doi: 10.5821/conference-9788419184849.66

# TEXT ANALYTICS ON MOOCS
## A COMPREHENSIVE ANALYSIS OF EMOTIONS

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## ABSTRACT

The value of diversity in education is highly emphasized in recent years, particularly in the wake of the COVID-19 pandemic, by many scholars. Massive open online courses (MOOCs) have aided the evolution of online learning by broadening the range of learning opportunities available. They have gained popularity, especially in higher education by providing unlimited access to lectures and rich learning materials by renowned and respected academics in a wide variety of areas, with no restrictions and at very low fees. Furthermore, learners' motivations for enrolling in a MOOC may vary depending on their choices for the course's instructional design as well as their emotions.

Knowing this, the development of more effective online courses that address affective concerns would appeal to a wider audience and improve the learning experience. This research aims to uncover the emotional characteristics of MOOCs to better understand why learners choose a specific course among hundreds of options available on MOOC sites. For extracting the learners' emotions from user reviews, the study used Kansei Engineering approach, which is enhanced with text analytics techniques. The research methodology entails gathering reviews from MOOCs and analyzing them using natural language processing (NLP) techniques to discover Kansei words that characterize MOOCs, notably for courses in the discipline of Data Science. The expected output of this study is a Kansei corpus for online courses in this discipline.

***Keywords***: *Kansei Engineering, Text Analytics, MOOCs*

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## 1. INTRODUCTION

The value of diversity in education is highly emphasized in recent years, particularly in the wake of the COVID-19 pandemic, by many scholars. Massive open online courses (MOOCs) are a relatively new addition to the online learning scene and have aided the evolution of online learning by broadening the range of learning opportunities available. Since 2008, several public and elite schools, mainly in North America, have provided MOOCs. Many academics are interested in MOOCs because they see the potential for global education. Some of these academics are taking a research-oriented approach, and academic papers describing their research are starting to appear in peer-reviewed publications (Liyanagunawardena et al., 2013)

MOOCs have gained popularity, especially in higher education by providing unlimited access to lectures and rich learning materials by renowned and respected academics in a wide variety of areas, with no restrictions and at very low fees. Many academics and practitioners believe that MOOCs can improve equity in higher education by reaching a wider audience and removing barriers to high-quality education given by top schools. Unlike university-sponsored online courses, MOOCs have no enrollment limits, no required units or credentials, and no requirement that learners complete a program beyond a single course (Baturay, 2015; Deng et al., 2019). Especially for students who are interested in more than one field, the opportunity to choose courses from different fields increases the preference of students. Also, the completion time and course selection depend entirely on students that provides high flexibility. Considering all these, it can be said that MOOCs have been accepted as a new branch of higher education.

MOOCs not only shape the personal development of students who continue in higher education but also offer learners who have adopted the philosophy of lifelong learning, the opportunity to gain the knowledge and skills required by the current age. From this point of view, it is expected that the stages such as enrollment mechanism, curriculum, and content development, teaching strategies and technologies, and assurance of learning, which are followed and developed in higher education processes, should also effectively be managed on MOOC platforms. With the demand for MOOCs and rapid adaptation, new initiatives continue to emerge with many different business models and strategies. However, scientific research on this subject has revealed that existing platforms still have controversial aspects in terms of the models they adopt (Dennis, 2012; Burd et al., 2015; Kim, 2016). Therefore, it is essential to systematically monitor and evaluate the perceptions and experiences of learners to provide input for continuous improvement activities in MOOCs. Learners' motivations for enrolling in a MOOC may vary depending on their choices for the course's instructional design as well as their emotions. Knowing this, the development of more effective online courses that address affective concerns would appeal to a wider audience and improve the learning experience. This study aims to uncover the emotional characteristics of MOOCs to better understand why learners choose a specific course among hundreds of options available on MOOC sites.

Kansei Engineering (KE) is a way for concretizing a product's image in people's minds and transforming consumer wants into design aspects for product delight. In Kansei engineering, researchers or designers use various words such as adjectives, adverbs, and sense-related vocabularies to capture customer needs. These are known as Kansei words, and they are the simplest way to access consumer feelings in this methodology.

Several methods, including surveys, interviews, and focus groups, have been used successfully to collect Kansei data. However, they are only used once, are small-scale, time-consuming, and costly to collect and update. For example, questionnaires used to collect Kansei words and customer feedback are typically designer-oriented and do not fully reflect customer perspectives (Wang, 2022). Customers, on the other hand, can easily share their experiences, positive or negative opinions, feelings, and thoughts about the product or service they purchase in consumer web blogs, social networks, and even review sections in product websites (Chen et al., 2019; W. M. Wang et al., 2019). Contrary to abovementioned limited conditions, a large volume of data from customers, can be collected within these platforms in free-text or structured forms. These customer reviews, as digital Voice of the Customer, are valuable as much as the data obtained through other traditional methods (Kapucugil-İkiz & Özdağoğlu, 2015; Özdağoğlu et al., 2018) and they would also be one of the primary sources of Kansei words and product attributes.

The common methods used to analyze the Kansei data include mostly multivariate statistical analysis such as partial least squares regression (PLS), principal component analysis, factor analysis, artificial neural networks, genetic algorithm, and rough set analysis (Akgül et al., 2021; D. Chen & Cheng, 2021; Y. Chen et al., 2021; Ding et al., 2021; Ishihara et al., 1995; Kobayashi et al., 2022) The proliferation of customer reviews has also led to the development of sophisticated techniques for extracting hidden patterns from these reviews. Today, in a conjuncture where big data is integrated to all aspects of research as a hot topic, text analytics is now a promising method in Kansei engineering literature to identify product features or Kansei words (Jin et al., 2021; W. Kim et al., 2019; Kobayashi & Kinumura, 2017; Li et al., 2020; Wang, Li, Liu, et al., 2018). It is a method of extracting high-quality information from unstructured text using NLP and machine learning (Lai, 2012). Text analytics, unlike typical Kansei engineering studies that use questionnaires, allows researchers to work with a larger dataset. Text analytics studies are generally conducted for 300 or more user comments and reaching the same number of respondents through the standard questionnaire method is quite challenging.

In this study, Kansei Engineering, enhanced with text analytics techniques, is used to extract learners' emotions from their massive open online course experience to better understand their needs. The research methodology entails gathering reviews from MOOCs and analyzing them using NLP techniques to discover Kansei words that characterize MOOCs, notably for courses in the discipline of Analytical/Quantitative Methods.

The preliminary findings of this ongoing project, which requires long-term data collection and analysis, are presented through the reviews obtained from the selected courses on Coursera. From the platform, course reviews have been scraped from ‘Data Science’ category and the expected output of this study is a Kansei corpus for online courses in this discipline.

The organization of the rest of this paper is as follows. Section 2 reviews previous studies on text analytics in the context of Kansei engineering. Section 3 explains the methodology implemented in this study. Section 4 presents the results and findings of this methodology for analyzing online user reviews on MOOCs from the field of Data Science. Section 5 covers the concluding remarks.

## 2. RELATED WORK: TEXT ANALYTICS IN KANSEI ENGINEERING STUDIES

Kansei engineering is a kind of methodology which transforms customer needs to design elements for pleasure from the product (Nagamachi, 2002). This methodology is frequently employed in the development of a variety of products in a variety of sectors. Similarly, studies that use text analytics in the Kansei-driven design process have a wide range of application areas. Kobayashi and Kinumura (2017) used text mining in their Kansei engineering study to design office chairs, Li et al. (2018) for smart watches, and Lai et al. (2022) for new energy vehicles. In addition, Jin et al. (2021) proposed a framework that integrates Kansei Engineering and Kano model. In their proposed framework, firstly, customer affective emotions are derived from internet reviews. Then, using syntactic relations and a clustering method, related product features are positioned. By the help of Kano model, product characteristics are prioritized based on affective emotions to demonstrate their significance in terms of customer satisfaction. Then, they conducted two studies on smartphones and cameras to prove the feasibility and reliability of their proposed framework. While Kim et al. (2019) suggested a model in which users' affective variables were extracted from online reviews and categorized using a self-organizing map (SOM) to build an affective variable extraction methodology that can effectively and efficiently reflect users' implicit demands and performed an experiment on recliner for verification of their proposed model, Chen et al. (2019) used text mining to extract Kansei words and hotel service characteristics.

Text analytics can be used in Kansei engineering studies by employing ready-made text analytics programs or libraries written in a variety of programming languages. Kobayashi and Kinumura (2017) used KH coder text mining software to collect Kansei words, whereas Sakornsathien et al. (2019) used RapidMiner to prepare for and carry out the data mining process. Chiu and Lin (2018) and Chen et al. (2019) used the web browser tool in conjunction with IBM SPSS Modeler in their studies on road bike design and hotel service development, respectively. Li et al. (2020) also used web crawler tool to collect customer reviews from Amazon.com for stuffed toys. Lai et al., 2022 stated that Scrapy and Selenium were the main tools for extracting information from websites and they worked with the Scrapy automated crawler framework using the Python programming language.

One of the primary benefits of using text mining is that it corrects the cognitive asymmetry caused by the gap between the designer and the customer. With a better understanding of user needs, text mining and NLP techniques have reduced the likelihood of failure in the designer's product development process (Wang, 2022). In these text mining studies; researchers can be more proactive and respond to changes in customer preferences more quickly. Indeed, text mining not only helps researchers in dealing with difficulties encountered while conducting the study, but it also helps them in taking quick action in detecting changes or innovations in customer preferences.

## 3. METHODOLOGY

The research methodology of this study is divided into six major stages (Figure 1). The product domain is determined first. The platform from which the comments will be extracted is then determined. In the third and first stages, the URLs from the specified platform are extracted, followed by the comments from the URLs, and the data containing the reviews is cleaned and analyzed using NLP techniques. At the conclusion of the analysis, a list of Kansei words (KWs) for the relevant domain is compiled.

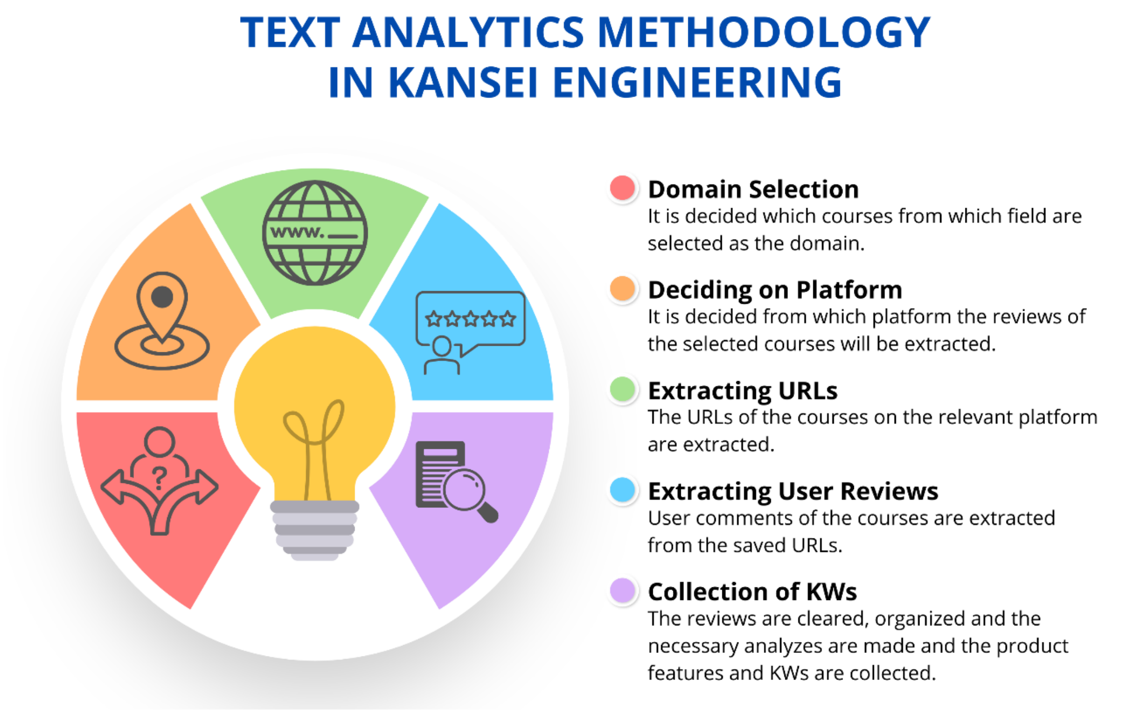


**Figure 1.** Text Analytics Methodology in Kansei Engineering

### 3.1 Domain Selection

The first stage of the methodology addresses domain selection. The product to be designed and who the product will serve are determined at this stage. The goal for this research is to develop a MOOC course as a final product. This study, however, will only determine Kansei words in this MOOC course design process. Online reviews, rather than traditional methods, will be used to investigate Kansei words from MOOC experiences in the 'Data Science' domain for this product.

### 3.2 Deciding on Platforms

MOOC platforms have grown in popularity, particularly during the pandemic, and thousands of students of all ages have begun to enroll in these courses. The high number of students brought with it the high number of user evaluations. As a result, the opportunity to work with big data has arisen. All MOOC platforms could be potentially included in the study as they offer a wide range of courses in data science. Coursera, on the other hand, was chosen as the primary platform in this study because it is in agreement with the authors' institution.

### 3.3 Extracting URLs and Reviews

Among the MOOCs released on the Coursera website, courses addressing business analytics, machine learning, and data science were identified, and web scraping codes were constructed to draw links to these courses as well as reviews on these links. Selenium (Thoughtworks, 2022) and BeautifulSoup (Richardson, 2019) together with the core libraries such as Numpy and Pandas were used in this procedure. The codes of Firebanks-Quevedo (2019), already publicly available, were utilized as a starting point, however they were adjusted to fit the new platform's new web source structure and updated library features. Additional codes were also created to address further requirements.

A total of 1000 courses in the discipline of data science on Coursera were found by extracting the URLs. Only English-instructed courses and those published in the domains of business analytics, machine learning, programming, statistics, and forecasting were preferred among these options. As a result, the authors decided to extract the reviews from 70 courses among 1000 courses. Web scraping codes were then executed to extract 60,000 reviews from the selected course URLs.

### 3.4 Collection of Kansei Words

The adjectives that can later be used as Kansei words for MOOCs were extracted from the reviews using text analytics techniques. The following procedures were used to process the reviews:

- Text cleaning
  - Tokenize
  - Remove punctuation, stop words, redundant spaces
  - Transform lowercase
  - Lemmatize
- Merging into a single document
- Extracting adjectives (Part-of-speech tagging)
- Extracting synonyms and antonyms

- Extracting distinctive adjectives

Python coding was used for all operations and calculations. The Spacy (Spacy, 2022) and Re (regular expression) libraries were utilized to perform the essential text processing in this process. To validate the extraction of adjectives for MOOCs, the preprocessed reviews were divided into two randomly selected parts, i.e., 75% for extraction and 25% for validation. Both samples were analyzed to filter the adjectives, and then the similarity between these samples were calculated. Cosine similarity is frequently used when computing similarity ratios between texts. In this case, the cosine similarity based on word embeddings and multi-dimensional meaning representations method in the Spacy library (Spacy API, 2022) was used to calculate the semantic similarity (99.9%). After the validation, term frequencies were tabulated and visualized. Synonyms and antonyms were extracted from WordNet (Fellbaum, 1998, ed.). Besides, the KeyBERT (Grootendorst, 2021) was used to extract key adjectives based on BERT embeddings (Sharma & Li, 2019). KeyBERT extracts the keywords that are the most comparable to the document. To obtain a document-level representation, BERT is used to extract document embeddings. Then, for N-gram words/phrases, word embeddings are extracted. Cosine similarity is used to find the most comparable words/phrases to the document.

The maximum sum similarity or maximum marginal relevance approaches can be used to obtain diversified key adjectives. In this approach, first, the 2 x top_n most similar words/phrases to the document were extracted. Then, top_n combinations from the 2 x top_n words were taken and the combination that was the least similar to each other were extracted based on cosine similarity. The diversity rate can be adjusted as a parameter in the related function.

For all coding, Jupiter notebooks were developed and executed in Anaconda or Google Colab regarding GPU requirements.

Authors evaluated all results along with the concepts of KE and finalized list of KE words.

## 4. RESULTS AND DISCUSSION

After performing NLP processes in the context of text analytics, the first adjective list was created. Figure 2 depicts a word cloud of adjectives based on their frequency of occurrence. As a result, the most frequently used adjectives include ‘good’, ‘basic’, ‘deep’, ‘nice’, ‘easy’, ‘interesting’, ‘excellent’, ‘useful’, ‘amazing’, ‘helpful’, ‘practical’, ‘great’, ‘informative’, ‘difficult’, ‘complete’, etc.


Figure 2. Word Cloud of Adjectives

Authors having prior experience in KE research processed this raw adjective list and developed a consolidated one. Additional procedures have been developed to extract synonyms and antonyms from WordNet for the remaining adjectives on this list. Table 1 shows a partial representation of all of 1325 adjectives, which are Kansei words obtained after this refinement. Supplementary synonyms and antonyms to the primary Kansei words can be used for further categorization.

Table 1. Partial Representation of Extracted Kansei Words

| Adjective | Synonyms | Antonyms |
|---|---|---|
| Ambiguous | Equivocal | Unequivocal, Unambiguous |
| Consistent | Logical, Uniform, Ordered, Coherent, Reproducible | Incoherent, Inconsistent, Unreproducible |
| Critical | Decisive, Vital | Uncritical, Noncritical |
| Desirable | Worthy, Suitable | Undesirable |
| Dissatisfied | Disgruntled | Satisfied |
| Honest | Reliable, Honorable, True, Fair, Dependable, Good | Dishonest |
| Humble | Small, Chagrin, Low, Mortify, Lowly, Humiliate, Base, Baseborn, Modest, Menial, Abase | Proud |
| Nice | Skillful, Decent, Overnice, Squeamish, Prissy, Gracious, Courteous, Dainty | Nasty |
| Palpable | Tangible | Impalpable, Intangible |
| Reproducible | Consistent, Reproducible | Unreproducible |
| Responsible | Creditworthy | Irresponsible |
| Informative | Informatory, Illuminating, Enlightening, Instructive | Uninstructive, Uninformative, Unenlightening |
| Tangible | Touchable, Palpable, Real | Impalpable, Intangible |
| Undefined | Vague | Defined |
| Worth | Deserving | Worthless |
| Manageable | Doable, Achievable, Accomplishable, Realizable | Unmanageable |

Following that, distinct adjectives were defined by using the KeyBERT technique to filter the entire list of Kansei words. The prominent findings include the adjectives ‘discouraging’, ‘disappointing/disappointed’, ‘dissatisfied’, ‘dismissing’, ‘erroneous’, ‘satisfactory’, ‘uneducated’, ‘informative’, ‘inadequate’, ‘reluctant’, disastrous’, ‘sophisticated’, ‘hesitant’, ‘confidant’, ‘noncomplete’, ‘shameful’, ‘shocking’. The adjectives that appear in this analysis are not those that are most frequently used, but rather those that best reflect the text semantically. Although positive words are present, it is striking to note that the prominent adjectives primarily express negative feelings. When this finding is evaluated, it can be said that users are more likely to share negative experiences than positive ones. As a result, these inferences should be interpreted as indicating that the courses do not have a completely negative structure, but rather that they have features that can be improved.

## 5. CONCLUSION

MOOCs have gained considerable momentum in the last decade, both in higher education and in lifelong learning activities. Many projects in this area have been launched, and a variety of platforms with various business models and strategies have been made available to anyone with an interest in learning. While every platform strives to create digital environments that maximize their technical potential, learner satisfaction is determined by how well these opportunities are presented to them and how well the course content meets their needs. As a result, gathering feedback on learning processes encountered on these platforms, as well as allowing students to freely share their experiences, are critical stages of continuous improvement efforts.

When evaluating user feedback and incorporating it into product development processes, various methodologies are used individually or in combination. Among these methods, Kansei Engineering was used in this study to understand the emotional characteristics of learner experiences published in MOOC reviews.

The first step in a KE study is to define the Kansei words for the product or service under consideration. Text analytics tools are critical in both data collection and the identification of Kansei words on platforms, such as MOOCs, where large amounts of text data are collected. Several experiments using a combination of KE and text analytics methodologies for various product types have been well documented in the literature.

Previously, Kansei words were mostly determined by experts based on their opinions, observations, or published works in literature, and the majority of text analytics efforts focused on extracting 'product features' in these studies. In contrast, this study presents a novel application of KE methodology by employing text analytics to identify Kansei words. Another distinct potential contribution worth mentioning is the application of KE to MOOCs as emerging service platforms.

NLP approaches were primarily used in this study's methodology. From the preprocessed terms, those that can be evaluated within the scope of KE were filtered, and a comprehensive list was created by drawing synonyms and antonyms at the same time. Following that, the KeyBERT technique, which uses similarity metrics to generate a list of distinct adjectives using word embeddings, produced results that supplemented the findings. This process was demonstrated on Coursera courses in the Data Science category. Except for the filtering of adjectives which are used for identifying Kansei words, all stages are automated by running scripts through the relevant Python libraries, such as retrieving course links, retrieving course reviews, and performing NLP operations.

It should be noted that this study presented preliminary findings from an ongoing study aimed at identifying and implementing service features to improve the quality of MOOCs.

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