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Opinion Mining and Perceptions of Self-Determination in Videoconference Classrooms Using Machine Learning and Multidimensional Sentiment Frameworks

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ABSTRACT

This study provides a comprehensive analysis of learner sentiments regarding learning in videoconference (VC) environments, highlighting critical areas for improving digital education. In the mixed method approach, Azure Machine Learning's (AML) three-category sentiment analysis as a quantitative approach is enhanced by a multidimensional sentiment model as a qualitative approach to analyse learner feedback. The sentiments are mapped onto the Self-Determination Theory (SDT) framework to highlight how autonomy, competence, and relatedness influence learner sentiments. Open-ended feedback to a prompt from 268 respondents across different education levels provided textual data captured through a Google form. AML provided sentiment scores that indicated the direction and type of sentiments. Combining with thematic analysis based on 5 sentiment categories enables the generation of richer and deeper insights into learner feedback. Findings indicate mixed user sentiments, with flexibility (autonomy) praised but technical issues and limited interaction (low competence and relatedness) criticised. Findings suggest enhancing interactivity, addressing technical barriers, and fostering engagement to improve learner experiences and meet diverse educational needs in digital classrooms. AML provides a broad sentiment classification with confidence scores that are more relatable and reliable. While recognising the overlapping sentiment categories in the two models, the approach offers more actionable insights for educators and platform developers. AML's model could benefit from incorporating more granular sentiment categories to capture the complexity of user feedback better. The study enables a broader view of the user's need to provide more useful information to developers, policymakers, and instructors regarding using VC and other online platforms for teaching.

Keywords: Azure Machine Learning; Opinion Mining; Sentiment analysis; Videoconference classroom; Online learning; Machine Learning.

INTRODUCTION

Technological advancement has continued to foster significant transformation in education, including the proliferation of online learning platforms. These advancements have also expanded distance learning opportunities as well as digital learning environments through video conferences (VC). They are offering unprecedented flexibility in terms of time and place and provide environments for integrating emerging tools into teaching and learning. VC platforms have evolved into VC Learning Platforms (VCLPs) as they became prominent mediums for facilitating remote education, allowing for synchronous interactions and real-time engagement. VC has been around since the 1920s. Early systems include reporters' AT&T's live video call with Herbert Hoover in 1927 (Uenuma, 2020), Bell Labs telephone conferencing in 1956 (ETHW.ORG, 2024) and AT&T's Picturephone exhibition in 1964 (Darlin, 2014). The first PC-based VC software, CU-SeeMe, was created in 1992 (Han & Smith, 1996) with video calling added to messaging services by mid-2000s and Zoom was launched in 2011. VC software/platforms have continued to evolve since then.

Prior to COVID-19, VC in education was limited to supplemental use in traditional classroom teaching or occasional distance learning and professional training. Technical challenges slowed down its adoption in mainstream classrooms. When COVID-19 emerged, education shifted rapidly online, forcing widespread adoption of VC for remote learning. This transition transformed teaching methods. Post-COVID, VC became a cornerstone of education globally, enabling virtual classrooms, remote collaboration, and blended learning. Platforms like Zoom, Webex, and Microsoft Teams gained prominence, reshaping education with enhanced interactivity, accessibility, and flexibility. As these platforms have become an integral part of modern education, it is imperative to critically examine the experiences and sentiments of learners as users to unveil both the positives and negatives of their utilisation from the perspectives of diverse learners. Understanding user sentiments is essential for enhancing the efficacy of these platforms and ensuring the holistic well-being and satisfaction of learners.

Studies in online learning have focused on the effectiveness of asynchronous tools in fostering deep learning (Zheng & Warschauer, 2015) and supporting higher-order thinking and engagement (Chen et al., 2018). Learning sentiments in online interactions are pivotal indicators of learning performance and cognitive processes (Huang et al., 2021) and analysing them can serve as a powerful tool for elucidating the collective voice of individuals, allowing identification of trends, and tailoring products/services to meet the preferences of target audiences (Danek et al., 2023; Jamalian et al., 2023). In education, it is pivotal in enhancing the efficacy of education processes, enabling educators to gain valuable insights into the factors influencing student learning outcomes (Munggaran et al., 2023; Sadigov et al., 2024) or identify areas of strength and those needing improvement within instructional materials, pedagogical approaches, and learning environments. Sentiment analysis thus enables personalisation of learning experiences, tailoring interventions to meet individual needs and contribute to the overall learner well-being and satisfaction.

While the literature has extensively explored learning sentiments in asynchronous online discussions, there is a dearth of empirical studies investigating the dynamics of sentiments within synchronous contexts, such as VCLPs. In addition, traditional sentiment analysis methods usually employ thematic analysis using multidimensional sentiment frameworks. Such techniques provide more nuanced feedback but are mostly based on manual, qualitative approaches, have relatively low accuracy, and often lack scalability and efficiency due to a significant level of human bias. This underscores the need for approaches that provide efficiency while eliminating human bias.

Current advancements in machine learning (ML) provide various tools employing Natural Language Processing (NLP) through deep learning (DL) for opinion mining and sentiment analysis. These tools can identify sentiments within textual data and provide quantitative feedback through sentiment scores, eliminating human bias. However, these techniques are also faced with issues of affective computing and the need for no- or low-code ML-based techniques that can cater to educators.

Categorisation of sentiments using these ML techniques is often limited to simple binary (true/false) or three-category (positive, negative, neutral) dimensions (Elgeldawi et al., 2021; Saura et al., 2023), underscoring the need for approaches that can provide non-biased, quantitative analysis combined with qualitative feedback without the loss of the nuances that are critical in human communication. Therefore, this study aims to address the gaps by examining user sentiments toward VCLPs, based on more efficient mixed methodologies that support a more comprehensive understanding of user sentiments. The study employed the no-code Azure Machine Learning (AML) combined with Huang et al. (2021) multidimensional sentiment framework to analyse learner feedback. AML categorises sentiment into three positive, negative and neutral, which can overlook deeper insights into data. The multidimensional framework provides additional sentiment categories that offer deeper insight. The categories are mapped to the Self-determination theory (SDT) elements (MacIntyre et al., 2018) to provide a more comprehensive exploration of learner sentiments.

Understanding how different sentiments manifest and evolve in real-time interactions on VCLPs is crucial for informing instructional design, fostering meaningful engagement, and addressing potential challenges that users (learners) may encounter. This study, therefore, aims to address the following research questions (RQ):

1) RQ1: What are respondents' sentiments emerging from learning on VC platforms based on (a) AML and (b) multidimensional sentiment frameworks?
2) RQ2: What patterns do learners demonstrate regarding the self-determination elements?
3) RQ3: What are the differences in sentiment patterns based on respondent characteristics?
4) RQ4: How might a hybrid sentiment model based on AML be leveraged to support more effective analysis?
5) RQ5: What do the expressed sentiments communicate regarding the future of VCLPs?

RELATED WORK

Online Education and VCLPs

VCLPs have become a cornerstone of modern education, enabling virtual classrooms and fostering remote learning opportunities (Melati & Hazairin, 2020). They offer various features crucial for online/remote learning (Nadire & Daniel, 2021). Advanced options also integrate features like lecture recording, automated transcripts (Forman et al., 2012), breakout rooms and other features that enhance engagement and accessibility (Lim, 2020; Siddiqui & Ahmad, 2022). VCLPs offer numerous benefits, including flexibility, facilitating synchronous communication with geographically dispersed students (Cardullo et al., 2021) and promoting active learning through interactive features. Polls/online quizzes can streamline assessment by enabling immediate feedback, while the recording feature allows learners to revisit content at their own pace (Edwards

& Edwards, 2022) and enables instructors to focus on real-time interaction and address student questions. Integration of emerging technologies like AI and immersive media (e.g., augmented reality and virtual reality) are also being explored to create innovative learning experiences (Bailey et al., 2024; McGivney et al., 2022).

Despite their numerous advantages, VCLPs also present challenges, including technical difficulties like internet connectivity issues that can disrupt learning experiences (Sun, 2023). The lack of physical proximity can hinder engagement and social interaction compared to traditional classrooms. Additionally, ensuring equitable access to technology and fostering a sense of community in online environments requires careful consideration. As VCLPs evolve with technological advancements, they hold immense potential to shape the future of remote and blended learning experiences.

Sentiment and Emotion Analysis in Educational Settings

Sentiment analysis holds a strong significance for understanding user emotions in various domains (Giatsoglou et al., 2017; Manjula et al., 2021; Yadollahi et al., 2017), including educational settings. They can provide insights into student engagement, satisfaction, and learning difficulties (Alm & Nkomo, 2020), enabling educators to personalise learning experiences, identify struggling students, and improve pedagogy (Pant et al., 2023). Beyond traditional, qualitative sentiment analysis, recent research is exploring advanced techniques like deep learning (Dake & Bada, 2023; Qorib et al., 2023) to offer powerful tools that go beyond simple keyword matching (Trojahn & Goularte, 2021) to capturing context and sentiment. Recurrent Neural Networks (RNNs), like Long Short-Term Memory (LSTM), can handle long sentences and complex emotions (Omarov & Zhumanov, 2023; Shrivastava et al., 2019). Platforms like AML offer pre-trained models that require minimal coding and simplify the process for educators who do not have extensive programming knowledge (Harfoushi et al., 2018; Harfoushi & Hasan, 2018).

Sentiment Analysis with ML

Various ML models approach sentiment analysis through different means and differ in the type of data for which they are effective. For example, Support Vector Machines (SVMs) are effective for identifying the best separation line between different sentiment classes and exploring high-dimensional data (Khan et al., 2024; Pambudi & Suprapto, 2021). RNNs are particularly useful for sequential data (e.g., social media comments and tweets) as they can capture long-range text dependencies (Alhumoud & Al Wazrah, 2022; Kurniasari & Setyanto, 2020). For large datasets, Naïve Bayes is very efficient for calculating the probability of a word appearing in a certain sentiment class (Azhar et al., 2020; Siswanto et al., 2022), while Convolutional Neural Networks (CNNs) are useful for extracting key phrases (Nedjah et al., 2022; Refat et al., 2022) and identifying essential features in the text by applying filters. Models like AML platforms (Harfoushi & Hasan, 2018) offer user-friendly interfaces and simplicity and can support various ML algorithms. They employ NLP techniques to identify emotions and tones in textual data to categorise sentiments.

Studies exploring sentiment analysis with AML highlight its accessibility for various applications. Powell et al. (2021) and Hafourshi et al. (2018) demonstrated AML's effectiveness in analysing social media sentiments. Similarly, Manjula et al. (2021) used AML to analyse customer reviews for product sentiment. Its application in education has been reported; for example, Ananthi and Arul (2023) used AML to gauge university students' risk prediction and cognitive learning outcomes, and Kumar et al. (2023) explored students' perceptions, emotions, and behaviour in a classroom activity. AML thus represents a promising avenue for sentiment analysis in education, but its limitations may be mitigated through hybrid approaches using other models to achieve higher dimensionality.

Multidimensional Sentiment Analysis Framework

Sentiments are very complex, and three categories may not adequately capture the complicated emotions expressed in sentiments. Huang et al. (2021) categorised sentiments into six as positive, negative, neutral, insightful, confused, and joking. This sentiment classification has been used in online learning studies (Nishiwaki et al., 2023). Sentiments have also been explored based on the SDT framework's autonomy, competence, and relatedness elements. In a study of patient feedback by Holmberg et al. (2022), the researchers focused on keywords and phrases related to the three core psychological needs of the SDT framework. A similar method was adopted in this study. To create a hybrid, multidimensional framework, the three dimensions of the AML methodology were merged with five of the six dimensions of Huang et al. (2021). The sixth dimension, 'joking' was not considered relevant to the study. With three matching sentiment categories, the resulting five-dimensional framework consisted of 'positive', insightful', 'neutral', 'negative' and 'confused' categories. These categories were used in developing the coding scheme employed in the qualitative part of this mixed-method study.

THEORETICAL FRAMEWORK

The AML methodology leverages NLP and ML to analyse contextual meaning, tone, and polarity in textual data. The framework is widely used in customer feedback analysis (Singh & Sharma, 2021), social media monitoring (Powell et al., 2021; Qorib et al., 2023), and business intelligence (Harfoushi & Hasan, 2018). It provides a foundation for sentiment analysis in this study. The SDT posits that individuals are driven by the three basic psychological needs of autonomy, competence, and relatedness (Chiu, 2024). Autonomy refers to the sense of control over one's actions and decisions; competence pertains to the feelings of mastery and effectiveness, while relatedness refers to the need for social connection and belongingness. In education, SDT suggests that learners are more likely to engage in learning activities and experience positive sentiments when they i) perceive a sense of choice in their learning experiences, ii) feel competent about mastering the learning materials, and iii) feel connected to the learning community.

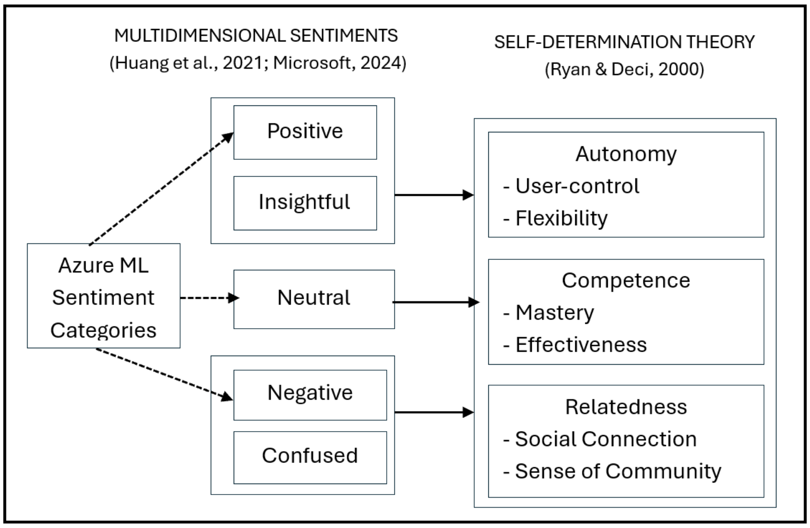
The quantitative sentiment categories based on AML provide information on the direction and types of sentiments. Sentiment scores are provided alongside sentiment labels, offering a more practical and objective interpretation of text sentiment. The scores allow for a more precise understanding of sentiment intensity and confidence (Microsoft, 2025), and the granularity enables the making of informed decisions based on the strength of sentiment expressed rather than relying solely on broad categories, as is the case in theme-based categories generated from multidimensional frameworks. The scores also facilitate threshold customisation, enhancing the tool's adaptability to specific use cases (Microsoft, 2024). In addition, AML's sentiment analysis provides pre-trained models that are ready to use, eliminating the need for large datasets and extensive model training (Microsoft, 2025). The cloud-based service is scalable and cost-effective, reducing computational resource requirements (Harfoushi et al., 2018). The sentiment analysis can also be easily integrated into applications, significantly reducing development time (Microsoft, 2024).

However, the tool has critical limitations. The training data is from product and service reviews and thus faces challenges in dealing with scenarios outside this scope, leading to reduced accuracy. It fails to identify context-dependent nuances like sarcasm or sentence importance and cannot effectively evaluate emojis or sentiment intensity (Microsoft, 2024; Dilmegani, 2024). These limitations do not apply to multidimensional sentiment categories as they can capture context-specific emotions and underlying themes, enabling the identification of nuanced opinions across diverse domains. The qualitative framework is faced with the challenge of subjectivity in theme interpretation. In addition, it is unable to differentiate thin lines between sentiment categories, such as the AML, which identifies differences in sentiment scores of 0.5000 and 0.5987. The multidimensional framework can distinguish between positive and insightful emotions and negative and confused, which is impossible with the AML. Combining these dimensions and mapping them onto the SDT framework provides a foundation for this study's hybrid, multidimensional theoretical framework.

Three categories of the multidimensional sentiment model (Huang et al., 2021) are similar to the AML dimensions. As the dimension ‘joking’ was not relevant to this study, it was excluded, and the hybrid framework thus features five dimensions with three common to both frameworks. Figure 1 shows the multidimensional sentiment framework adopted in this study. The framework features five sentiment categories: positive, insightful, neutral, negative, and confused. Insightful and confused, the positive and negative sentiment categories are extended, respectively, to highlight deeper sentiments. The framework combines insight based on AML sentiment scores and thematic analysis based on the multidimensional model. The themes are generated from the manual, and the content analysis of the text is based on the SDT framework. The hybrid framework extends the AML into a multidimensional sentiment framework that maps onto the three elements of the SDT, highlighting and explaining students’ conceptions of the impact of VCLPs on autonomy, competence and relatedness.

Figure 1

The Theoretical Framework



METHODOLOGY

This study employed a mixed-method design. Sentiment analysis is based on the AML methodology and multidimensional sentiment categories (Huang et al., 2021). Quantitative analysis is based on the AML approach with feedback as sentiment confidence scores and the qualitative multidimensional sentiment categories. The sentiments are mapped onto the SDT framework to understand how autonomy, competence, and relatedness influence learner experiences and opinions regarding VCLPs. The AML methodology leverages a suite of tools and services offered by Microsoft's Azure platform to extract insights from textual data. It has the advantage of seamless integration with other Azure services like Azure Cognitive Services, which provide pre-built Application Programming Interfaces (APIs) for NLP tasks. This integration streamlines the development process and allows for efficient scaling and deployment of sentiment analysis models. Additionally, AML offers robust data preprocessing, feature engineering, model training, and evaluation capabilities, empowering the creation of highly accurate and reliable sentiment analysis solutions tailored to specific needs and requirements.

Participants and Data Collection

Participants in the study were two hundred and sixty-four online learners (i.e., 124 females, 140 males) aged 17 - 60 years recruited through online platforms, including multiple social media platforms. Data was collected over a period of 20+ weeks in 2023-2024. Fifty-six respondents have completed only high school education, while two hundred and eight hold a bachelor's degree or higher. Data was collected as open-ended feedback through a survey instrument. The instrument captured demographic information, including respondents' level of education/age group (post-secondary or bachelor's degree and higher), access to ICT gadgets and internet connection (limited or good), and level of ICT skills (low or high). Participants responded comprehensively to a single-item question: "*Please describe, in your own words, what you consider to be the good, the bad, and the ugly of learning in videoconference classrooms*." Responses were captured through Google Forms and downloaded as an Excel file for analysis.

Preprocessing and Coding Scheme

Initial data processing steps involved the removal of missing rows to uphold data integrity. Subsequently, comments were tokenised to break them down into individual sentences. Data processing was done to de-noise, standardise text format, and remove incomplete information to ensure the analysis was conducted with clean, consistent, and reliable data. To process the textual data, a custom C# app was developed. This app, designed to handle CSV-formatted data, underwent several preprocessing steps. Stop words and words possessing limited semantic value were removed. Additionally, predefined survey structure templates were removed from the responses, ensuring that only relevant content was analysed. AML sentiment analysis tools utilise pre-trained NLP models to automatically classify text sentiments at both document and sentence levels, assigning confidence scores for positive, neutral, and negative categories (Harfoushi & Hasan, 2018). The system leverages logistic regression and SVM algorithms optimised for social media text analysis (Liu, 2022).

Data processing involved submitting raw learner feedback through AML's Representational State Transfer (REST) API endpoint after configuring an Azure AI-Language resource with authentication keys. The service returned JSON-formatted results containing aggregate sentiment labels (positive/neutral/negative), confidence scores quantifying prediction certainty and aspect-based opinion mining identifying specific platform features discussed (e.g., "video quality", "chat functionality"). Sentiment scores were interpreted using threshold parameters where confidence scores ≥ 0.6 indicated strong agreement with the assigned label, while scores between 0.4–0.6 required manual verification (Liu, 2022; Rienties & Toetenel, 2022). This approach enabled efficient analysis of large text volumes while maintaining interpretability through AML's standardised scoring framework, validated in recent educational technology research using comparable methodologies (Rienties & Toetenel, 2022).

A qualitative coding scheme was established for the multidimensional sentiment analysis with mapping to the SDT elements. In line with the theoretical framework, Table 1 describes the coding scheme for the analysis with examples of coded observations. Two raters coded portions of the data to validate the codes and the corresponding descriptions and examples, and inter-rater reliability was calculated based on the 2 ratings. Samples of the coded observation with the sentiment label and SDT element, coded manually, are also shown in Table 2. Cohen’s Kappa calculated for the two raters was 0.96, indicating that the analysis was highly reliable (Cohen, 1988). The validated codes were used to train the ML model.

Table 1

Coding Scheme for User Sentiments in Online Learning

	Elements	Description	Coded References Related to:
Autonomy	Choice and control	In Self-Determination Theory (SDT), *choice* describes autonomy because it enables individuals to act volitionally and self-endorse their behaviours. Autonomy is not merely independence but involves making intentional decisions aligned with one's authentic self and intrinsic motivations (Deci & Ryan, 1985). Autonomy is, therefore, described by elements in the text that describe the frequency and variety of options (choices) that students have in activities, discussions, and learning pathways within the VCLP environment.	Breakout room selection, asynchronous learning
	Flexibility	Satisfaction with scheduling options, flexibility in deadlines for adjusting the learning pace and analysis of platform features that offer flexibility.	Lecture recording, video/audio options
Competence	Perceived learning	Perceived learning is a critical element that reflects *confidence* within SDT. Competence represents the belief in one's ability to successfully perform tasks and achieve outcomes (Deci & Ryan, 1980). Perceived learning outcomes reinforce this sense of mastery, fostering intrinsic motivation and self-efficacy (Joo et al., 2013). Perceived learning is a tangible indicator of confidence rooted in SDT principles. Thus, texts describing competence describe perceptions of one's own knowledge and skill development after learning activities, including analysis of VCLP features that promote self-assessment.	Quizzes or polls with immediate feedback
	Mastery experiences	Experiences of success (e.g., completing tasks, participating in discussions), including analysis of platform features that promote mastery experiences.	Completion badges, progress tracking tools
Relatedness	Social interaction & connection	Perceptions of interactions with instructors and peers through the VCLP, including analysis of VCLP features that facilitate interaction.	Chat function, collaborative whiteboards, breakout room
	Sense of Community	Feelings of belonging and support within the online learning community fostered by the VCLP, including analysis of platform features that promote community building.	Group projects, forums, stickers (emoticon).

Table 2

Sample Coded Observations for Manual Codes

Sentiment Category	Sample Text Coded	SDT Element
Positive	Makes teaching and learning process easier. Learning in video conference classrooms makes teaching and learning process easier.	Autonomy
Negative	While for the negative side is we might feel not productive and demotivated at times.	Confidence
Negative	There are much distraction from it and secondly it encourages examination malpractice. sometimes the disruption of internet connection might annoys me during learning; cheating when quiz, doing other things when off camera.	Relatedness
Neutral	I am comfortable with any form of learning.	Confidence
Insightful	Learning online has its benefits but it's not for everyone so instead of making learning online, hybrid classes should be implemented to accommodate everyone.	Autonomy
Insightful	Learning online disturbed by home environment (disturbed by others, doing housework etc.).	Relatedness
Confused	Tha (sic) bad is the memory, situation and feeling is not anymore same with physical class.	Confidence

RESULTS

RQ1a: What are Respondents' Sentiments Emerging from Learning on VC Platforms Based on AML?

Tables 3, 4, 5 and 6 present the sentiment analysis output details for positive, wrongly categorised positive, negative and neutral sentiments, respectively. The columns show sample comments (1), AML sentiment score (2), AML sentiment label/type (3), SDT element (4), and the element's confidence score (5). The AML sentiment score indicates the strength of the sentiment assigned to the feedback. It is typically a value between 0 and 1, where scores closer to 1 suggest strong positive sentiment, scores around 0.5 indicate neutrality and scores closer to 0 suggest strong negative sentiment. SDT confidence scores represent probability estimates that a particular piece of text aligns with a specific SDT element (see Table 1). A score of 0.925441 under "Choice and control" thus indicates high confidence that the text strongly relates to autonomy, whereas 0.645924 under "Sense of community" shows moderate confidence in relatedness.

Table 4 highlights the limitations of the AML approach, with the high sentiment scores (>0.6) resulting in the wrong sentiment label. All scores shown in the table align with values for positive sentiments. However, a closer look at the text (manual qualitative analysis) shows that these text segments were negative rather than positive. It underscores the noted limitation of the AML model in recognising tones and deeper emotions and the significance of the hybrid model. The qualitative multidimensional model not only identifies deeper sentiments not captured by ML but can also correctly identify sentiments wrongly categorised by ML based on scores.

Table 3

Output and Findings - Positive Sentiments

1 Sample Respondents' Comments (Verbatim)	2 Sentiment Category	3 AML Score	4 Generated SDT	5 Confidence Score
Learning in video conference classrooms makes teaching and learning process easier	Positive	0.632867	Choice and control	0.750029
Good of learning in video-conference classroom is about the recordable, reviewable, ability to show the subtitle.	Positive	0.697879	Flexibility	0.743671
Good and easy	Positive	0.822692	Choice and control	0.093076
Video conferencing is good for lessons, and face to face I better for hands on tutorial	Positive	0.7932	Flexibility	0.536298
Good; less anxious to talk and give suggestions	Positive	0.601328	Sense of community	0.645924
There's nothing compared to physical learning	Positive	0.605393	Mastery experience	0.500437
Distraction sometimes	Positive	0.702877	Choice and control	0.621144
The effectiveness of the network. If the network is poor, the participation of the students will be affected	Positive	0.730746	Interaction and connection	0.621255

Table 4

Output and Findings- Wrongly Categorised Positive Sentiments

1 Sample Respondents' Comments (Verbatim)	2 Sentiment Category	3 AML Score	4 Generated SDT	5 Confidence Score
No practical session in the vedio-conference classrooms.	Positive	0.626325	Perceived learning	0.947236
The good is it's availablity over time. The bad is the network challenge. The ugly is the fund of the electronic materials involved.	Positive	0.602543	Perceived learning	0.689838
Less interaction with other students	Positive	0.765811	Interaction and connection	0.673501
Late feedback from colleagues and instructors	Positive	0.673706	Sense of community	0.739375
Lack of direct assistance and explanation from instructor	Positive	0.625872	Choice and control	0.510518
There's nothing compared to physical learning	Positive	0.605393	Mastery experience	0.500437
Distraction sometimes	Positive	0.702877	Choice and control	0.621144
The effectiveness of the network. If the network is poor, the participation of the students will be affected	Positive	0.730746	Interaction and connection	0.621255

Table 5

Output and Findings - Negative Sentiments

1 Sample Respondents' Comments (Verbatim)	2 Sentiment Category	3 AML Score	4 Generated SDT	5 Confidence Score
Bad internet connection, hardware price, basic skill to handle software	Negative	0.353584	Perceived learning	0.589213
Cheating when quiz, doing other things when off camera n using recorded session to learn later time, learning online disturbed by home environment (others, doing housework etc.)	Negative	0.31912	Choice and control	0.657244
Apart from the inability to control every single learner remotely, I am comfortable with any.	Negative	0.23192	Choice and control	0.188038
Learning online has its benefits but it's not for everyone so instead of making learning online, hybrid classes should be implemented to accommodate everyone.	Negative	0.112616	Choice and control	0.043006
Video conference classroom though it was very helpful during the pandemic but it should be totally avoided because there are much distraction from it and secondly it encourages examination malpractice.	Negative	0.351972	Mastery experience	0.608121
Learning in video - conference classrooms a times is passive and learners tend to get bored and tired than when they engage physically in classrooms.	Negative	0.200236	Interaction and connection	0.584378
Ugly; sometimes the disruption of internet connection might annoys me during learning	Negative	0.351913	Choice and control	0.925441
Easy to fall behind if student does not have time management skills	Negative	0.318728	Choice and control	0.434575

Table 6

Output and Findings - Neutral Sentiments

1 Sample Respondents' Comments (Verbatim)	2 Sentiment Category	3 AML Score	4 Generated SDT	5 Confidence Score
Bad; difficult to communicate with the right person	Neutral	0.589172	Sense of community	0.668416
Some instructors have a negative attitude toward online technology, this could be because they are temporarily removed from their comfort zone	Neutral	0.535147	Interaction and connection	0.717828
From my opinion learning through video conference has its pros and cons as for the pros we can be more relax and take more time to settle down on each lesson. While for the negative side is we might feel not productive and demotivated at times.	Neutral	0.500852	Choice and control	0.614465
From my opinion learning through video conference has its pros and cons as for the pros we can be more relax and take more time to settle down on each lesson. While for the negative side is we might feel not productive and demotivated at times.	Neutral	0.500852	Choice and control	0.614465

Table 7 shows feedback from the data regarding the confidence scores and their alignment with SDT. It identifies participant comments, the assigned confidence scores and how they are interpreted in alignment with SDT elements:

Table 7

SDT Confidence Scores

Comment	Score	Alignment
"Ugly; sometimes the disruption of internet connection might annoys me during learning"	0.925441	Strong relevance to autonomy
"Cheating when quiz, doing other things when off camera..."	0.657244	Moderate relevance to autonomy
"Good of learning in video-conference classroom is about the recordable, reviewable, ability to show the subtitle"	0.743671	Strong alignment to flexibility
"No practical session in the video-conference classrooms"	0.947236	Strong relevance to competence
"Good; less anxious to talk and give suggestions"	0.645924	Moderate relatedness
"Late feedback from colleagues and instructors"	0.739375	High alignment with relatedness

RQ1b: What are Respondents' Sentiments Emerging from Learning on VC Platforms Based on the Multidimensional Sentiment Frameworks?

This deeper analysis explores the sentiments using the five sentiment categories captured in the theoretical framework. Table 8 shows the positive, negative, neutral, insightful, and confused sentiment categories with sample descriptive comments. These findings are compared to AML's three-sentiment categories (positive, neutral, negative), offering insights into how the categorisation impacts the depth of the analysis.

Table 8

Multidimensional Sentiment Category

Sentiment Category	Description	Sample Data
Positive	Highlights the strengths of videoconferencing platforms, particularly their flexibility, time-saving features, and convenience.	*"I can rewatch the video anytime"*
Insightful	Absent in AML. Particularly valuable in capturing forward-looking or reflective statements that goes beyond AML's simple "positive" categorisation. Offer deeper reflections tied to all SDT elements, showing respondents' understanding of their experiences.	*"Learning online has its benefits but hybrid models should be considered to accommodate everyone."*

(continued)

Sentiment Category	Description	Sample Data
Negative	Revolved around technical issues, reduced engagement, and challenges with maintaining focus; map closely to the competence and relatedness dimensions reflecting dissatisfaction with the technical and social interaction aspects.	*“The bad is learners not concentrating fully or being absent.”*
Confused	Captures a distinct form of dissatisfaction. AML will classify this broadly as "negative," missing the unique challenges of confusion and reducing precision in identifying areas needing improvement.	*“The bad is the memory situation; feeling is not anymore same with physical class”*
Neutral	Often represented a balanced view of online learning, highlighting both its pros and cons.	*“I am comfortable with any form of learning or teaching.”*

RQ2: What Patterns do Learners Demonstrate Regarding the Self-determination Elements?

The multidimensional analysis of learner sentiments based on SDT elements reveals that positive feedback highlights the benefits of flexibility, mastery, and engagement in online learning environments, while negative sentiments reveal barriers such as technical issues, poorly tailored content, and social isolation. These insights emphasise the importance of addressing technical and instructional challenges to enhance learners' autonomy and competence while fostering meaningful peer connections to improve relatedness in virtual settings. Table 9 shows the feedback from the data in relation to the SDT elements.

Table 9

Multidimensional Sentiment Category

SDT Element	Description	Sample Data
Autonomy	Positive feedback highlights flexibility: Learners appreciate the ability to study according to their schedules,	*“I can re-watch lessons anytime, which helps with self-paced learning.”*
	Negative sentiments reveal barriers like unstable Internet: This indicates frustration when autonomy is hindered by technical constraints.	*“Connectivity issues cut me off mid-session, disrupting my learning flow.”*
Competence	Positive sentiments emphasise perceived mastery, supporting competence as learners feel more confident through revisiting materials.	“*Access to recorded sessions lets me revisit difficult concepts.*”
	Negative remarks underscore limitations: These comments reflect a lack of competence reinforcement due to poorly tailored content.	“*Instructors struggle with adapting materials, reducing the effectiveness of sessions.*”
Relatedness	Positive insights reflect engagement opportunities. Remarks highlight successful social interaction features.	“*Group discussions in breakout rooms helped us connect despite the distance*.”
	Negative feedback underscores isolation, indicating challenges in fostering relatedness.	“*Online environments make it hard to build relationships with peers*.”

RQ3: What are the Differences in Sentiment Patterns Based on Respondent Characteristics?

Access to IT infrastructure and the level of IT knowledge appear to be key factors influencing sentiments. Specifically, reliable access to gadgets and the Internet correlates with positive sentiments, emphasising flexibility and convenience. Conversely, respondents with poor access or limited IT knowledge often express negative or confused sentiments due to challenges in engagement, technical issues, and difficulties navigating online platforms. Table 10 provides a description of the differences in sentiment patterns based on respondent characteristics. Addressing the noted disparities by improving digital infrastructure and providing affordable tools could significantly improve user experiences.

Table 10

S*entiment Patterns Based on Respondent Characteristics*

Characteristic	Description	Sample Comments
Access to infrastructure	Data strongly indicates that access to gadgets and reliable Internet significantly influences sentiments. The barriers directly affect competence by hindering ability to engage effectively with the platforms and relatedness by limiting interaction and participation. Positive sentiments often stem from those with reliable access, praising the flexibility and convenience of online learning.	*"The effectiveness of the network. If the network is poor, the participation of the students will be affected",* *"Not all can afford the hardware needed to run virtual classes."*
Level of IT Knowledge	Data suggest differences in sentiments related to the level of IT knowledge or technical proficiency. Respondents who mentioned difficulties in handling technical issues or navigating VC platforms often expressed negative or confused sentiments, reflecting challenges and incompetence, while those with higher technical competence likely viewed the platforms more positively, focusing on flexibility and autonomy.	*"Bad internet connection, hardware price, basic skill to handle software."* or *"Some instructors have a negative attitude toward online technology, possibly due to being removed from their comfort zone."*

All respondents have access to gadgets and the Internet to access online classrooms. One hundred and seven respondents noted that they have low-to-medium level IT skills (they can handle basic ICT-related tasks). One hundred and fifty seven identified themselves as having high-to-expert IT skills (e.g., very conversant with technology or professional skills). Overall, all respondents have the minimum required level of knowledge to participate in a VC classroom. The respondents were also broadly categorised into two groups based on education: 'high school leavers' and 'respondents with a bachelor's degree or higher'. This characteristic was extended to include categorisation as 'younger adults' or 'more mature adults'. Categorisation based on gadgets and internet accessibility includes 'low-to-medium' and 'high' accessibility. Table 10 highlights how personal experiences and demographic characteristics might affect sentiment and perception. The finding also highlights a critical equity issue in the adoption of VC for education.

RQ4: How Might a Hybrid Sentiment Model Based on AML be Leveraged to Support More Effective Analysis?

AML's strengths lie in its simplicity and clarity. Its three-sentiment categories provide an efficient, high-level summary of feedback. The sentiment scores accurately reflect the overall tone of the feedback, providing high confidence in sentiment direction. The limitations of the AML approach are reflected in the loss of nuance. There are also potential technical limitations (e.g., training data), which can result in incorrect results. In addition, with AML, insight and confusion are lumped up into "positive" or "negative", respectively, resulting in the loss of valuable distinctions that the multidimensional sentiment categories provide. In addition, AML fails to identify reflective or forward-looking comments that the 'insightful' category captures, thus reflecting a lack of contextual depth. Insightful and confused categories allow a clearer understanding of user needs and challenges. The additional sentiment categories thus allow for more granularity in analysis. This capturing of subtle variations in user experiences enables more targeted recommendations for platform improvement.

Integrating both approaches highlights the broad overlap of the sentiments across both models and the advantages that might be derived from the hybrid model. The insightful and confused categories of the multidimensional model provide a richer understanding of user feedback that the AML model cannot achieve. The model also highlights the categorisation that might have been wrongly done by the AML based on scores, allowing corrections and potential areas for AML model improvement. The hybrid framework integrates AML with multidimensional sentiment analysis mapped to SDT elements, impacting sentiment assessment by providing more objective insights (Giatsoglou et al., 2017). It leverages AML's efficiency (Microsoft, 2023) while capturing context-specific emotions. Validation involved qualitative assessment by domain experts who evaluated thematic relevance and accuracy. Expert feedback indicated that the framework facilitated a more comprehensive understanding of learner sentiment than using AML alone (Microsoft, 2024). This enhanced understanding helps improve interventions and personalise learning experiences (Chiu, 2024).

RQ5: What Do the Expressed Sentiments Communicate Regarding the Future of VCLPs?

Analysis of sentiments toward VCLPs reveals key areas for future design. Participants express the need for designs that foster relatedness, competence, and autonomy, all of which are critical for positive user experiences. The following design priorities address these needs and offer a pathway for developing more engaging and effective virtual collaborative learning platforms. The results suggest several design priorities for VCLPs to include:

- Enhancing interactivity through improving the functionality of collaborative tools like breakout rooms, polls, and games to improve relatedness.
- Improving technical infrastructure through addressing connectivity issues and platform stability to support competence.
- Flexible design that focuses on retaining autonomy-enhancing features like recording sessions and customisable schedules and providing more user options.
- The hybrid framework.

DISCUSSION

The analysis revealed mixed sentiments. Positive sentiments predominantly highlighted the flexibility and accessibility of VCLPs, such as the ability to *rewatch recorded sessions* and *learn at one's own pace*. However, negative sentiments frequently underscored issues like *poor internet connectivity*, *reduced engagement*, and *challenges in maintaining focus*. Neutral sentiments reflected a blend of *appreciation for autonomy and dissatisfaction with poor relatedness (lack of interactivity)*. These findings align with prior research that emphasises flexibility as a core strength of online platforms but also echo concerns regarding learner isolation and technical barriers (Pravat, 2020; Kaur & Kumar, 2022; Smit et al., 2021). The results mapped clearly onto the SDT framework. Autonomy was supported through features like asynchronous access to materials and customisable learning schedules. Technological difficulties, among other issues, hindered competence. Relatedness emerged as the weakest dimension; respondents highlighted reduced interaction with peers and instructors. The patterns resonate with studies suggesting that online learning often prioritises autonomy at the expense of social connectedness (Men et al., 2023; Palmer et al., 2023; Xie et al., 2023).

Findings regarding differences in sentiment patterns based on respondent characteristics show that sentiment patterns varied across age groups or educational levels, aligning with literature emphasising the diverse needs of learner demographics (Firat & Bozkurt, 2020; Zamecnik et al., 2022). Regarding implications of expressed sentiments for the future of VCLPs, respondents' feedback indicates that the future of VCLPs lies in balancing flexibility with enhanced interactivity and reliability. Features like real-time interaction tools, integrated technical support, and improved design for peer collaboration could address relatedness and competence deficits.

CONCLUSIONS

The study highlights a complex landscape of sentiments, with VCLPs enabling flexibility while facing challenges in social interaction and technical reliability. This study explored user sentiments across diverse educational contexts, revealing a spectrum of experiences that align with the SDT dimensions of autonomy, competence, and relatedness. Positive sentiments highlighted flexibility, accessibility, and the ability to learn at one's pace, while negative sentiments emphasised challenges such as poor connectivity, diminished engagement, and limited interaction. Differences in sentiment patterns among different respondent groups underscored the diverse needs of these groups, suggesting the need for VCLPs to adapt to their varied expectations. The findings provide critical insights into the strengths and limitations of VCLPs as educational tools. Future research on VCLPs needs to focus on further exploration of user (learner) perceptions and best practices for fostering a sense of community and promoting student engagement in online environments.

The study relied on self-reported feedback with the potential to introduce response bias. Furthermore, while enriching the dataset, the diversity of respondents' educational levels complicates generalisations about specific learner groups. Future research could focus on longitudinal studies to track changing sentiments over time, include a more detailed analysis of cultural and regional differences, and explore platform-specific usability features in relation to SDT dimensions. The mapping of age group to educational level is a broad generalisation that may have overlooked deeper differences among respondents; future studies can focus on clearer delineation based on demographics. The study did not focus on gender as a factor for comparison; future studies can explore gender factors in relation to the use of VCLPs and other online platforms.

In addition, feedback from different learner groups on what features they would like to see integrated in future VCLPs can also yield useful information for developers. For example, some respondents suggest enhancing interactive tools to improve engagement: *"Adding live polls or games could make sessions more engaging."* Additionally, addressing technological inequities is critical, as shown in the result. By addressing these insights and limitations, future VCLPs can evolve into tools that effectively balance flexibility, competence-building, and social engagement, meeting the diverse needs of learners across educational contexts.

More research is also needed on the effectiveness of AI-powered features and the pedagogical implications of new media integration in VCLPs (Wang et al., 2023). Analysing user sentiments offers significant value in understanding the evolving role of VCLPs in education. By identifying learner experience patterns, this study provides a clear view of how these platforms support or hinder educational outcomes. Sentiment analysis allows educators and platform developers to make informed decisions to enhance user experiences. For policymakers, the findings offer a roadmap for prioritising investments in digital infrastructure and supporting initiatives that bridge the digital divide.

The use of AML for sentiment analysis demonstrated its effectiveness in extracting meaningful insights from diverse feedback. The integration of AML's sentiment categories with the SDT framework proved valuable in mapping learners' experiences to psychological needs, offering a structured approach to understanding sentiments in education. While AML facilitated efficient analysis of large datasets, future iterations could benefit from more nuanced algorithms capable of detecting complex emotions and cultural subtleties, especially incorporating more granular sentiment categories like insightful and confused to capture the complexity of user feedback better. The multidimensional sentiment approach offers more actionable insights for educators and platform developers. Combining both approaches can achieve a more comprehensive analysis of user feedback, bridging high-level categorisation with a detailed exploration of unique sentiments. Overall, this study underscores the potential of AI-powered tools like AML to inform evidence-based improvements in educational technologies, paving the way for more adaptive, learner-centric platforms.

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