VEMeter: A Tool for Evaluating Participation Levels in Virtual Class Sessions

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***Abstract*— While online education and virtual meetings increasingly form part of the modern learning environment, it is uniquely difficult to gauge participant engagement in virtual class sessions. Traditional approaches are usually based on either attendance counts or observation by a moderator and can seldom offer real-time, precise feedback as to the degree of individual contribution. This kind of approach is surely unsuitable for a large learning setting or even for remote learning, where active participation may be more difficult to gauge. The existing limitations, therefore, raise the need to introduce VEMeter, a tool designed to measure and quantify the level of participation in virtual class sessions. VEMeter analyzes transcripts and chat logs from virtual meetings using state-of-the-art text-processing techniques, including TF-IDF and Cosine Similarity. These techniques help in measuring the participant engagement against those of the presenter or facilitator. This enables a more objective and correct analysis of how participants in the session interact and contribute. To enhance its analysis, VEMeter cleans text by applying several advanced techniques: stopword removal, lemmatization, contraction expansion, and tokenization. Through the application of these pre-processing techniques, it will be easier to eliminate irrelevant content and noise inside the text for the generated engagement metrics to reflect meaningful participations and not trivial ones. Data privacy and security are at the very core of VEMeter. The tool anonymizes participant data through name encryption; thus, it guarantees protection of participants' personal information in an ethical analytics ecosystem. This already allows VEMeter to provide insights into engagement without compromising participant confidentiality. VEMeter enables rich analytics and visualizations through bar charts, scatter plots, and correlation heatmaps that explain the level of engagement and variation of participation based on the word count. Educators can track participation in virtual sessions in real time through these insights and make timely interventions to enhance engagement. This study contributes to engagement level assessment by introducing an NLP-driven participation analysis tool. Practically, it effectively provides educators with a data-driven methodology to measure student engagement in virtual classrooms. The following paper designs, implements, and evaluates a proof-of-concept VEMeter to enrich virtual education by supplying real-time insights into participant engagement.**

***Index Terms*— virtual, transcript, engagement, TF-IDF**

I. Introduction

Virtual classrooms and workspaces due to COVID-19 have created new demands on individuals [1]. The traditional ways of self-reporting surveys and manual observation are highly subjective, take too much effort to do in a timely fashion where the data may still be relevant, and lack granularity in measuring how an individual contributes during a virtual session [2].

Face-to-face interaction allows educators to be guided by their students' body language, physical presence, and directed interactions, where they can determine student engagement in three dimensions: emotive, cognitive, and behavioural [3]. However, the question of how to improve student retention has been a long-standing issue, especially in online education [4], but this also presents opportunities. Online education generates large amounts of unstructured and heterogeneous text data in the form of course descriptions, lecture scripts, session's transcripts, forum discussions, and student assessments, which are difficult to process automatically, thereby fully advanced tools with powerful capabilities should be developed or utilized for managing and explaining this type of information [5].

In the online environment, quantifying or assessing how engaged a student is and their performance remains problematic, so there are many investigations into different forms of automation. Lahitani et al. [6] introduced a unique AES-based cosine similarity with the TF-IDF method for extracting features in this area. They pre-processed all student essays first to clean out noise and normalize the text by deleting stop words and lemmatizing, which means turning a word into its root form. Their discovery helps establish the fact that cosine similarity is a highly effective method in text-based evaluation within educational domains, and it can be utilized as a stepping stone for more advanced designs if other such automated scoring systems were ever to appear.

In the year 2021, Kulkarni and Padaki [7] introduced a video transcript summarization tool that utilizes natural language processing techniques such, as TF IDF, Cosine Similarity and Gensim. This tool is designed to condense online course transcripts into summaries efficiently. The effectiveness of their system is measured by evaluating the quality of the summaries using ROUGE metrics. Studies have shown that this method achieves a cosine similarity score of 95% highlighting its potential, in this field.

Vadlamudi et al. [8] used a methodology in developing the Meeting Summarizer. Their approach utilized two algorithms, namely TextRank and TF IDF for summarizing transcripts of calls fairly effectively. Important sentence identification by the TF-IDF algorithm and the PageRank Algorithm, which gives a score for the relevance of the sentence in this research process, eliminates irrelevant information. This paper presents an effective method which is used to determine sentences to extract for further processing when text summarization methods are applied to digital transcripts.

This paper employed VEMeter in this study to subject an online application to analyse and quantify participants' engagement in virtual meetings, especially in learning contexts. This is done by transcript and chat log data processing from the virtual sessions to quantify the amount of engagement. VEMeter enables educators to obtain a comprehensive picture of participant engagement by processing transcript and chat log data, within which it will be easy to find out the active students in contribution and those who may need some extra care. We employed some advanced techniques in natural language processing, including TF-IDF (Term Frequency-Inverse Document Frequency) and cosine similarity, to measure the degree of participant involvement. Pre-processing of the text was made first. Further, the application performs TF-IDF vectorization joined with cosine similarity calculations of contributions made by the presenter and other attendees.

VEMeter identifies the main presenter in the session by word count and compares the contributions of other participants to this baseline. This gives a really robust data-driven way to measure engagement and allows educators to gain real-time insight into student participation during these sessions. Finally, the cosine similarity score was calculated between the presenter and other attendees' TF-IDF vectors to identify engagement levels for the session's attendees. NLP is a robust technique by which robots can process spoken or written language; popular artificial intelligence systems such as Alexa and Siri make use of it [9]. Sentences can also be structurally extract their intents using natural language processing (NLP) without necessarily putting much emphasis on the specific words [10]. The TF-IDF vectors assist in filtering and extracting the most relevant terms from the corpus. It is an assessment of the importance of a word within a document relative to its importance across the whole document, calculated by multiplying the term frequency in a document by the inverse document frequency [11].

Cosine similarity is a measurement of the similarity between two items by calculating the cosine value from the vectors of words in any two given texts [12]. The output varies from −1 (totally opposed) to 1 (totally the same), while 0 means orthogonality (no similarity) [13]. **VEMeter** application identify engagement level based on cosine similarity score, as shown in Table I.

TABLE I
Cosine Similarity Score in VEMeter

Cosine Similarity Score	Similarity Level
1	Perfect Similarity
0.7 - 0.99	High Similarity
0.4 - 0.69	Moderate Similarity
0.1 - 0.39	Low Similarity
0.0 - 0.09	Very Low Similarity
0	No Similarity
-1	Complete Opposition

This paper describes the design and implementation of a newly developed instrument, **VEMeter** that addresses these concerns associated with measuring participant engagement in a virtual environment. With the use of text analysis techniques, **VEMeter** offers educators a tool to assess and enhance student participation in classrooms.

The theoretical implications of this study are shown in its demonstration of the effective application of natural language processing (NLP) techniques, including TF-IDF and cosine similarity, to quantify student engagement in virtual learning environments, thereby contributing to computational engagement assessment. This study enhances the application of text analysis to deliver objective, scalable evaluations of engagement, beyond traditional self-report surveys and manual observations. **VEMeter** provides educators with a data-driven instrument to assess classroom engagement patterns, recognise passive participants, and improve student participation through text-based analytics. **VEMeter** enhances the precision and efficacy of participation tracking, consequently fostering the creation of more inclusive and successful virtual learning environments.

Unlike traditional engagement tracking solutions, which rely on attendance records or basic word count analysis, **VEMeter** separates itself by objectively quantifying textual participation using TF-IDF and cosine similarity. Current methods are inadequate in identifying significant contributions from generic replies; however, **VEMeter** improves engagement evaluation by utilising advanced text analytics to offer a more context-sensitive and scalable solution.

This paper is organized as follows. Section II presents a detailed overview of the design of the **VEMeter** in terms of its architecture, technological stack, and the process of turning raw data into meaningful insights. Section III presents the experimentation and demonstration of application tools in real-life virtual classroom settings and how such tools have affected the enhancement of quality online education. Finally, Section IV concludes with final remarks on the potential that **VEMeter** has for transforming engagement monitoring and optimizing digital learning experiences.

II. VEMETER DESIGN

VEMeter is a tool that provides accurate assessment and measurement of participant engagement in virtual meetings. It applies text-analytic methods to deliver information about participant engagement levels to educators and professionals for the assessment of their virtual exchange importance. This system aims at offering data to enhance the effectiveness and efficiency of virtual meetings by recommending ways of improving the engagement in areas where participants need attention or fail to attend.

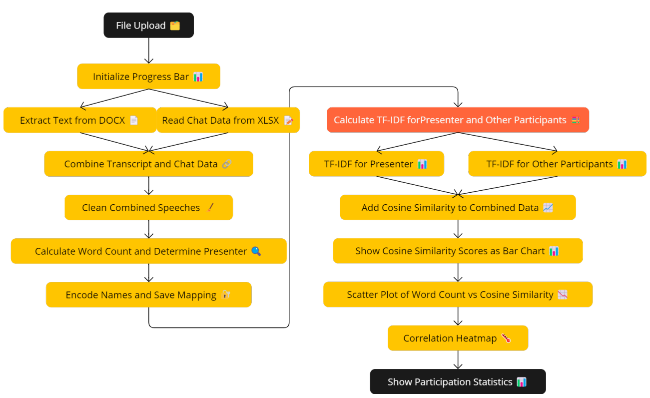


Fig. 1. Architecture of our proposed application **VEMeter**.

VEMeter is a software created with a mix of robust Python libraries and frameworks, ensuring its strength and user friendliness. It was built using PyCharm [14]. Streamlit was used in developing the web interface for **VEMeter** owing to the fact that it is open source and the ease of developing applications with it involves a minimal number of codes [15]. This framework supports dynamic result visualization and offers a user friendly interface enabling file uploads and real time result visualization [16]. To initiate a web application, on our computers terminal command line interface (CLI), we simply type 'streamlit run app.py' [17].

NLTK is a Python toolkit for NLP 18. Some of the pre-processing tasks of VEMeter include tokenization, which means breaking text into words or phrases, filtering out commonly used words that do not carry significant meaning (stopword removal, e.g., "the", "and", "is"), and reducing words to their base or root form. Removal of stopwords ensures that the meaningful contributions in conversation are what constitute the engagement analysis, rather than engaging in 'filler words' thus giving better accuracies to the TF-IDF weighting. VEMeter makes use of Scikit Learn-a flexible machine learning tool-to compute cosine similarity and TF-IDF vectorization [19].

Two Python libraries commonly employed for data visualization are Seaborn and Matplotlib. Although Seaborn allows for the creation of intricate visual representations by building upon Matplotlibs foundation and offering features such as correlation heatmaps to illustrate the connections between various engagement metrics. On the other hand Matplotlib offers a wide range of plotting functions to produce fundamental visualizations, like bar graphs and scatter plots [20].

VEMeter goes through five stages to effectively process text data from virtual meetings and turn it into valuable information. The user begins by uploading transcripts in DOC format and conversation logs in Excel format (xlsx), next the extracted text undergoes cleaning by removing words (stopwords) lemmatization (group similar word forms together), expanding contractions and tokenization for better understanding. Tokenization splits participant responses into individual words or phrases, allowing **VEMeter** to analyse the frequency and semantic importance of each term in the engagement assessment process. Attendees' names are encoded for privacy protection purposes. The text is transformed using TF IDF vectorization to assess the significance of terms. Cosine similarity calculations are carried out to evaluate each participant's level of engagement by comparing their contributions, to the presenter's discussion. The structure of **VEMeter** is illustrated in Figure 1.

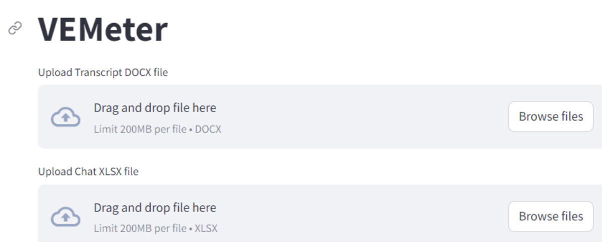
When creating **VEMeter's** design we made sure to prioritize privacy protection. To ensure privacy the app includes a feature that changes each participants name to a generic identifier like "Attendee_1" while keeping the presenter identified as "Presenter." This anonymization process ensures that the analysis is kept confidential and secure [21]. An xlsx file can be downloaded containing a list matching names with their encoded versions. The meeting organizer can use the names as a reference if necessary making sure that the data shown in the application stays anonymous.

The design of **VEMeter's** user interface (UI) focuses on simplicity and ease of use to ensure that users can interact with the application even without advanced technical skills. It is created using Streamlit. Offers important features like File Upload options, for Progress Tracking and Result Visualization. The aim is to offer an experience that enables users to swiftly understand participant engagement levels without having to dive into technical complexities.

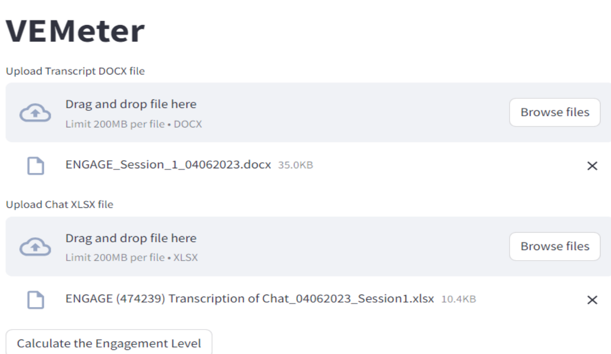
III. Experimental Outcome and Demo

This section aims to illustrate how **VEMeter** can be practically applied to analyse and measure participant engagement in virtual meetings, particularly within educational settings. Through this demonstration, we seek to show how the technology can provide instructors with real-time insights into student involvement, helping them identify active contributors and those who may benefit from additional support [22].

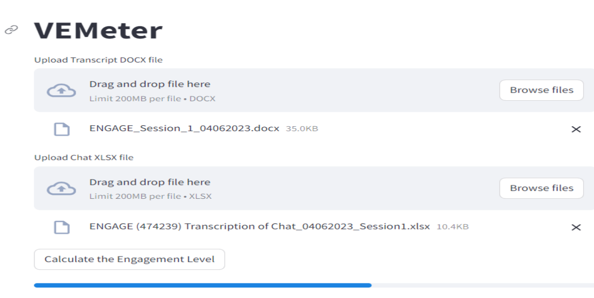
VEMeter's pipeline's first step is to upload the data which is the session's transcript in docx format and chat log in xlsx format, as shown in Figure 2a. This initial step ensures that all textual data is accurately captured and properly structured for subsequent analysis. Users click the "Calculate the Engagement Level" button to initiate the engagement analysis after the data has been uploaded, as shown in Figure 2b. When this task is activated on the tools text processing workflow system it involves steps, like breaking down the text into tokens and removing words or phrases through lemmatization and expanding contractions [23]. The progress bar visually displays these activities as shown in Figure 2c.



(a) First Page from our proposed application VEMeter.



(b) Starting process by clicking to calculate the engagement level



(c) Showing process of calculation

Fig. 2. Working prototype of **VEMeter**.

After the processing is done, **VEMeter** presents the outcomes using visual representations offering a detailed overview of how engaged each participant was compared to the presenter [24].

The bar chart in Figure 3 shows the cosine similarity scores between every attendee and the presenter. A high similarity score indicates that a participant's textual contributions are closely aligned with the presenter's discussion, suggesting a high engagement level. Conversely, low similarity scores suggest minimal interaction or off-topic responses [25]. The presenter is indicated at the top of the bar chart based specifically based upon calculations such, as the highest word count and is highlighted. Significant ratings suggest a stronger connection because the attendees' comments closely match those of the presenter. The visual representation effectively distinguishes between participants who're highly engaged and those who might benefit from additional assistance or focus.

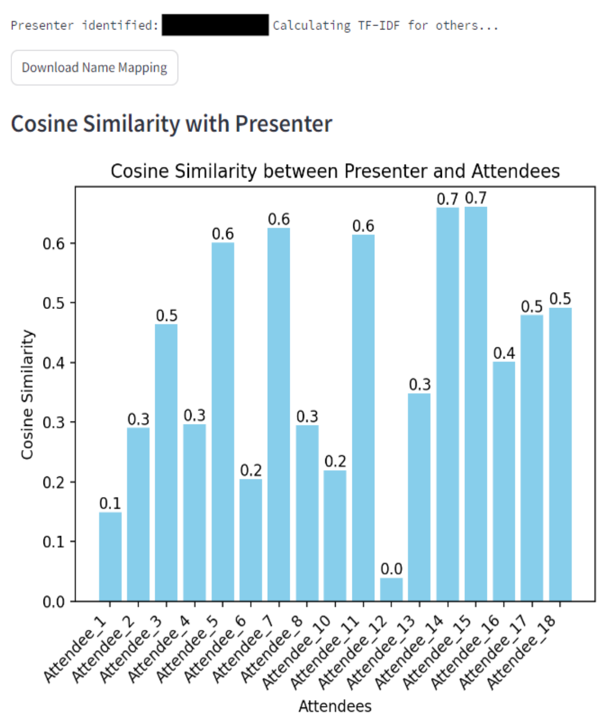


Fig. 3. Identifying presenter and result of cosine similarity

In this scatter plot displayed in Figure 4 presents the relationship between word count and engagement levels, we can see how the number of words spoken by each participant relates to their similarity to the presenter through cosine similarity calculations. While a higher word count generally suggests increased participation, the cosine similarity metric provides a more nuanced view, showing whether the participant's contributions were contextually relevant to the session [26]. The plot offers a glimpse into the significance of both the quantity and quality of contributions by indicating whether those who spoke more also delivered captivating or pertinent content.

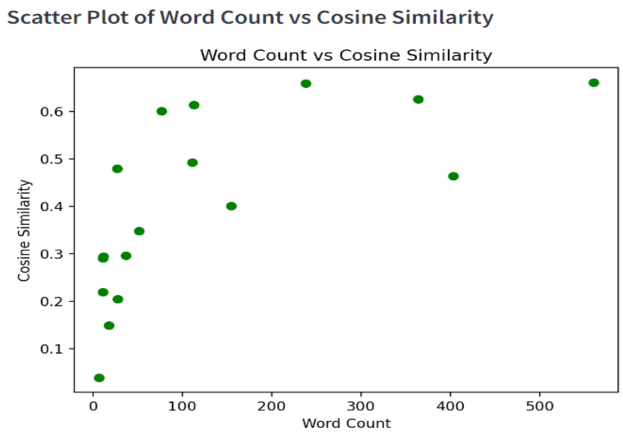


Fig. 4. Scatter Plot of Word Count vs Cosine Similarity

The heatmap shows how the number of words and cosine similarity are connected in Figure 5. It indicates that people who has more words are likely more interested in the content when there is a strong correlation, between them. On the other hand a weaker correlation could mean that despite having more words the contributions may not be as significant.

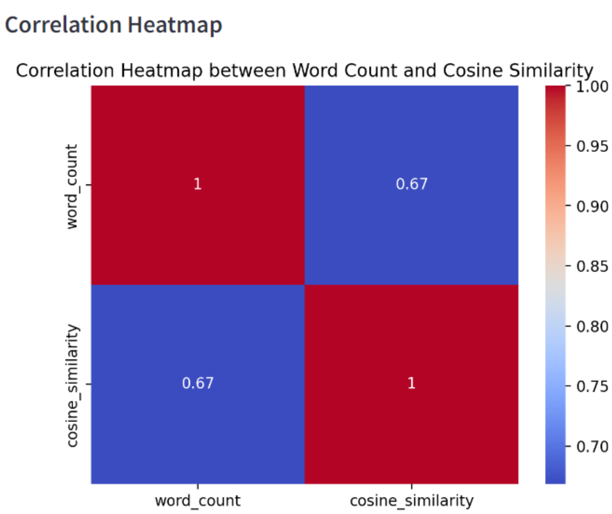


Fig. 5. Correlation Heatmap

The demonstration of **VEMeter** effectively demonstrates how it measures and displays engagement during meetings by combining transcript and chat log data with text analysis methods to offer educators valuable insights that can improve the educational experience remarkably [27]. The visual displays of engagement indicators enable the identification of strong and weak points, for making instant adjustments and creating a more vibrant and efficient virtual learning space in the end.

IV. Concluding Remarks

VEMeter's strategy and methodology are based on natural language processing (NLP) methods and a design philosophy that prioritizes the user's needs. By preparing text data and using advanced analysis techniques such as cosine similarity and TF IDF, **VEMeter** offers a dependable tool for assessing participant engagement. Its design focuses on both data security and user friendliness to enable use in a range of virtual meeting situations particularly, in educational environments. **VEMeter** creates scatter plots and correlation heatmaps with cosine similarity scores that enable an individual to make sense of the interactional dynamics of a meeting environment. Such observations allow educators to reorganize their approach to creating a classroom environment that is more interactive and friendly for all participants. Yet, there are still some limitations, especially in understanding involvement in context, responding in real-time, and promoting participation based on motivation.

In the future, VEMeter will overcome this limitation by integrating advanced NLP techniques, real-time monitoring, and gamification features. Presently, most of the adopted techniques in this system are frequency-based, including TF-IDF and cosine similarity, although the future versions also foresee sentiment analysis for participant contributions to understand if engagement comes out to be positive, negative, or neutral. Furthermore, topic modelling methodologies will be used to understand the themes of the session and assess variation in engagement across diverse topics. Real-time tracking tools will enable facilitators to get feedback on participation levels to adjust their approaches during the delivery of that session itself in order to enhance the level of student engagement in live sessions [28]. A low-engagement alert system-on the occurrence of participation below a certain threshold-it will trigger automated calls to action from educators during sessions.

Lastly, based on work by Schindler et al. about student engagement, gamification aspects, such as points, badges, and leaderboards, will be part of VEMeter in order to drive high-quality contributions rather than word count alone. With these integrated advances, VEMeter will become more dynamic, context-sensitive, and interactive; it will therefore be a tool with which educators can cultivate virtual learning environments that are far more inclusive and engaging.

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