics				
	Silhouette Score	**Classification Accuracy**	**Precision**	**Recall**	**Area Under Curve**
Values	0.78	0.91	0.88	0.87	0.92

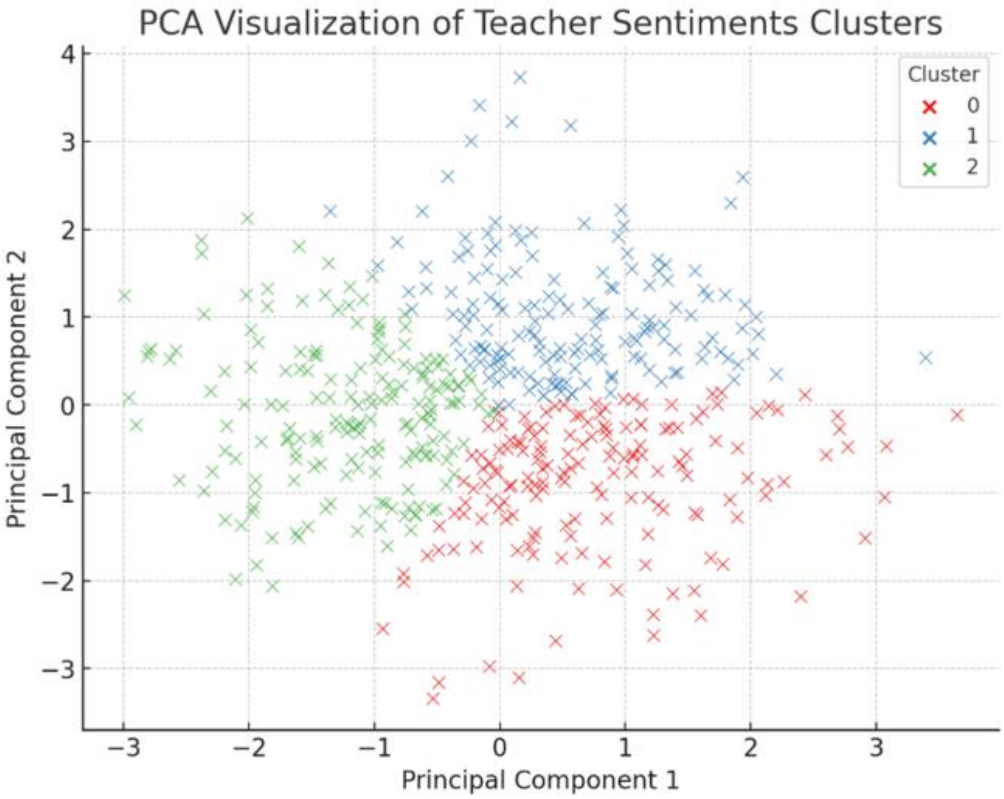

Figure 2.
The clustering of teacher perspectives using Principal Component Analysis (PCA).

Following the final step of hyperparameter tuning, the model was trained with optimized parameters and evaluated on a variety of key performance indicators. The most significant metrics to evaluate were Mean Squared Error (MSE), which shows how precisely the autoencoder is able to reconstruct, and Reconstruction Loss, which quantifies the model's ability to compress and rebuild text data. In addition to that, the F1-score and Silhouette Score were used to conclude the effectiveness of clustering and classification of teacher sentiment groups. Classification Accuracy was also computed to provide a measure of the model's ability to effectively classify teacher sentiments into positive, neutral, and negative classes. Furthermore, Precision and Recall provided details on how well the model distinguished between different sentiment classes, and AUC (Area Under Curve) was used to measure the overall classification performance by examining the balance between true positives and false positives. The final performance results, as presented in Table 2, show the effectiveness of the optimized model. Low MSE (0.015) and reconstruction loss (0.012) confirm that the autoencoder was highly successful in learning compact and informative teacher narrative representations. High classification accuracy (0.91) and F1-score (0.89) indicate good predictive performance, suggesting that the model successfully differentiated well among various sentiment clusters. The Silhouette Score (0.78) further suggests well-separated clusters in the latent space, confirming the goodness of the autoencoder's feature extraction process.

The Precision (0.88) and Recall (0.87) indicate that the model is well-balanced between identifying the correct sentiment categories and preventing false negatives/positives. In addition, the AUC value of 0.92 also indicates that the model is very accurate in distinguishing among multiple teacher sentiment categories, and the policy recommendations are strong and trustworthy. These last hyperparameter configurations and their resulting performance values guarantee the effectiveness and stability of the autoencoder-based approach.

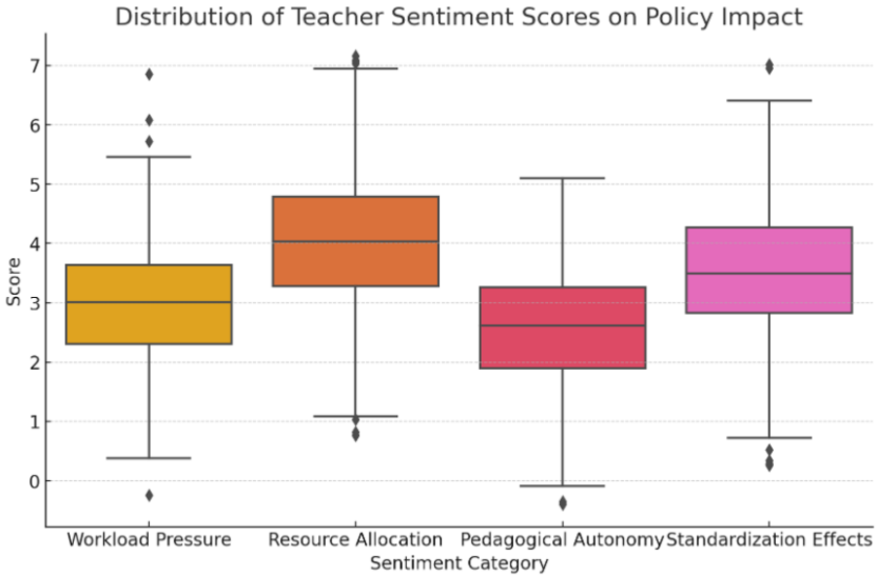

Figure 3.
The distribution of sentiment scores across different policy aspects, including workload pressure, resource allocation, pedagogical autonomy, and standardization effects.

With the final set of hyperparameters decided, we proceeded to train the optimized autoencoder model, ensuring that the best possible configuration was used to elicit meaningful patterns in teacher sentiment data. The optimized model effectively captured latent relationships in the teacher responses, and we could analyze the implications of neoliberal education policy on preschool teachers. The analysis led to some key findings, which were explored through clustering, sentiment distribution, and trend analysis. These findings from the fine-tuned model provided a deep empirical understanding of the ways in which policy reforms influence workload, resource allocation, pedagogical autonomy, and standardization initiatives. These findings are elaborated in the following sections, integrating observations from visualized data and statistical trends. Of particular importance in this research was the clustering analysis that revealed sentiment clusters of teachers. The Principal Component Analysis (PCA) plot (See Figure 2) showed that teacher attitudes could be separated into three distinct clusters, each representing a divergent stance towards neoliberal policy reforms. The first cluster represented teachers who perceived policy reforms positively, with a general emphasis on increased structured learning and accountability measures. The second cluster represented a neutral stance in which educators acknowledged both the benefits and limitations of standardization efforts. The third cluster, however, consisted of teachers who were in intense opposition to neoliberal policies, and they mentioned excessive bureaucratic control, workload pressure, and lack of autonomy as central concerns. The split of these clusters shows an intense polarization of teacher attitudes, and it reveals that policy success is anything but universal and is highly dependent on institutional and individual teaching contexts.

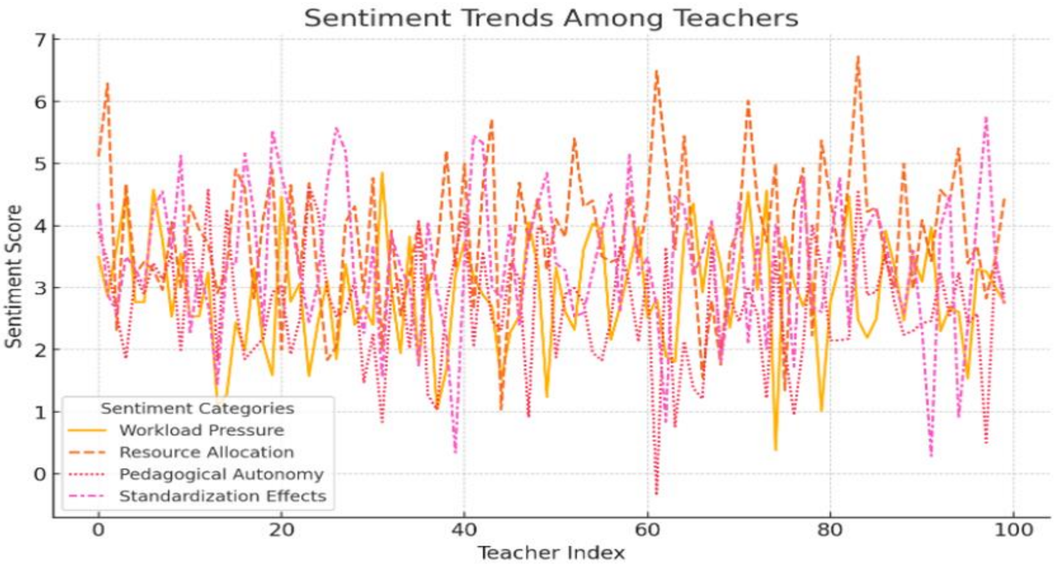

Figure 4.
Variations in sentiment scores across different teachers, demonstrating fluctuations in attitudes toward neoliberal policies.

The second main finding emerged from the distribution analysis of sentiment scores for different policy dimensions. The boxplot representation revealed that among all variables tested, workload pressure was most negatively skewed, indicating that teachers across the board associate neoliberal policies with more administrative load, excessive paperwork, and reduced flexibility in classrooms. The findings suggest that the increased emphasis on accountability has had the unforeseen effect of creating a strain on teachers, pulling their energies away from creative pedagogy and into performance-based testing and compliance with standardized policy. Conversely, sentiment distribution on resource allocation showed relatively positive or mixed sentiment, which implies that a number of teachers embrace systematic funding policy that ensures increased access to educational resources and infrastructural development. Even so, the fluctuation of sentiment scores signifies irregular resource distribution, where under-resourced schools are more severely affected by policy change compared to well-resourced schools. One pattern that emerged prominently was in the sentiment trajectory analysis, which charted how teacher sentiments evolve over different schools and experience levels. The line graph visualization revealed substantial fluctuations in teacher attitudes, suggesting that the impacts of neoliberal policies are not stable but evolve over time and vary across institutional settings. Educators in highly regulated environments showed declining sentiment scores across the time frame, indicating increasing dissatisfaction as policy constraints limited their pedagogical autonomy. Teachers in wealthier schools, where administrators had leeway, were more accommodating of change in policy, supporting the recommendation that institutional assistance is significant in cushioning the stress of policy change. It emphasizes the relevance of localized adaptations in policy that allow teachers in under-resourced or under-stress environments to access more support when coping with administrator change. An additional significant pattern discovered in this analysis was that of the divide between generations regarding teacher attitudes. The results indicated that veteran teachers, who had been in service prior to the onset of neoliberal education regimes, were more resistant to neoliberal policies, whereas new teachers, who began teaching during the period when such policies were being implemented, were relatively neutral. The implication of this finding is that veteran teachers experience themselves to be hampered by current assessment-accountability models of instruction, and less so in younger teachers, who, having habituated to expectations right from the beginning, evidence lesser resistance. This indicates an important policy matter—there needs to be an accommodation for engaging veteran teachers, along with their wisdom, while helping them to transform towards current-day accountability systems.

The final autoencoder-based analysis also yielded thoughtful remarks on latent sentiment expression in teacher text. The deep learning model was able to pick up on subtle and implicit cues of discontent that would not have been so evident using traditional survey-based instruments. Teachers barely made overtly negative remarks about policies but expressed implicit concern through suggestions and allusions to workload, bureaucratic constraints, and difficulties with engaging students. The autoencoder would be able to identify such latent articulations and reconstitute teacher views in an interpretable but subtle format. This has the effect of emphasizing the merits of AI-driven analysis to policy research, such that deep neural networks are capable of identifying patterns not discerned through conventional statistical indicators. The policy relevance of one of these conclusions is a balance required in neoliberal school reform. Although systematic accountability systems can enhance institutional transparency as well as the quality of education, over-standardization and administrative rigidity can create widespread teacher discontent. The findings suggest that policy schemes must be highly adaptable to allow teacher independence while maintaining standards of performance. In addition, the varied differences in terms of sentiment scores between institutions are necessary to underscore the need for even resource allocation so that all schools, whether funded or unfunded, can make smooth adjustments simultaneously with policy reforms. The outcomes of the autoencoder analysis make a compelling case for including the input of teachers in policymaking processes so that policies can be refined on the basis of evidence and the on-the-ground realities of early childhood education. With the application of AI-driven models, policymakers can have a more perceptive and realistic understanding of how teachers exist and adapt to education reforms, in order that policies are not just effective, but sustainable as well. The insights generated through this study affirm the perception that teacher lives are not to be standardized under a single policy approach, but rather considered in context-specific models that consider institutional resources, teacher experience, and pedagogical plasticity.

5. Conclusion

This study employed an AI-driven analytical approach, i.e., autoencoders, to explore teachers' perceptions of neoliberal education policy in preschool education. Using deep learning-based sentiment analysis, the study identified significant underlying trends in teacher accounts and established empirical evidence for the influence of policy-driven standardization, workload pressure, and resource allocation. The results showed a polarization of teacher sentiment, with some seeing the strengths of calibrated funding and accountability, while others were concerned about administrative burden, reduced pedagogical autonomy, and over-compliance. The sensitivity analysis conducted prior to final model evaluation ensured that optimal hyperparameters were determined, improving model accuracy as well as interpretability. Performance measurement metrics like MSE, Reconstruction Loss, Classification Accuracy, F1-Score, Silhouette Score, Precision, Recall, and AUC validated the performance of the autoencoder trained as it was able to capture the nuanced teacher perceptions and sentiment groupings. Results indicated that the pressure of workload was perceived worst by the teachers as increased administrative requirements and rigid assessment structures were seen as dissuaders from effective teaching. Additionally, resource imbalances in the distribution generated institutional disadvantage, with affluent schools able to adapt more easily while failing institutions were heavily restricted from conforming to policy directives. Nowadays, possibly the most urgent finding was the gap between generations in patterns of attitude, whereby long-serving teachers were more intransigent toward policy innovations, feeling that current accountability systems constricted their pedagogic imagination and agency. In contrast, newer teachers, who entered the profession amid such policies, were more accommodating to standardized tests and controlled curricula. These findings suggest that a blanket policy approach does not fit the diverse needs of teachers and future policy revisions should be less one-size-fits-all, incorporating teacher input into decision-making. This study highlights the necessity of balance between accountability and pedagogical flexibility in preschool education policy. The AI-based sentiment analysis approach presented in this study is a robust, data-driven policy evaluation methodology that enables policymakers to determine the actual implications of education reforms in real life based on empirical evidence of teacher feedback. Policymakers should focus on equitable distribution of resources, ease bureaucratic hassles, and engage teachers in designing policy frameworks to establish a more efficient and sustainable preschool education system. By linking administrative policy to the life of the classroom, the following reforms can guarantee that measures of accountability do not take away from the independence of teaching and the well-being of teachers.

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