**Original Manuscript ID:** #21419

**Original Article Title: “**Optimizing Latent Space Representation with Metaheuristic Algorithm: A Case Study in Topic Modeling”

**To:** Journal of Robotics and Control (JRC) Editor

**Re:** Response to reviewers

Dear Editor,

Thank you for allowing a resubmission of our manuscript, with an opportunity to address the reviewers’ comments.

We are uploading our point-by-point response to the comments (below) (response to reviewers) and a native speaker has proofread the manuscript to ensure linguistic precision.

We look forward to the possibility of our revised manuscript being suitable for publication.

Best regards,

Thinzar Aung Win, Khamron Sunat

**Point-to-Point responses**

**#Title, Reviewer#A, Concern # 1: The title provides a clear indication of the research focus, which is optimizing latent space representation in the context of topic modeling, particularly applied to social media data in the tourism industry. However, the title could be more concise. Consider streamlining it to capture the essence of the study while maintaining brevity. For example, "Optimizing Latent Space Representation for Tourism Insights: A Metaheuristic Approach."**

**Author response:**

Thank you for your suggestion to refine the title. We have adopted your recommendation and will use 'Optimizing Latent Space Representation for Tourism Insights: A Metaheuristic Approach’ to more effectively and concisely summarize the main points of our research.



**#Abstract: All of the reviewers suggested focusing on enhancing clarity, conciseness, and the accessibility of technical language in the abstract. They also emphasize the importance of explicitly stating the problem statement, the novelty of the approach, the practical implications of the results, and the real-world application of the research. Lastly, adding "Natural Language Processing" as a keyword is advised to reflect its importance in the study.**

**Author response:**

We appreciate your feedback on streamlining the abstract's introduction. The abstract now specifies the challenges posed by diverse and detailed content in travel reviews, providing the clarity recommended. The language around BERT, LDA, ELM-AE, and PPSO is more integrated and contextualized, potentially making the technical aspects more accessible without sacrificing the essence. The uniqueness of the hybrid LDA-BERT model is articulated, highlighting the novel combination of techniques for text clustering. The mention of rapid training and minimal loss addresses the results. The analysis of TripAdvisor reviews and its implications for understanding customer experiences is well-stated, aligning with the suggestion to emphasize real-world applications. "Natural Language Processing" has been added to the keywords.



**#Introduction: The reviewers emphasize the need for a clearer, more accessible introduction that precisely defines the research gap, simplifies technical details, logically organizes content, and upfront highlights the study's unique contributions and anticipated impact.**

**Author response:**

Thank you for responding and providing comments. We revised the manuscript in accordance with the reviewer's guidelines.

* Contextualizing Social Media's Role in Tourism:
  + Acknowledged the transformative role of social media in reshaping travel planning and destination selection.
  + Emphasized technological advancements and shifts in consumer behavior affecting travel information dissemination.
* Research Gap Identification:
* Clarified the need for semantically based text representation methods to address the analytical challenges of high-dimensional text data.
* Aimed to bridge this gap through the integration of BERT, LDA, and ELM-AE for advanced text analysis.
* Technical Language Simplification:
* Provided explanations for key methodologies (BERT, LDA, ELM-AE) in accessible language.
* Focused on their integration's role in refining text representations for improved topic modeling and clustering accuracy.
* Logical Flow Improvement:
  + Ensured smooth transitions from the impact of social media to the analysis challenges and the proposed methodology.
  + Demonstrated how the proposed approach addresses the outlined challenges.
* Early Statement of Contributions:
  + Listed main contributions at the introduction's beginning, highlighting the novel integration of BERT with LDA and the optimized use of ELM-AE with PPSO.
  + Emphasized the application of K-means clustering for efficient topic categorization.
* Challenges of High-Dimensional Data Analysis:
  + Discussed the limitations of traditional clustering methodologies and the significance of dimensionality reduction.
  + Highlighted the role of neural network architectures in addressing these challenges.
* Methodological Choices Justification:
  + Explained the selection of ELM-AE and PPSO for their efficiency and effectiveness in hyperparameter optimization.
  + Noted the superiority of PPSO in improving convergence rates and precision.
* Research Significance Recap:
* Restated the study's impact on enhancing text analysis in tourism and its implications for industry practices.
* Asserted the contribution to data-driven decision-making for improved customer experiences.



**#Method, #DataCollection: The reviewers commend the clear documentation of the data collection process but express concerns about potential biases from relying on a single platform and the ethical considerations of web scraping. They also suggest improvements in the clarity and structure of the methodology section.**

**Author response:**

We sincerely appreciate the insightful feedback from Reviewers regarding our method section, particularly concerning the data collection process, clarity of methodology phases, and ethical considerations. In response to your valuable comments, we have made the following revisions and clarifications in our manuscript:

* **Enhanced Clarity in Methodology Phases:** We have now explicitly labeled and described each phase of our methodology within the text, as suggested by Reviewer B. Figure 1 illustrates the three-stage process of our proposed system: "Phase 1: Data Collection and Pre-processing," "Phase 2: Dimensionality Reduction through ELM-AE with PPSO," and "Phase 3: K-means Clustering for Topic Segmentation." This structure aims to provide readers with a clearer understanding of our systematic approach.
* **Addressing Potential Biases in Data Collection**: Both reviewers highlighted the importance of discussing potential biases arising from using a single platform, TripAdvisor, for data collection. In our revised methodology section, we explicitly acknowledge the potential for sample bias due to the dataset's derivation from a singular platform, which may not fully represent the wide spectrum of tourist demographics. We believe this acknowledgment is crucial for understanding the context and limitations of our findings.
* **Ethical Considerations and Web Scraping**: Responding to concerns about the ethical implications of web scraping, we have elaborated on the procedures followed to ensure compliance with ethical standards. Our data extraction process, utilizing the "BeautifulSoup" library, was conducted meticulously, adhering to TripAdvisor's usage policies. We emphasized our commitment to ethical research practices by maintaining the anonymity of user data and ensuring that our web scraping activities respected the terms of service of the source platform.

**#Method, #Data-preprocessing: The reviewers commend the comprehensiveness of the data pre-processing sectionbut express a need for further clarity on several aspects. Reviewer A emphasizes the importance of detailing how potential biases introduced by the exclusion of specific types of reviews, such as invalid ones, are managed, alongside a clearer explanation of how missing data are handled to ensure the transparency and representativeness of the final dataset. Similarly, Reviewer B suggests expanding on the potential impact of text pre-processing steps, particularly how the removal of elements like emoticons or stopwords could influence the sentiment or meaning of the data, especially within the context of tourism.**

**Author response:**

We are grateful for the insightful feedback from Reviewers regarding our data preprocessing approach. In response, we have elaborated on our preprocessing methods to address your concerns about potential biases, transparency, and the impact of preprocessing on our analysis.

In our revised section on data preprocessing, we provide a detailed account of our comprehensive text processing pipeline applied to TripAdvisor reviews. We have clarified the steps taken to ensure the integrity and representativeness of our dataset:

* **Language Identification and Exclusion Criteria**: We meticulously identified and excluded non-English reviews, removing only 10 out of 8,262 reviews (0.12% of the dataset). This process was essential for maintaining analytical precision, as our model is specifically calibrated for English text analysis.
* **Removal of Extraneous Elements and POS Tagging**: We systematically removed URLs, emails, punctuation, emoticons, and numerical characters to minimize noise. Part-of-Speech (POS) tagging was then employed to highlight grammatical structures and facilitate typographical error correction with the “SymSpell” algorithm, significantly enhancing spelling accuracy.
* **Strategic Exclusion and Lemmatization**: Our approach strategically excluded certain grammatical categories (e.g., Determiners, Conjunctions) that contribute minimally to the analytical context, focusing instead on nouns and verbs to improve the clarity and relevance of topic modeling. Lemmatization via the WordNet Lemmatizer ensured terminological consistency, standardizing word variations to their base forms.

These steps were carefully designed to mitigate potential biases introduced by preprocessing and enhance the dataset's analytical value. By focusing on grammatical structuring and lexical standardization, we aimed to maintain the dataset's thematic integrity, ensuring that the removal of certain elements like emoticons or stopwords did not detrimentally affect the sentiment or meaning of the reviews in the tourism context.

**#Method, # LDA-BERT Architecture: The reviewers commend the clarity and integration of LDA and BERT but express a need for additional justification and clarification regarding the selection of topics based on coherence scores.**

**Author response:**

We thank the Reviewers for their constructive feedback on the LDA-BERT architecture section of our manuscript. In response to their suggestions, we have made the following revisions and clarifications:

* **LDA’s Probabilistic Vectors and Topic Definition**: We have expanded our discussion on the LDA model to include a detailed explanation of how we determined the optimal number of topics. Utilizing the Gensim package, we experimented with multiple LDA models varying in topic quantities (k) and selected the model with the highest coherence score as our criterion for optimal topic number. This process led to the identification of eight coherent and interpretable topics, chosen based on a comprehensive analysis of coherence scores across different models, thereby ensuring a meaningful thematic structure within our dataset.
* **Clarification on BERT’s Bidirectional Nature**: To address Reviewer A's suggestion for a layman's explanation of BERT, we elaborated on the significance of BERT's bidirectional encoding capability. Unlike traditional models that process text in a single direction, BERT analyses text context from both preceding and succeeding text, enabling a deeper understanding of language nuances. This bidirectional approach allows for a more nuanced and context-aware analysis of textual data, significantly enhancing the model's ability to understand and interpret complex language structures.
* **Sensitivity Analysis for Topic Numbers**: In response to Reviewer B's recommendation for a deeper analysis of different topic numbers, we have included a sensitivity analysis that evaluates the coherence scores for varying numbers of topics. This addition strengthens the methodological robustness of our approach by justifying the selection of eight topics as not only statistically optimal but also most representative of the data's underlying thematic content.

**#Method, #FeatureExtractionPipeline, #ReviewerA: The reviewer commends the detailed explanation of the Extreme Learning Machine Autoencoder (ELM-AE) but suggests that the article should include a discussion on the interpretability of the features extracted by ELM-AE. Specifically, clarifying what each dimension in the new feature space represents would enhance the method's transparency.**

**Author response:**

In response to your insightful feedback regarding the interpretability of features extracted by the Extreme Learning Machine Autoencoder (ELM-AE), we have made several enhancements to our manuscript to address this concern directly. We appreciate the emphasis on the importance of transparency in the methodological exposition, particularly regarding the dimensionality reduction process and the interpretability of the resultant feature space.

* **Clarification of Dimensionality Reduction Process:** We have revised our manuscript to include a more detailed explanation of how the ELM-AE performs dimensionality reduction. Specifically, we elucidate the process by which high-dimensional data, initially represented through BERT-LDA vectors, is transformed into a lower-dimensional, more interpretable feature space via the ELM-AE. This explanation aims to provide readers with a clearer understanding of the transformation and reduction mechanisms at play.
* **Introduction of UMAP for Enhanced Interpretability:** To further address concerns regarding feature interpretability, we have incorporated the use of Uniform Manifold Approximation and Projection (UMAP) as an additional dimensionality reduction technique applied subsequent to ELM-AE processing. UMAP aids in visualizing the distinct groupings within the dataset, thereby offering a visual confirmation of the thematic structures and contextual nuances captured by our model. This visualization is presented in the experimental results and discussion section, where we demonstrate how UMAP reveals distinct clusters in the data, underscoring the effectiveness of our feature extraction pipeline in identifying coherent and interpretable groupings.

**#Method, #PhasorParticleSwarmOptimization, #ReviewerA: The reviewer finds the use of Phasor Particle Swarm Optimization (PPSO) interesting but notes the article's lack of discussion on the potential challenges or trade-offs associated with this optimization technique. They also mention that while comparisons with traditional Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are referenced, the article should include quantitative results to substantiate claims of PPSO's superiority.**

**Author response:**

Thank you for your insightful feedback regarding the need for a discussion on the potential challenges or trade-offs introduced by the Phasor Particle Swarm Optimization (PPSO) technique and the necessity for a more robust comparative analysis with traditional Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). In response to your valuable suggestions, we have made the following revisions to our manuscript:

* **Discussion on Limitations of PPSO**: We have added the limitations and potential challenges associated with PPSO. This addition aims to provide a balanced view of PPSO's applicability and its comparative advantages and disadvantages in the context of optimization techniques.
* **Comparative Analysis with PSO**: To substantiate claims of PPSO's superiority, we have incorporated findings from a new reference article that explicitly states, "The PPSO algorithm outperforms established PSO variants across benchmark functions. [34]" This statement is supported by quantitative results demonstrating PPSO's enhanced performance in terms of accuracy and efficiency on standardized benchmark functions compared to traditional PSO variants.
* **Evaluation with GA:** Regarding the comparison with the Genetic Algorithm (GA), we clarify that our evaluation did not encompass a direct performance measurement across all three methods (PPSO, PSO, GA) in a unified context. Instead, the Extreme Learning Machine Autoencoder (ELM-AE) network's efficacy was assessed by comparing it against PSO and GA techniques independently. This comparative analysis, involving multiple iterations, provided a stable set of results indicating the optimal configuration for the hidden layer nodes and the penalty coefficient parameter through each optimization technique. The comparative analysis conducted serves to identify the most effective number of hidden layer nodes (n\_h) and penalty coefficient (C), aiming to strike an optimal balance between minimizing loss and achieving efficient training durations.

**#Method,#RepresentationLearningbyELMAuto-encoderwithHyperparametersOptimization, #ReviewerA: The reviewer appreciates the detailed description of hyperparameter optimization using PPSO in the article but notes a lack of clarity regarding the computational cost of this approach compared to traditional methods. They suggest that discussing any limitations or constraints in the implementation would be beneficial.**

**Author response:**

Thank you for your feedback on the computational aspects of using Phasor Particle Swarm Optimization (PPSO) for hyperparameter optimization. We've updated our manuscript to clarify that while PPSO is more computationally intensive than traditional methods due to its iterative optimization of larger parameter space, it significantly enhances hyperparameter tuning for the ELM-AE model by offering a balance between model accuracy and computational efficiency. This addition aims to provide a clearer understanding of PPSO's computational demands and its methodological benefits, enriching our discussion on its application.

**#Method, #TopicSegmentationbyK-MeanClustering, #ReviewerA: The reviewer suggests that the article should provide more detail on why K-means clustering was selected for topic segmentation, address potential challenges with this method, and offer insights into how the optimal number of clusters (K) was determined to strengthen the robustness of the clustering results.**

**Author response:**

Thank you for your insightful feedback requesting further clarification on our choice of K-means clustering for topic segmentation, the challenges associated with this method, and our determination of the optimal number of clusters (K). In response, we have enhanced our manuscript with the following details:

* **Figures and Tables:** We have ensured that Figure 1, as mentioned in the text, is now included and clearly visible in the revised version of our manuscript.
* **Rationale for Choosing K-means Clustering**: We selected K-means clustering due to its proven efficacy in constructing topic modeling applications, particularly when integrated with BERT-LDA representations. This choice is supported by significant outcomes from related studies [88], [89], which demonstrate the method's effectiveness in grouping enhanced latent vector representations into coherent topics, especially within business-related datasets.
* **Determining the Optimal Number of Clusters (K):** To ensure the robustness of our clustering results, we employed a systematic approach using the elbow method and silhouette analysis. These methods assess the coherence and separation of clusters at varying K values, enabling us to select an optimal number of clusters that achieve a balance between granularity and thematic distinctness. This process, implemented using the scikit-learn library in Python, allows for a data-driven determination of K, enhancing the accuracy and interpretability of our topic segmentation.

**#Method, #ReviewerB: The reviewer emphasizes enhancing the manuscript by including clear and visible figures or diagrams for better understanding, making technical details accessible to a wider audience, detailing validation or testing processes for the methodology, and discussing potential limitations and directions for future research at the end of the methodology section.**

**Author response:**

Thank you for responding and providing comments. We have made the following revisions to our manuscript in response to your comments:

* **Technical Details Accessibility:** In the revised manuscript, we have taken special care to present technical details in a manner that is accessible to readers without extensive backgrounds in machine learning or natural language processing.
* **Validation of Methodology**: To validate our methodology, we have introduced two new sections that demonstrate the efficacy of our approach:
  + The first section focuses on evaluating the Extreme Learning Machine Autoencoder (ELM-AE) for dimension reduction. We present validation loss as a key metric to assess the performance of the optimization algorithm, providing quantitative evidence of the method's effectiveness.
  + The second section assesses the optimized LDA-BERT representation within clustering algorithms, specifically K-means. We utilize the Silhouette Coefficient and coherence scores as metrics to evaluate the clustering method's performance, offering a robust analysis of the approach's validity in grouping topics cohesively.
* **Limitations and Future Work:** While we have acknowledged the limitations of the techniques employed directly within the revised methodology section, we have reserved a more extensive and thoughtful discussion on the potential limitations of our methods and the avenues for future research for the experimental results and discussion section.



**#ResultsAndDiscussion, #ReviewerA: The reviewer appreciates the detailed description of the experimental setup, including hardware and software details, but notes a lack of specific information about the dataset used, questioning the generalizability of the findings. They recommend including clear details on the dataset's characteristics and its relevance to the study to enhance transparency and allow readers to evaluate the robustness of the results.**

**Author response:**

In the revised section titled "Experimental Configuration,” we’ve updated our manuscript to include a detailed description of the dataset comprising 9,588 TripAdvisor reviews from top Thai shopping venues, and our experimental configurations. We clarify preprocessing steps, the application of LDA and BERT models, dimensionality reduction via ELM-AE, and hyperparameter optimization with PPSO. Additionally, we detail our experimental environment on Google Colab Pro, ensuring transparency and allowing readers to assess our methods' robustness.



**#ResultsAndDiscussion, #ELM-AE Optimization: The reviewers highlight areas where the manuscript could be improved to provide a more detailed, statistically rigorous, and comprehensive understanding of the ELM-AE optimization and its comparative performance.**

**Author response:**

In response to the insightful comments concerning the optimization algorithms for the Extreme Learning Machine Autoencoder (ELM-AE) and the need for a more detailed discussion on the limitations and statistical validation of our findings, we have further refined our manuscript.

* **Optimal Hyperparameter Selection for ELM-AE**: Our revised section delves into the comparative analysis of PPSO, PSO, and GA optimization algorithms, with a particular focus on balancing the trade-off between reconstruction loss and computational expense. We detail the iterative process employed across each algorithm, iterating 10 times to derive mean values for loss, training time, and optimal hyperparameters. The results, presented in Table I, illuminate the intricate relationship between the number of hidden nodes (N\_h) and the penalty coefficient (C), and their collective impact on the model's loss and training duration.
* **Hyperparameters’ Impact Analysis**: We reveal that an optimal range for N\_h is between 300 to 400, a finding graphically depicted in Fig. 2, which marks a critical equilibrium point where further increases in N\_h yield diminishing returns in loss reduction at a manageable increase in training time. This equilibrium also depends on the optimal setting of C, illustrating how higher network complexities necessitate stronger regularization to maintain model accuracy without excessively prolonging training.
* **Inclusion of Additional Performance Metrics**: In line with Reviewer B's suggestion, we have included additional metrics such as validation loss in our analysis. This approach provides a more holistic view of the optimization algorithms' performance, particularly emphasizing the model's capacity to generalize to new data.
* **Comparison with State-of-the-Art Models**: To establish the ELM-AE model's efficacy further, we have compared its performance against traditional autoencoders, showcasing its competitive edge in feature extraction from BERT and LDA generated vectors.
* **The interpretability of semantic features**: We undertook a detailed qualitative analysis to assess the most influential features within each cluster, closely examining the associated terms and phrases within the textual data. This approach allowed us to elucidate the semantic meaning of the compressed representations generated by the models, shedding light on their practical utility and relevance to potential application scenarios.



**#ResultsAndDiscussion, #Evaluation\_of\_Text\_Representation\_Techniques, #ReviewerA: The reviewer appreciates the use of K-means clustering and silhouette scores but notes the article's lack of discussion on K-means clustering's challenges or limitations, such as its sensitivity to cluster shapes and sizes. They suggest that addressing these considerations would enhance the reliability and completeness of the clustering results.**

**Author response:**

**K-means Clustering Limitations**: We have elaborated on the known limitation of K-means clustering related to its sensitivity to the initial selection of cluster centroids. To mitigate this issue, we referenced an approach from previous research that employs a Genetic Algorithm-based K-means (GA-K-Means) to refine the initialization phase, thereby enhancing the reliability of the clustering outcomes.



**#ResultsAndDiscussion,#Optimized\_LDA-BERT\_Model\_Performance,#ReviewerA: While acknowledging the superior performance of the optimized LDA-BERT model, the reviewer points out the absence of a detailed discussion on the model's limitations or potential failure scenarios. They recommend exploring situations where the model may not perform as expected or optimization does not lead to improvements, providing readers with a more nuanced understanding of the model's applicability.**

**Author response:**

**LDA-BERT Model Performance:** The manuscript now acknowledges the limitations inherent in clustering analysis, specifically the potential oversimplification of complex textual relationships when using the elbow method and silhouette scores for cluster determination. This addition aims to present a more nuanced view of the challenges in achieving accurate textual data clustering.



**#ResultsAndDiscussion, #Cluster\_Optimization\_and\_Word\_Cloud\_Analysis,#ReviewerA: The reviewer finds the analysis of cluster optimization and word cloud representations effective but highlights the lack of discussion on the biases introduced by word clouds. They argue that addressing these issues would improve the credibility of determining cluster count and thematic analysis.**

**Author response:**

We introduced the use of UMAP visualization to complement our clustering analysis, providing a visual confirmation of the distinct groupings within our multidimensional dataset. While UMAP visualization and word cloud analysis enhance our thematic analysis, we acknowledge their limitations in fully capturing the high-dimensional data's complexity. Our discussion now includes a call for further exploration into methods that can more effectively capture nuanced inter-cluster dynamics, indicating areas for future research.



**#Conclusion**

**#Concern1: Add future work: Motivate other researchers by suggesting areas for further exploration related to your work.**

**#Concern2: Update theoretical contributions: Explicitly state the new insights or advancements the research offers to the field of topic modeling.**

**#Concern3: Mention limitations and future research: Briefly acknowledge any limitations of the study and how future work could address them.**

**#Concern4: Summarize key results: Condense the main findings and re-emphasize their significance for relevant stakeholders.**

**#Concern5: Contribution to new knowledge: Clearly specify what the research adds to the existing understanding of topic modeling.**

**Author response:**

Thank you for your valuable feedback on our conclusion. We have carefully considered your comments and made the following revisions:

1. **Future Work:**

We expanded the future work section to highlight specific research avenues:

* Explore BERT variants and Deep Neural Networks (DNNs) for broader applicability beyond English reviews.
* Adapt the framework to analyze datasets in various languages using multilingual models.
* Apply the methodology to different sectors like health, education, and politics to mine sector-specific topics.

2. **Theoretical Contributions:**

We explicitly stated the theoretical contributions within the conclusion:

* Demonstrated the effectiveness of combining BERT and LDA for unsupervised clustering.
* Showcased the efficacy of using PPSO for optimizing ELM-AE in feature extraction and dimensionality reduction.
* Gained novel insights from applying the model to Thailand's tourism reviews, highlighting its potential for various domains.

3. **Limitations and Future Research:**

We elaborated on the limitations and how future research might address them:

* Acknowledged potential user bias and the complexity of deciphering emotions in reviews.
* Mentioned limitations of chosen metrics or datasets and how future studies could explore alternative approaches.

4. **Key Results and Significance:**

We condensed the first paragraph, summarizing key findings:

* Achieved superior performance in topic extraction compared to existing methods.
* Preserved semantic integrity and generated contextually rich topic information.
* Provided actionable insights for stakeholders in analyzing tourism reviews.

5. **Contribution to New Knowledge:**

We clearly stated our specific contributions:

* Introduced a novel hybrid BERT-LDA clustering framework for improved topic modeling.
* Demonstrated its effectiveness in extracting coherent topic clusters using tourism reviews as a case study.
* Showcased the framework's potential for broader applicability across various domains and languages.

6. **Further revisions:**

We included a statement in the section on future work that discusses how the framework may be modified to examine sentiment and emotions within the subjects that were retrieved.