Unsupervised Topic Modeling with LDA for Textbook Content Comprehension, a qualitative survey

Abstract

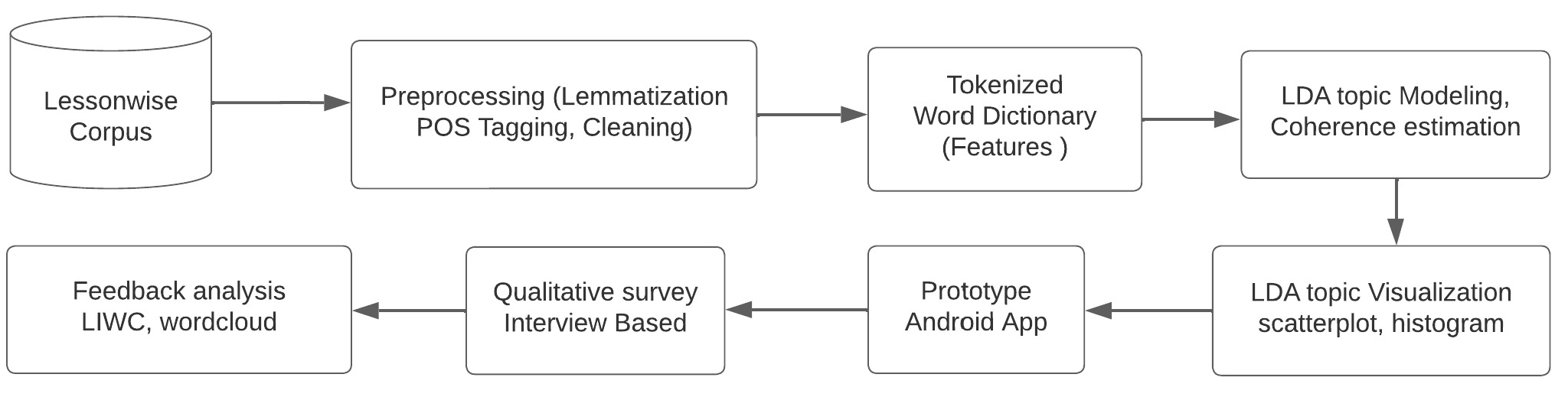
In this research Natural Language Processing (NLP) driven exploratory analysis is shown to depict various keywords related to subtle topic in context. Leveraged by Latent Dirichlet Allocation (LDA), this research study identifies latent topics within textbook corpus by uncovering word to extract coherent themes from textual data, aims to improve the curriculum provided English textbook content synthesis and acquisition skill of learners. Our anticipation extracted topics from the English textbook, enabling readers to comprehend the curriculum material more efficiently. Unsupervised topic modeling application LDA is applied. Extensive analysis is conducted to visualize, high impact keyword, co-occurrence patterns and correlation of extracted topics is depicted. A prototype mobile app is developed in which topic modeling extracted keywords are included. Furthermore, qualitative research survey is undertaken to evaluate its effectiveness on end-users specifically on course instructors of Bangladesh's higher secondary school. The challenges, and future potential of integrating mobile app into the learning process powered by NLP extracted content is explored. After collecting feedback, word clouds were used to analyze the frequency of the participants' recommended terms, and the LIWC approach was used to estimate overall sentiment. LIWC score showed positive sentiment and survey process enticed the participants instructors which demonstrates learners eager to use NLP technology driven topic modeling approach in teaching and learning, and there are tremendous opportunities.

**Introduction**

In Bangladesh there is lacking in effective acquisition, synthesis skill of English language from National Curriculum and Textbook Board (NCTB) curriculum provided textbook [1]–[4]. Simplest solution could be adoption of mobile app based English learning [20]–[22] [9]–[13] [5]-[8] using the curriculum provided contents. Mobile app-based language learning can be very beneficial if it is managed in a systematic way considering the context. In [16] Yu, et.al (2023) designed an experiment to examine the effect, and found that “students enjoyed to learn new words with the help of their mobile phone, motivation was significantly stronger compared to traditional English language learning. In order to test the effectiveness of mobile games based English vocabulary test is conducted in [17]. The results of these study showed students preferred the mobile learning approach way more than the conventional approach. Mobile assisted language learning first appeared around 2005 in USA universities [14] Afterwards around 2009 has been implemented in Turkey, Kuwait, Iran, neighbor country India and now spread globally [27], [28] [15]. Numerous English learning apps are available in Google play and iOS stores. Some renowned app is: Duolingo, Busuu, Babel, Voxy etc [25]. Across all applications, 55% have activities for vocabulary learning and other exercises are about 41% [18], [19]. A few applications provided quizzes, tests, and game for enhancing learners’ comprehension and self-checks [17]. One caveat is these apps cannot able to attract a large number of students like Bangladesh who are only depended on Curriculum Board provided Textbook for learning English. Topic modeling can play a significant role for context understanding for curriculum provided English textbook. It can help identify the main themes, concepts, and topics within the textbook's content, enabling instructors to tailor the learning experience to individual students. It provides coherent topics, dominant keywords, latent combination of features that characterizes similarities between topics. Topic modeling is a subfield of natural language processing and machine learning, offers a promising unsupervised approach to identify latent topics within provided documents. To grasp the English language knowledge from curriculum provided textbook this unique approach unsupervised Topic modeling using textbook corpus is adopted and exploratory analysis is demonstrated in this study. Our anticipation is through this way student can able to interpret meaningful information facilitates students to understand the correlated topics and important keywords related to that topics leads to understand the subtle meaning of the textbook context.

**Research Overview**

LDA is a widely used probabilistic topic modeling technique which can automatically identify underlying themes or topics within a corpus of given text. It leverages learning experience, improve interpretation and knowledge acquisition. The synthesis of existing research sheds light on the potential of topic modeling to create adaptive and tailored learning experiences, ultimately improving student engagement, comprehension, and knowledge retention.LDA doesn't directly account for student engagement in interactive activities such as learning tasks in mobile apps. Hence a prototype app is developed and survey is conducted to observe the sentiment impact. Overview of the research is depicted follows

 Workflow of research

The methodology involves preprocessing textual data to remove noise and standardize text, followed by the application of LDA to identify underlying topics, coherence measurements.

**Qualitative Survey**

This study seeks to ascertain if students can learn English better if a mobile app is introduced which includes NLP's LDA driven topic modeling applied extracted keywords and analysis.

A prototype mobile app is developed to incorporate the topic modeling extracted keywords into the app. Qualitative survey research is undertaken to evaluate the effectiveness of unsupervised topic modeling LDA Bangladesh's National Curriculum Textbook Board (NCTB) provided English Textbook for Higher secondary school education. This article presents the key findings and insights from the survey, shedding light on the prospective of learners especially instructors. In the survey questions, it was indicated whether the students, teachers/instructors, and government organizations would find it acceptable and appreciated if textbook information were made available through a mobile app and presented in interactive format. To demonstrate the mobile app idea during the interrogation survey session a prototype is also prepared. Participants were asked for suggestions on how to make the app better and about any shortcomings. After collecting feedback, word clouds were used to analyze the frequency of the participants' recommended terms, and the LIWC approach was used to estimate overall sentiment. The survey's findings show that teachers are eager to use NLP provided extracted keywords technology in teaching and learning, and there are tremendous opportunities.

**Topic Modeling**

**Different techniques have been developed to perform topic modeling in unsupervised topic modelling in NLP, having their own strengths and limitations. Apart from LDA, Mallet LDA, STM (Structural Topic Model), and HDP (Hierarchical Dirichlet Process) etc are also prevailing. Algorithms like Non-Negative Matrix Factorization (NMF) or Latent Semantic Analysis (LSA) can also be considered. However, as a baseline model LDA is often considered one of the most prominent choices.**

**Latent Dirichlet Allocation (LDA):**

LDA is a probabilistic model that assumes documents are mixtures of topics, and each topic is a distribution over words. The goal is to infer the hidden topic assignments and the topic-word distributions that best explain the observed documents. The joint distribution of LDA model can be expressed as

Where The word in document d, the topic assigned to the word in document d, are the Dirichlet LDA model parameters. controls per-document topic distribution, and per topic word distribution. represent the topic distribution. Dirichlet distribution representing the document-topic distribution, is the word topic assignment for the word in document , is the distribution representing the observed word given a topic

In this research LDA is used for latent topic modeling for NCTB’s English curriculum provided textbook. In this study Textbook corpus is divided into lessons which is a mixture of topics and using LDA expecting to determine which word in the lesson belong to Lesson's topics. Here how many topics are ideal need to determine and topic modeling quality depends on that.

Topic models comparative analysis

While some variations of LDA, like Mallet LDA, focus on scalability, LDA in general can still be efficiently applied to moderately sized corpora. If large corpus needs to analyze, Mallet LDA might be more suitable. Analyzing topics within the context of metadata, STM could be a better fit. Hierarchical Dirichlet Process (HDP) can be useful when we cannot guess the number of topics in advance.

Baseline Model:

LDA produces interpretative results for exploratory topic analysis. The identified topics are represented as distributions over words, making it easy to assign meaningful labels to topics. Provided by most of the libraries and tools, making it easy to implement and can be integrated into existing workflows. Hence, LDA serves as a solid baseline for topic modeling tasks. It's a starting point for researchers to experiment with and compare against other techniques. Hence, we have chosen LDA for baseline statistical topic modeling tool

**Determining Optimal Topics with Coherence**

Coherence score measure how coherent or interpret the words in that topic and estimates number of topic clusters. Coherence score assess the quality of the topics produced by LDA and ensures that the topics generated are statistically significant. Coherence can be expressed as follows

Where, represent pointwise mutual information statistical association between two words occurring together. PMI score indicates that the two words are more closely related within a topic. can expressed as

where is joint probability of occurrence of words and .

To calculate the coherence score genism library provides range of options such as . and These two methods are most popular. For given topic with words a fixed context window size is provided (default size 10 words) then coherence score is calculated using an equation which provides negative coherence score. can be expressed as

in which represent the pairwise similarity between terms based on scores. provides a positive coherence score.

Higher coherence values indicate that the topics are more coherent and representative of meaningful themes within the text data. Coherence score 0.5 are fairly good, according to John McLevey (source: Doing Computational Social Science: A Practical Introduction By John McLevey).

**Literature Review**

It is a probabilistic model that assumes each document is a mixture of a small number of topics and that each word's presence in a document is attributable to one of the document's topics. The goal of LDA is to uncover these latent topics from a collection of documents without needing any prior labeling or categorization of the content. LDA based topic modeling has been used for semantic search, ontology exploration, classification, dominant keywords searching in many research studies. For curriculum based textbook study it could be an option is not revealed from rigorous search in online repositories. Investigation of Julio Guerra in 2013 showed how LDA model can be used for textbook content linking and it can be further applied to facilitate content modeling and context understanding of collections of reference books of same subject [33]. The dataset was collections of textbooks of two domains Elementary Algebra and Information Retrieval. They inferred LDA topic modeling recommendation and navigation support for e-educational systems is promising. Educational content-based topic modeling for an Intelligent system to develop a tutoring system is proposed in [34] by researcher Stefan Slater in 2017. It is proposed a personalized learning system using correlated topic modeling, a natural language processing approach, to analyze the linguistic content of mathematics problems. For solving mathematics problems, a range of potentially meaningful and useful topics within the context is explored. They showed that Correlated topic modeling is an effective approach for automatically labeling for personalized learning system. For key terms detection within articles LDA based topic modeling has been used in many research studies in which dominant keywords reveals future research trends or most prominent topics.In 2020 Kazi Masudul Alam demonstrated that The LDA-based topic modeling can observe the trend of Bangla news [35]. Their experiments prove that proper corpus and labeled LDA is a good model for news topic modeling and articles become more human-readable assigning user-defined Labels. Research trends related to 'COVID-19 and sports' were analyzed using topic modeling in 2022 by J. Lee [36]. The LDA topic modeling technique revealed the latent knowledge dimension and structures in 'Sports-COVID-19' articles. In 2022 Rahul Gupta [37]involves the analysis of research trends in 3269 articles published under “Applied Intelligence’’ from 1991 to 2021, using the application of LDA. Topic modeling using BoW as well as using TF-IDF score was performed. Their analysis showed that BoW outperforms the TF-IDF. In this research BoW is also used for LDA model.In 2019 Wafa Shafqat [38] proposed an architecture model for better understanding of crowdfunding comments posted by the investors to understand their motive to classify whether comments are scam or legitimate comments. Deep neural network Language modeling either LSTM or RNN encoded vectors are fed into a LDA based topic modeling model to understand the context of discussion trends. Afterwards compared the results with simple Neural Networks (NNs) and non LDA based approach which shows their model can play a substantial role in a better understanding of crowdfunding comments context understanding.

Sentiment analysis has been a key research area of NLP based research domain, where LDA has been applied to determine significant features and those features contributes to segregate sentiments and provide recommendations. LDA based topic modeling has been used in sentiment analysis task. In 2021 Y. Cho published research study of LDA-based topic modeling sentiment analysis using topic/document/sentence (TDS) model is proposed in this article [39]. This article proposed TDS novel approach that combines LDA-based topic modeling for sentiment analysis within documents.The authors used LDA-based topic modeling and sentiment analysis to explore the Chinese public's perception of Omicron variants on social media Sina Weibo 121,632 pieces of omicron data [40]. From topic analysis they realized omicron's impact, infection situation, pandemic prevention and control geographically. Hence, it is actually revealed LDA based topic modeling can be used for understanding subtle topics and exploring various facts. In 2021 Krishna Raj [41] explained The human brain has a tendency to overlook a number of minor details about the events in the book. The model can scan massive amounts of text in the book and display interesting ideas derived from the given book. LDA Machine learning and lexical approaches can be used to analyze literary works. LDA model can aid in the easy and accurate adaptation of a book, making the learning process much simpler and precise. Research by Rani In 2020 [42]topic modeling text summarization approach for Hindi novels and stories was proposed. The proposed model is implemented by infusing linguistic features into LDA based topic modeling to discover a set of topic-words from the provided document. Hence, from the above literature review we can infer LDA could help analyze the content of the textbook and identify the main topics covered. This information could then be used to customize the learning experience.

**Methodology:**

The methodology involves preprocessing textual data, training the LDA model on the preprocessed text, and subsequently interpreting and visualizing the generated topics. Collect and preprocess the text data from the English textbook, breaking it down into individual documents (such as chapters, sections, or paragraphs). Clean the text by removing stopwords, punctuation, and special characters. Train the selected algorithm on the pre-processed text data. The algorithm will automatically discover latent topics within the documents based on word co-occurrences. Analyze the topics generated by the model. Each topic will be represented by a set of words. Interpret these words to understand the main concepts associated with each topic. This step might require manual review and adjustment to ensure the topics make sense.

**Data Processing and Feature Extraction**

* 1. First NLP’s data processing or data mining techniques are applied for meaningful token or feature extraction. Text is converted to Lowercased and Normalized to ensure consistent pre-processing.
     1. Data cleaning (unwanted characters Punctuation and Special Character Removed and stop words (such as "and," "the," "is," etc) are removed) spacy’s English word model and NLTK’s stopwords list are used together. Also Words less than two characters are removed such as: I, Hi, Oh etc. Hence, Noise is Removed and irrelevant characters, symbols, or data artifacts that have been introduced during data collection or scraping from pdf file to text file generation are separated. Hence, we found a cleaned corpus.
     2. Lemmatization (Root words are collected words to their dictionary form (lemma) is extracted) using NLTK’s WordNetLemmatizer package. Stemming Reduce words to their base or root form is not used since sometimes it changes the actual words.
     3. Part-of-Speech Tagging: Spacy’s English model ‘en\_core\_web\_sm’ is used to extract interested words (such as noun, verb, adjective) and excluded (CCONJ, AUX, DET, INTJ, PART etc which are Coordinating Conjunction, Auxiliary, Determinator, Interjection, Particle etc) thereby token is collected for only which are not punctuation, conjunction, symbol etc.

**Exploratory analysis of Textbook content**

Extensive exploratory analysis is conducted to visualize the topic modeling outputs. NLP’s in general data pre-processing and data mining approach is conducted to visualize the content. Here whole book is segregated into Lessons and we wanted to explore the important topics within the content. Similar topic words remains together. Therefore assumptions is, it helps students to understands the words, sentences and context of the book. At first ideal number of topics are determined using coherence score

**Coherence for LDA model**

To measure coherence in the context of LDA, following steps are followed:

1. Cleaned document samples are prepared using python’s NLP data mining techniques explain in detailed in data reprocessing section. Prepared set of tokens in Documents for document samples in corpus .
2. Doc to BOW corpus dictionary is prepared with Doc2Bow vector. This vector can be represented as where denotes the count of words for the document .
3. Trained LDA Model: During the training phase gensim’s MulticoreLDA model with four CPU worker thread is applied. Doc2Bow dictionary is applied along with 20 iterations is invoked. The rest of the parameters for LDA model training was default parameter settings of gensim library.
4. Calculate Coherence: To Calculate the coherence score for each LDA model for number of topics step 3 is iterated for times.
5. Iteration result coherence score for number of topics are saved in a list and plotted using seaborn.

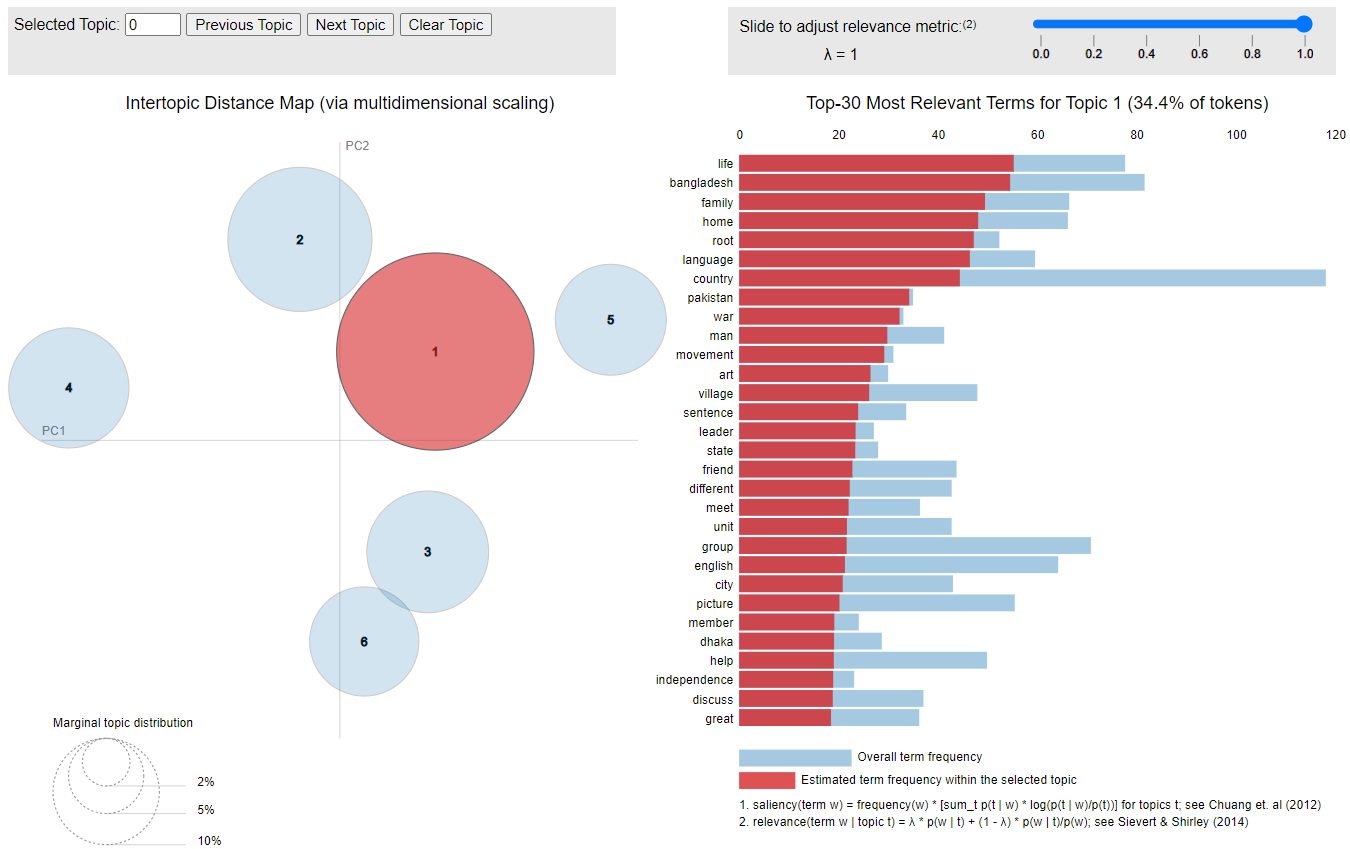
|  |  |
| --- | --- |
|  |  |
| From the chart we can see that six topics are dominant in our provided corpus. The chart shown at the left shows the coherence score for and the right chart represents the score for for multiple iterations. Using 6 topics we can see the output of corresponding topic and top 10 words in a topic.  Topic: 01 ["energy" 0.060, "source" 0.029, "renewable" 0.018, "water" 0.016, "use" 0.013, "gas" 0.013, "produce" 0.013, "green" 0.013, "warm" 0.013, "cause" 0.012,]  Topic: 2 ["pastime" 0.024, "computer" 0.024, "social" 0.023, "user" 0.022, "network" 0.020, "student" 0.019, "class" 0.017, "change" 0.016, "book" 0.015, "survey" 0.013,]  Topic: 3 ["mother" 0.083, "buy" 0.021, "love" 0.018, "child" 0.014, "worker" 0.014, "begin" 0.013, "cultural" 0.012, "observe" 0.012, "thing" 0.012, "language" 0.011,]  Topic: 4 ["life" 0.016, "Bangladesh" 0.016, "family" 0.015, "home" 0.014, "root" 0.014, "language" 0.014, "country" 0.013, "Pakistan" 0.010, "war" 0.010, "man" 0.009,]  Topic: 5 ["country" 0.031, "river" 0.022, "India" 0.022, "land" 0.021, "boat" 0.015, "small" 0.015, "population" 0.015, "lake" 0.013, "group" 0.012, "house" 0.011,]  Topic: 6 ["job" 0.064, "English" 0.023, "learn" 0.021, "teacher" 0.017, "use" 0.016, "dream" 0.016, "think" 0.016, "thing" 0.015, "school" 0.014, "education" 0.013]  **Word count vs Relative Importance measurement**  Word frequency in each document is measured as below which identifies the most frequent words within each document and across the entire corpus. s    we can visualize relative importance of any keywords in terms of frequency and plotted inclined with LDA provided weights. | |
|  | |

**Dominant topic and contribution**

In LDA models, each document is composed of multiple topics. But, typically some specific topics are dominant. The following experiment extracts this dominant topic for each sentence and shows the relative weight of the topic and the keywords. It estimated which document belongs predominantly to which topic. How frequently the words have appeared in the documents and the weights of each keyword in the same chart, words that occur in multiple topics and the ones whose relative frequency is more than the weight.

**Topic-Term Matrix Visualization and Inter-Topic Distance Map**

We trained a LDA model using library pyLDAvis, Gensim and Scikit-Learn parameters was provided four CPU core, 100 passes, 20 iterations and corpus’s token frequency’s enumerated data dictionary. pyLDAvis facilitates us to extract the necessary information from the trained LDA model, such as topic-term distributions and topic-document assignments. The pyLDAvis library depict visualization and interpret the results by interactive web-based visualization. It combines various visualizations to understand the underlying topics, their relationships, and the distribution of words within each topic. pyLDAvis creates a scatter plot where each circle represents a topic. The distance between circles indicates the similarity between topics. pyLDAvis displays a bar chart histogram that represents the top terms contributing to that topic. This visualization helps understand the most salient words associated with each topic. The visualization also includes a heatmap that shows the similarity between topics. Topics that are closer together in the map are more similar in terms of the distribution of words. This helps you understand the spread of word probabilities within a topic.



pyLDAvis library generated interactive chart is represented above shows four different topics in four circles. PCA dimensionality reduction technique is applied here to embed the LDA result into a 2D plain scale. Project the data onto the lower-dimensional subspace by computing eigenvectors and eigenvalues of the covariance matrix, reduced the circle overlapping. This interactive chart provides the opportunity of hovering effect over a circle. It displays different words on the right, showing word frequency (blue) and estimated term frequency within the selected topic (red). The visualization on the right side shows the top 30 most relevant words per topic the blue shaded bar represents the occurrence of the word in all topics and the red bar represents the occurrence of the word within the selected topic. Topics closer to each other are more related. The distance between bubbles represents the semantic distance between topics, and in case bubbles are overlapping that means there are a lot of common words. In our case topics are well separated and do not overlap. In addition, the area of the topic bubbles represents coverage of each topic, and topic 1~4 are equally significant. On top of it, you can see a slide to adjust the relevance metric λ (where 0 ≤ λ ≤ 1) and λ = 1 tunes the visualization for the words most likely to occur in each topic, and λ = 0 tunes for the words only specific for the selected topic.

**Englisher Mobile App:**

A mobile application (Englisher) is being created with content from the NCTB English Textbook. We have gathered all the words and sentences from the "English for Today" textbook for class six using NLP data mining techniques (such as: Lemmatization) [29], [30]. The data list for words and sentences is then cleaned by eliminating extra characters like apostrophes, commas, semicolons, etc. The keywords are organized into a number of categories sections, chapters, lessons, exercises, and quizzes. Each sentence's and word's Bengali meaning is provided in accordance with the chapter or lesson. A quiz is used to ascertain word meaning. Students can take quizzes, and their results are recorded in the history so that history can be reviewed and performance can be improved by more practice in the future. Students can learn how to respond to questions from a variety of options by taking the quiz. This app uses a quiz game-based learning strategy. For the following version, synonyms antonyms were proposed. The terms' synonyms will be shown, providing a wide selection of answers to the various questions pertaining to that subject. The app will provide example phrases to demonstrate how to use synonyms. Gradually, either teachers or pupils will learn how to properly and efficiently use specific words.



|  |  |  |
| --- | --- | --- |
| C:\Users\Zafor Iqbal\Desktop\Elogo\unnamed (1)\unnamed (4).png |  |  |

**Qualitative survey**

In the survey questions, it was indicated whether the students, teachers/instructors, and government organizations would find it acceptable and appreciated if textbook information were made available through a mobile app and presented in interactive format. To demonstrate the mobile app idea during the interrogation survey session a prototype is also prepared. Participants were asked for suggestions on how to make the app better and specify shortcomings. Presumably It provides an insight of teacher’s emotion about inclusion of mobile technology in higher secondary English education system.

**Survey Planning**

The survey was conducted over a period of four weeks, with 50 High schools in Dhaka and Bogura district of Bangladesh. It encompasses only English subject areas Teachers who teaches in high schools from class six to class Ten and teaches regularly in the school. A questionnaire was distributed to teachers allowing us to gather questionnaire answer.

**Survey Results:**

We have done extensive analysis with the survey data collected. In our data collection highest priority is given for the secondary class student teachers who teach between 6-10th class about 46%. High school, KG college and KG High school. Details about the statistics are depicted in the following figure. Adjacent chart explains the percentage of teachers who teach in which class. Hence, from these two figures we can get a vivid image of collected dataset resources about the participating teachers.

|  |  |
| --- | --- |
| Forms response chart. Question title: 3. School Type. Number of responses: 50 responses. | Forms response chart. Question title: 13. English Teaching class or level. Number of responses: 50 responses. |

The infrastructure's overall quality and condition, which is generally above average (76% good and 26% considered as average), are shown in the following statistics. The majority of school owners are privately held 45%, yet there are some of variable quality. 32% of which are MPO institutes—non-government educational institutions that receive funding from the government nonetheless—and 22% of which are government institutes. There are quite a few students overall. Over 1000 students attend almost 40% of the institutions. A sizable number of pupils are present in each section and class. A significant percentage of classes—38%—have a size greater than 50. So, we can presume that the participating teachers have quite a bit of experience teaching a lot of children.

|  |  |
| --- | --- |
| Forms response chart. Question title: 6. Total Number of Students Estimated. Number of responses: 50 responses. | Forms response chart. Question title: 7. Number of Students in Each Class or Section. Number of responses: 50 responses. |

For the data privacy and security issues Teachers were reluctant to provide their social website address to the surveyor. Among 50 participants only 12 has, that means 24% attendees provided their social sites address to use them for research purpose.

The following graphs give an overview of the English teaching experiences of the teachers as well as the general consensus regarding the use of digital content and mobile apps in everyday teaching and learning. Almost 62% of teachers have been teaching for more than 8 to 10 years, and some of them have been teaching for decades in higher secondary education. 32% of teachers have three to eight years of experience, while just 6% are fresh to the profession. Around 83.7% of teachers the language of instruction during their graduation was English, and their major was also English. Very few teachers 13.3% graduation major is something other than English yet teaching English in secondary schools probably have sufficient English language proficiency.

|  |  |
| --- | --- |
| Forms response chart. Question title: 11. Experience of Teaching English (years). Number of responses: 50 responses. |  |
|  |  |

**Analysis Facts:**

More than half of teachers, or 58%, have no prior experience utilizing mobile apps or technology for teaching, but 90% of them agree, and more than 45% strongly agree, that it encourages pupils to engage actively in their learning. However, they (almost 60%) also hold the opinion that a notebook cannot be completely replaced, despite the fact that mobile apps may solve many problems and provide technological support for teaching and learning. Promisingly optimistic approximately 40%, although thinking that the notebook-based content memorizing learning method can be replaced, feel that mobile app-based learning can replace it permanently.

|  |  |  |
| --- | --- | --- |
| **Questions** | **yes** | **No** |
| Do you use digital content for teaching or digital medium for teaching and learning | 84% | 16% |
| Have you ever used Internet or Mobile app to teach students or asked students to find learning materials from internet or Mobile App such as (e.g. Youtube Tutorials) | 76% | 24% |
| Education during graduation was English and English was used for learning | 83.70% | 16.30% |
| **Customized mobile app for Learning and Teaching English** | | |
| Do you think teacher will use this mobile app for teaching | 92% | 8% |
| Do you think students will use this app for learning? | 80% | 20% |
| Do you think mobile app based learning can improve English proficiency of students | 86% | 14% |
| Do you think Govt should promote these types of innovation for education sector | 98% | 2% |

This study proposes the Englisher mobile app and presents it to the participating teachers to gather their insightful feedback. 92% of teachers reported that they would use this type of mobile app for teaching if it were made available after using the trial version of the offered customized Englisher app. Teachers anticipate that 80% of students will utilize this app during class. 86% of respondents believed it may help students' English proficiency, and 98% agreed that the government should support this kind of innovation in the education sector.

**Linguistic Inquiry and Word Count (LIWC) for Qualitative sentiment**

Linguistic Inquiry and Word Count (LIWC) [31], [32] is a text analysis tool to measure psychological or emotional characteristics. It aims to quantify sentiment by examining the frequencies of different linguistic terms within given text based on predefined dictionary of words associated with various categories.

Let’s assume text as a sequence of words: and M different linguistic categories: . Proportion of words in each category where T is the total number of Text. Now, a matrix can be formed, where represents the frequency of the word in the linguistic category . LIWC vector containing the proportions of words in each linguistic category can be expressed as .

In this research LIWC is used to ascertain the general sentiment of the responses given by the survey participants.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Traditional LIWC Dimension | Answer Text | Standard Commercial Language | Answer Text | Standard for Formal Language | Answer Text | Standard for story language |
| Positive Tone | 2.54 | 3.96 | 3.91 | 2.33 | 3.22 | 2.18 |
| Negative Tone | 0 | 1.1 | 0 | 1.38 | 0 | 1.75 |
| Social Words | 2.54 | 6.87 | 5.65 | 6.54 | 4.08 | 10.5 |
| Cognitive Processes | 13.56 | 9.35 | 18.26 | 7.95 | 15.88 | 8.7 |
| Allure | 2.54 | 7.79 | 3.04 | 3.58 | 2.79 | 5.48 |
| Moralization | 0 | 0.2 | 0 | 0.3 | 0 | 0.21 |

From this LIWC table higher proportion of words related to positive emotions indicate a positive emotional tone in the text in the answer for the questions related to “How this app can be improved” and “How English learning can be improved using Mobile App”. LIWC is applied for three different categories “commercial writing”, “Formal language”, and “story language” and in all the categories answer text showed highly positive sentiment from the survey user. Though respondents had a mix of optimism and skepticism regarding the use of mobile apps in teaching and learning. During the interrogation session, their tone was positive and enticed participants.

**Visualize participants response with Word cloud:**

LIWC involves linguistic analysis using mathematical expression but using word cloud survey answers can be visualized vividly in interpretable interactive format. Word cloud consider a set of words extracted from Text document and associated frequencies , represent the proportional size of the word in the cloud can be expressed as where normalized frequency .

|  |  |
| --- | --- |
|  |  |
| Fig: word cloud for the question regarding English learning app improvement | Fig: word cloud for the question regarding app improvement |

The word cloud is generated from the answers provided question “how the app can be improved” and followed by more generalized question “how English learning can be improved using an App”. The participants narrated varieties of viewpoints for the questions. From the word cloud it is inferred adding graphical content would enhance the apps' usefulness and make them more visually appealing to users. More practice resources for listening and exercise would be helpful. Another suggestion is to include synonym, and syllabus-related instances as well as audiovisual engagement with the app. Add additional vocabulary and involve more experience teachers who have greater experience in digital learning and teaching.

Special Remarks:

For the data privacy and security issues many Teachers were reluctant to provide their social website address to the surveyor. Among all the participants only 24% attendees provided their social sites address to use them publicly for research purposes.

General Discussion and outcomes:

The study concludes apps seem effective as they provide a personal and learner-centered learning opportunity ubiquitously. However, apps need to be improved by including collaborative form of learning. Their recommendation is to make it specific. In our case we will make the app specific for NCTB Books only for particular class. This approach is also our goal considering NCTB Books.

The survey revealed that digital mobile-based learning significantly improved learning flexibility for the context of Bangladesh. Most of the participating teachers are enthusiastic about diverse Learning resources related to technology incorporating into pedagogy. Participants appreciated the diverse range of learning resources available through mobile devices, including interactive e-books, dictionary, educational apps, and multimedia content. Teachers admitted that available digital resources facilitated a deeper understanding of topics and catered to different learning styles, nurturing more engaging learning environment. This will positively impacted student motivation and overall engagement and hence boost overall learning. Some crucial suggestions were improving the graphics of the app so that it becomes interactive and guardian involvement can be introduced. Based on the survey results, it is revealed the potential for digital mobile-based learning in school is immense. Government should take initiatives to incorporate it into course curriculum syllabus and could impose ordinance to adopt mobile app based learning teaching in the school.

To evaluate the effectiveness of this approach, a series of experiments are conducted using a diverse range of textbooks from various disciplines. The results demonstrate that LDA-based topic modeling significantly enhances content comprehension by providing concise summaries of the material. Readers can grasp the main ideas and connections between topics, aiding in retention and knowledge acquisition. Additionally, the interactive interface receives positive feedback for its user-friendly design and utility in assisting readers' navigation through the textbook.

**Limitations**

In a personalized learning context, the goal is to tailor the educational experience to the individual needs and preferences of each learner. This involves understanding the learner's strengths, weaknesses, interests, and learning style. While LDA could be useful in some aspects of this process, it might not directly address all the requirements of personalized learning for an English textbook.

In this research study we showed that LDA based topic modeling could be a solution to enhance the context understanding of the learners. However from the survey it is revealed that app was not sufficient. Learners oriented topic-document distribution to identify which topics are most relevant to a specific student can be provided. App can provide additional explanations, examples, or resources to cater to their individual learning style. Assessments and exercises focused on the topics that need reinforcement for each student. Monitor their progress and adjust the learning path accordingly. Analyze students' performance, engagement, and feedback to refine the topic modeling process and its integration into the learning environment.

In summary, while LDA could play a role in understanding the topics covered in an English textbook and potentially aiding in content customization and topic relevance for personalized learning, it's just one tool in a larger toolkit. More sophisticated approaches, such as adaptive learning systems and AI-based tutoring, might be needed to truly personalize the learning experience in a comprehensive manner.

Conclusion:

By employing topic modeling in a personalized learning context, educators can create a more engaging and effective learning experience. This approach allows for the alignment of content with individual students' learning needs and preferences, ultimately enhancing their understanding and retention of the material.

The school survey on digital mobile-based learning reaffirmed its potential to revolutionize education, promoting flexibility, engagement, and personalized learning experiences. In the survey questions, it was revealed teachers/instructors would find it acceptable and appreciated if textbook information were made available through a mobile app and presented in interactive format. The study concludes apps seem effective as they provide a personal and learner-centered learning opportunity ubiquitously. Reveal to user as a complementary essential material to learn English Textbook quickly and effectively. However, apps need to be improved by including collaborative form of learning.

References

[1] S. Report, “Schools of 0,” *The Daily Star*, May 09, 2018. https://www.thedailystar.net/frontpage/schools-0-1573576 (accessed Jul. 28, 2023).

[2] W. B. Habib and T. S. Adhikary, “English, maths drag results down again,” *The Daily Star*, May 07, 2018. https://www.thedailystar.net/frontpage/ssc-examination-result-2018-bangladesh-english-maths-drag-results-down-again-1572613 (accessed Jul. 28, 2023).

[3] “Bangladesh Education Statistics 2021.” http://banbeis.portal.gov.bd/sites/default/files/files/banbeis.portal.gov.bd/npfblock/Bangladesh%20Education%20Statistics%202021\_compressed-1-235.pdf (accessed Jul. 28, 2023).

[4] B. B. of E. I. and Statistics, *Bangladesh Educational Statistics 2016*, First Edition. Bangladesh Bureau of Educational Information and Statistics, 2017.

[5] J. Sandberg, M. Maris, and K. de Geus, “Mobile English learning: An evidence-based study with fifth graders,” *Comput. Educ.*, vol. 57, no. 1, pp. 1334–1347, Aug. 2011, doi: 10.1016/j.compedu.2011.01.015.

[6] S. Hu, K. Laxman, and K. Lee, “Exploring factors affecting academics’ adoption of emerging mobile technologies-an extended UTAUT perspective,” *Educ. Inf. Technol.*, vol. 25, no. 5, pp. 4615–4635, Sep. 2020, doi: 10.1007/s10639-020-10171-x.

[7] R. Shadiev, T. Liu, and W.-Y. Hwang, “Review of research on mobile-assisted language learning in familiar, authentic environments,” *Br. J. Educ. Technol.*, vol. 51, no. 3, pp. 709–720, 2020, doi: 10.1111/bjet.12839.

[8] S. F. Isamiddinovna, “Mobile Applications As A Modern Means Of Learning English,” in *2019 International Conference on Information Science and Communications Technologies (ICISCT)*, Nov. 2019, pp. 1–5. doi: 10.1109/ICISCT47635.2019.9011897.

[9] M. M. Elaish, L. Shuib, N. A. Ghani, and E. Yadegaridehkordi, “Mobile English Language Learning (MELL): a literature review,” *Educ. Rev.*, vol. 71, no. 2, pp. 257–276, Mar. 2019, doi: 10.1080/00131911.2017.1382445.

[10] B. Klimova, “Impact of Mobile Learning on Students’ Achievement Results,” *Educ. Sci.*, vol. 9, no. 2, Art. no. 2, Jun. 2019, doi: 10.3390/educsci9020090.

[11] M. L. Bernacki, J. A. Greene, and H. Crompton, “Mobile technology, learning, and achievement: Advances in understanding and measuring the role of mobile technology in education,” *Contemp. Educ. Psychol.*, vol. 60, p. 101827, Jan. 2020, doi: 10.1016/j.cedpsych.2019.101827.

[12] S. Criollo-C, A. Guerrero-Arias, Á. Jaramillo-Alcázar, and S. Luján-Mora, “Mobile Learning Technologies for Education: Benefits and Pending Issues,” *Appl. Sci.*, vol. 11, no. 9, Art. no. 9, Jan. 2021, doi: 10.3390/app11094111.

[13] X. Chen, “Evaluating Language-learning Mobile Apps for Second-language Learners,” *J. Educ. Technol. Dev. Exch.*, vol. 9, no. 2, Dec. 2016, doi: 10.18785/jetde.0902.03.

[14] V. N. Hoi, “Understanding higher education learners’ acceptance and use of mobile devices for language learning: A Rasch-based path modeling approach,” *Comput. Educ.*, vol. 146, p. 103761, Mar. 2020, doi: 10.1016/j.compedu.2019.103761.

[15] K. R. M. Rafiq, H. Hashim, and M. M. Yunus, “Sustaining Education with Mobile Learning for English for Specific Purposes (ESP): A Systematic Review (2012–2021),” *Sustainability*, vol. 13, no. 17, Art. no. 17, Jan. 2021, doi: 10.3390/su13179768.

[16] Z. Yu, W. Xu, and P. Sukjairungwattana, “Motivation, Learning Strategies, and Outcomes in Mobile English Language Learning,” *Asia-Pac. Educ. Res.*, vol. 32, no. 4, pp. 545–560, Aug. 2023, doi: 10.1007/s40299-022-00675-0.

[17] Z. Xu, Z. Chen, L. Eutsler, Z. Geng, and A. Kogut, “A scoping review of digital game-based technology on English language learning,” *Educ. Technol. Res. Dev.*, vol. 68, no. 3, pp. 877–904, Jun. 2020, doi: 10.1007/s11423-019-09702-2.

[18] Y. Hao, K. S. Lee, S.-T. Chen, and S. C. Sim, “An evaluative study of a mobile application for middle school students struggling with English vocabulary learning,” *Comput. Hum. Behav.*, vol. 95, pp. 208–216, Jun. 2019, doi: 10.1016/j.chb.2018.10.013.

[19] B. Klímová and A. Berger, “Evaluation of the Use of Mobile Application in Learning English Vocabulary and Phrases – A Case Study,” in *Emerging Technologies for Education*, T. Hao, W. Chen, H. Xie, W. Nadee, and R. Lau, Eds., in Lecture Notes in Computer Science. Cham: Springer International Publishing, 2018, pp. 3–11. doi: 10.1007/978-3-030-03580-8\_1.

[20] C.-H. Chen and C.-C. Tsai, “In-service teachers’ conceptions of mobile technology-integrated instruction: Tendency towards student-centered learning,” *Comput. Educ.*, vol. 170, p. 104224, Sep. 2021, doi: 10.1016/j.compedu.2021.104224.

[21] I. García-Martínez, J. M. Fernández-Batanero, D. Cobos Sanchiz, and A. Luque de la Rosa, “Using Mobile Devices for Improving Learning Outcomes and Teachers’ Professionalization,” *Sustainability*, vol. 11, no. 24, Art. no. 24, Jan. 2019, doi: 10.3390/su11246917.

[22] H. Oz, “An Investigation of Preservice English Teachers’ Perceptions of Mobile Assisted Language Learning,” *Engl. Lang. Teach.*, vol. 8, no. 2, pp. 22–34, 2015.

[23] J. Kacetl and B. Klímová, “Use of Smartphone Applications in English Language Learning—A Challenge for Foreign Language Education,” *Educ. Sci.*, vol. 9, no. 3, Art. no. 3, Sep. 2019, doi: 10.3390/educsci9030179.

[24] Z. Jie and Y. Sunze, “Investigating pedagogical challenges of mobile technology to English teaching,” *Interact. Learn. Environ.*, vol. 31, no. 5, pp. 2767–2779, Jul. 2023, doi: 10.1080/10494820.2021.1903933.

[25] R. Metruk, “The Use of Smartphone English Language Learning Apps in the Process of Learning English: Slovak EFL Students’ Perspectives,” *Sustainability*, vol. 13, no. 15, Art. no. 15, Jan. 2021, doi: 10.3390/su13158205.

[26] M. Shortt, S. Tilak, I. Kuznetcova, B. Martens, and B. Akinkuolie, “Gamification in mobile-assisted language learning: a systematic review of Duolingo literature from public release of 2012 to early 2020,” *Comput. Assist. Lang. Learn.*, vol. 36, no. 3, pp. 517–554, Mar. 2023, doi: 10.1080/09588221.2021.1933540.

[27] P. Poláková and B. Klímová, “Mobile Technology and Generation Z in the English Language Classroom—A Preliminary Study,” *Educ. Sci.*, vol. 9, no. 3, Art. no. 3, Sep. 2019, doi: 10.3390/educsci9030203.

[28] R. Kaliisa, E. Palmer, and J. Miller, “Mobile learning in higher education: A comparative analysis of developed and developing country contexts,” *Br. J. Educ. Technol.*, vol. 50, no. 2, pp. 546–561, 2019, doi: 10.1111/bjet.12583.

[29] A. Kao and S. R. Poteet, *Natural Language Processing and Text Mining*. Springer Science & Business Media, 2007.

[30] P. M. McCarthy and C. Boonthum-Denecke, Eds., *Applied Natural Language Processing: Identification, Investigation and Resolution*. IGI Global, 2012. doi: 10.4018/978-1-60960-741-8.

[31] “Welcome to LIWC-22.” https://www.liwc.app/ (accessed May 06, 2023).

[32] “The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods - Yla R. Tausczik, James W. Pennebaker, 2010.” https://journals.sagepub.com/doi/abs/10.1177/0261927x09351676 (accessed Jul. 28, 2023).

[33] J. Guerra, S. Sosnovsky, and P. Brusilovsky, “When One Textbook Is Not Enough: Linking Multiple Textbooks Using Probabilistic Topic Models,” in *Scaling up Learning for Sustained Impact*, D. Hernández-Leo, T. Ley, R. Klamma, and A. Harrer, Eds., in Lecture Notes in Computer Science. Berlin, Heidelberg: Springer, 2013, pp. 125–138. doi: [10.1007/978-3-642-40814-4\_11](https://doi.org/10.1007/978-3-642-40814-4_11).

[34] S. Slater, R. Baker, Ma. V. Almeda, A. Bowers, and N. Heffernan, “Using correlational topic modeling for automated topic identification in intelligent tutoring systems,” in *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, Vancouver British Columbia Canada: ACM, Mar. 2017, pp. 393–397. doi: [10.1145/3027385.3027438](https://doi.org/10.1145/3027385.3027438).

[35] K. M. Alam, Md. T. H. Hemel, S. M. Muhaiminul Islam, and A. Akther, “Bangla News Trend Observation using LDA Based Topic Modeling,” in *2020 23rd International Conference on Computer and Information Technology (ICCIT)*, Dec. 2020, pp. 1–6. doi: [10.1109/ICCIT51783.2020.9392719](https://doi.org/10.1109/ICCIT51783.2020.9392719).

[36] J. W. Lee, Y. Kim, and D. H. Han, “LDA-based topic modeling for COVID-19-related sports research trends,” *Frontiers in Psychology*, vol. 13, 2022, Accessed: Aug. 26, 2023. [Online]. Available: <https://www.frontiersin.org/articles/10.3389/fpsyg.2022.1033872>

[37] R. K. Gupta, R. Agarwalla, B. H. Naik, J. R. Evuri, A. Thapa, and T. D. Singh, “Prediction of research trends using LDA based topic modeling,” *Global Transitions Proceedings*, vol. 3, no. 1, pp. 298–304, Jun. 2022, doi: [10.1016/j.gltp.2022.03.015](https://doi.org/10.1016/j.gltp.2022.03.015).

[38] “Topic Predictions and Optimized Recommendation Mechanism Based on Integrated Topic Modeling and Deep Neural Networks in Crowdfunding Platforms.” <https://www.mdpi.com/2076-3417/9/24/5496> (accessed Aug. 29, 2023).

[39] A. Farkhod, A. Abdusalomov, F. Makhmudov, and Y. I. Cho, “LDA-Based Topic Modeling Sentiment Analysis Using Topic/Document/Sentence (TDS) Model,” *Applied Sciences*, vol. 11, no. 23, Art. no. 23, Jan. 2021, doi: [10.3390/app112311091](https://doi.org/10.3390/app112311091).

[40] H. Wang, K. Sun, and Y. Wang, “Exploring the Chinese Public’s Perception of Omicron Variants on Social Media: LDA-Based Topic Modeling and Sentiment Analysis,” *International Journal of Environmental Research and Public Health*, vol. 19, no. 14, Art. no. 14, Jan. 2022, doi: [10.3390/ijerph19148377](https://doi.org/10.3390/ijerph19148377).

[41] K. Raj P M and J. Sai D, “Sentiment analysis, opinion mining and topic modelling of epics and novels using machine learning techniques,” *Materials Today: Proceedings*, vol. 51, pp. 576–584, Jan. 2022, doi: [10.1016/j.matpr.2021.06.001](https://doi.org/10.1016/j.matpr.2021.06.001).

[42] R. Rani and D. K. Lobiyal, “An extractive text summarization approach using tagged-LDA based topic modeling,” *Multimed Tools Appl*, vol. 80, no. 3, pp. 3275–3305, Jan. 2021, doi: [10.1007/s11042-020-09549-3](https://doi.org/10.1007/s11042-020-09549-3).