Evaluation of Vocational E-Learning Seminars

DIMITRIOS TSIMARAS
Aegean University
School of Humanities
GREECE

EMMANOUIL ZOULIAS
Health Informatics
Laboratory,
Faculty of Nursing,
National and Kapodistrian
University of Athens, Athens
GREECE

CHRYSSI VITSILAKI
Aegean University
Faculty of Humanities
GREECE

Abstract: The fourth industrial revolution emerges from a demanding need for reskilling and upskilling every active working person. Furthermore, the European Commission included key policy instruments for resilience, social fairness, and sustainable competitiveness in the European Skills Agenda. Distance training and education programs are key factors to succeed in the targets mentioned above. Due to the o COVID-19 pandemic, already 30% of the total education in European countries has further expanded. As a result, online evaluation approaches are more than necessary. Various methodologies have been applied to evaluate the online training sessions, from traditional statistics to context analysis and, the newly introduced text mining and sentiment analysis. This work used conventional descriptive statistical methods and advanced text mining methods to analyse data collected by private sector online training seminars—a total of 50 trainees in 5 seminars conducted by the private sector during COVID-19 pandemic training activities. A typical text mining analysis performed on a low is some open questions and a small number of texts.

Key-Words: training, evaluation, E-Learning, text mining, AI

Received: June 7, 2022. Revised: December 22, 2022. Accepted: January 24, 2023. Published: February 22, 2023.

1. Introduction

The fourth industrial revolution emerged, demanding frequent reskill and upskilling of the workers [1]. The European Commission included in the European Skills Agenda key policy instruments for resilience, social fairness, and sustainable competitiveness [2]. This is a crucial factor in the implementation of distance training and education programs. Nowadays, almost 30% of the total education is in European countries [3]. The COVID-19 pandemic further expands online learning activities within all sectors, private, public, non-profit, and engineering, either in rural or urban places [4-5].

In addition to that, the identification of robust and reliable online evaluation approaches online is more than important [6-7]. Educational and training evaluation procedures have been extensively examined in the literature during the last decade, leading to various methods and revealing the different strengths and weaknesses as needed concerning the other educational processes [8-10].

During the last decades, data mining was introduced as a set of new data analysis methods for general applications and applied to training and learning evaluation methods [11-13].

More specifically, newer text-mining methods have been used to evaluate healthcare training sessions [14]. Text mining aims to analyse data and find sentiment within the text. This approach snowballs to explore sensations, attitudes, moods, affection, sentiments, opinions, and appeals of text within any electronically written document [15]. The first applications were found in the scientific field of behavioural sciences [16] and then expanded to other scientific areas, including education [17-18]. Additional worth mentioning sentiment analysis techniques applied in the education field are [19], which enables educators to understand their students' needs and preferences, and [20], which helps to minimise the distance between the e-learners and the trainers in situations of distance learning seminars.

The present work applied both traditional descriptive analysis and text-mining methods to investigate the opinion of trainees. In addition, low-text data numbers' performance tests text mining's capabilities.

2. Data Description

The data are from 5 seminars during 2020-2022, performed as fully online synchronous and asynchronous seminars. A small number of about ten trainees took part in each seminar. For each seminar, the same questionnaire was provided to trainees as the evaluation method of the training program. This questionnaire is composed of a set of questions, both open and closed.

The questionnaire comprised 56 questions, and only 4 were open questions. Regarding the closed questions, a descriptive analysis was performed using simple percentage and counting methods. The four available questions were “If it's your choice, do you prefer to have the camera on or off during modern telelearning and why?”, “What do you think went well in modern distance learning c? What, what did you like?”, “What do you think did not go well in modern distance learning c? What, what did you not like?” and “Please provide a brief, additional comment or observation about distance education that you consider important” were further analysed with text mining analysis. The analysis is based on the open-text questions deployed by the RapidMiner tool using a text-mining method. The text mining analysis aimed to identify patterns in phrases, words, and sentences which declare a positive or negative position towards online training.

3. Classification Procedure

In this study, the initial data (sentences) were taken by the open-ended questions of the questionnaire mentioned above and retrieved as an excel file. The community-free version of RapidMiner software was used to apply the methodology.

The **initial step** was to load the data into the software (Figure 1 – Read Excel). **The second step** was the conversion of all nominal attributes to string attributes since the tools used later process only string attributes (Figure 1 – *“Nominal to Text”*). The step has only one parameter (attribute filter), which is set to *“all”* in this work. This resulted in selecting all available attributes of the example set.

The third step has various sub-steps. In Figure 1 is the operator named *“Process Documents from Data.”* This operator has a word as an input list and results in attributes as an output in the form of a processed word list. Within this step, data from files are converted to texts ready to be processed. The analysis of the third step to the sub-step appears in Figure 2.

There are various options on how to apply tokenization. The First Internal Step is “Tokenization” [21]. The work of tokenizing a document is to split every text into divided elements or items, such as words. In this work, the “Tokenize” operator is used (Figure 2) of the RapidMiner. This work selects splitting text into single words as an attribute. Clarifying this, the sentence "I already used Knowledge from the course in my Job,” the application of tokenization, will result in the following series of words: "I,” "already,” "used,” "Knowledge,” "from,” "the,” "course,” "in,” "my,” "Job.”

The second Internal step, the “Transform Cases” [22], is used to increase the number of common words. The aim is to identify all common words, avoiding, lowercase, uppercase, and mixed cases. In this work, all character’s issues within each document decided to be transformed to uppercase using the relevant operator. The application of the operator resulted in the fact that words in the document as “Like” and “like” are supposed to be equally and handled the same; in this specific example it means that students like something if they state “Like” or “like.” In this work it was decided to transform all document characters as lower case. The operator for that is the *“Transform Cases”* operator (Figure 2). This step is supposed to prepare for the following internal step of filtering stop words.

The third internal step is the *“Filter Stop Words”* [23] (Figure 2). The role of this step is to discriminate between non-case sensitive or case sensitive of the Greek dictionary. In a text mining analysis, the operator of Filter Stop Words is used for removing common words, in this case, Greek works, that do not add anything to text explanations. This work used a set of 847 Greek stop words as a dictionary for this implementation. An indicative example of the Filter Stop Words role is that the word “Like” is in the dictionary; this operator will remove the word “Like” for the analysis of texts.

The fourth internal step is about the generation of *“n-Grams.”* The term *“n-Grams”* [24] is a series of consecutive tokens of length n in any document. In this work, the n-Grams were generated using the operator *“Generate n-Grams”* of Rapid Miner. To fully understand the role of this operator, an indicative example will be presented. They suppose that a document includes the phrase “like a lot” composed of three different words, *"like," "a,"* and *"lot."* Supposing that the number attribute of Grams number is set to n=3, the operator will produce the output of all consecutive tokens one, two, and three lengths. Those are all possible combinations with one, two, and three words. The result of the operator will be six different Grams, which are: *"n-Grams": "a," "lot," "like," "like a," "a lot,"* and *"like a lot."* The Grams generated are made one-word word length, and two- and three-word length are extracted. In this work, the fourth internal step (Figure 2) sets the attribute of Grams number 5, which means (5-Grams).

The final fifth internal step, referred to as *"Filters Tokens"* (Figure 2) [22], deals with the length of the words, which means the number of characters of each word. These further filter common words like "and," "or" and words with a small length that do not have any value to the analysis of texts. This work selected that the minimum number of characters in each word included in the study will be from 5 to a maximum of 9999 characters.

Among the results received by the text mining analysis, some further contextual analysis was performed on the basis that ordinary meaning, equivalent, and meaning phrases and statements, not equal, are considered to express the same positive or negative information and are added to the occurrences. This context analysis is more critical since the initial documents are limited.

The applied process is illustrated in Figure 1 and Figure 2.

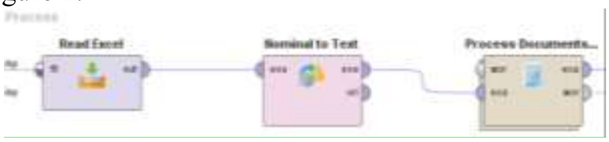

Figure 1

Figure 2

4. Results

In this work, only the most important results of the questionnaire are presented. The demographic profile of the trainees taking part was 52% female and 48% male. The age categories of the trainees were 30% (18-30), 14% (31-40), 30% (41-50), 20% (51-60), and 6% (>60). Furthermore, the educational level was 68% (higher education), 14% (post lychee), and 18% (lychee). The answer for the trainee's distance from the physical performance of the seminar was 70% up to 70 kilometres, 26% over 100 kilometres, and 4% between 51 and 100 kilometres.

Some other questions tried to investigate the situation and technical issues of the trainees. The systems used were desktops, laptops, tablets, and, to a small extent, smartphones. Furthermore, the equipment seems equal to 3 years (50% in total) and more than three years, and the operating system used is mainly Microsoft Windows (74%). Regarding the internet connection speed, 24,5% had VDSL over 100 Mbps and 40,8% 50 Mbps.

The method of attending the distance education courses was 55,1% blended, 38,8% Synchronous, and the remaining Asynchronous.

A a further context analysis was performed to find terms with shared meaning, which is essential to reach conclusions. Applying the above-described text mining methodology on all 50 trainees' replies resulted in 1340 primarily different appeared phrases/words. The expressions and words are separated into favourable positions (Table 1) and negative positions (Table 2). In Tables 1 and 2, the Occurrences refer to the times the statement appeared in various phrases but always with the same meaning.

Table 1 – Positive Emotion

Phrases/Words	Occurrences
Save time, money, and fatigue by avoiding motion	50
Exams sharing	19
Avoid disturbance	15
Follow the timeline	10
More multimedia material	5
Possibility to follow programs from far away Universities	5
Total	**104**

Table 2 – Negative Emotion

Phrases/Words	Occurrences
Need of proper equipment and connection, which costs	52
Need more intervals due to the tedious process	38
Live sessions are better	28
Prefer to have camera off, personal data	20
Teachers need to have the proper knowledge of technology	20
Tire complete process, too many hours in front of the camera	12
Total	**170**

The results in Table 1 and Table 2 reveal that trainees have either positive or negative positions toward online training activities during COVID-19. The phrases and words in Table 1 support the above statement. The most critical issue for the trainees was that they "*Save time, money and fatigue by avoiding motion"* (a number of 50), meaning towards the learning infrastructures. Near this point is the belief that they have the "*Possibility to follow programs from far away Universities"* (a number of 5). Furthermore, positive energy was the ability to *"Exams sharing"* (a number of 19) and the quieter environment in their homes (*"Avoid disturbance"*- a number of 15). Another point stated as a positive one was that during online training, they strictly follow the timeline (a number of 10). Finally, an expected issue is that they can access *"More multimedia material"* (a number of 5).

This was extracted after applying the text mining method, followed by a thorough context analysis of all final occurrences of positive and negative phrases. Phrases and words that seem similar or have similar meanings are combined to extract a better result.

5. Conclusions and Future work

Within this work, a former method [14] was applied to evaluate online seminars within the private sector. The current methodology and tools support administrative and training performers to locate strengths and weaknesses that have yet to be seen. An innovation of this work is that it applies those innovative methodologies to private sector online training sessions during the COVID-19 pandemic.

This work has been much more extended, and the main one is to apply the methodology to many texts from the private online training sector and a cross-country application. Finally, an exciting extension can be the application of a method on *"big data,"* resulting in a tool for learning analytics for the private sector.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.