UNIVERSITY OF BIRMINGHAM

BERT-Based Sentiment Analysis Application: HSBC Study Case

This assignment is submitted as partial fulfilment of MSc in Mathematics, Operational Research, Statistics and Econometrics (MORSE) 2022-23.

Abstract

The paper aimed to find an effective way for HSBC to express sincere concern regarding sustainable development to customers. The purpose was to build a trusting relationship between the company and its customers regarding green initiatives without direct advertising. Three strategies were suggested to solve the problem and achieve the desired customers' perspective regarding HSBC's activism. An online survey was conducted to grasp the customers' points of view about the strategies, and it asked people to express their attitudes in a couple of sentences towards each strategy. AI-based sentiment analysis was implemented using the Bidirectional Encoder Representations from Transformer (BERT) model as an effective method to analyse people's opinions and feelings and provide a numerical estimation of the sentiments of each strategy: the method calculated the level of satisfaction (from 1 to 5) for every collected answer. It produced the distribution of the estimated emotion of a strategy. The received distributions of feelings about each strategy were represented by their mean values and compared using the statistical method of t-test. As a result of the research, the overall emotions regarding the strategies were calculated numerically, and the most effective one, according to the survey, was distinguished to solve the research problem. The investigation had constraints in the sample size of the collected data due to the existing time limit. Overall, the research produced an outstanding result suggesting the possible solutions for the problem, giving some insights about further direction and investigation for HSBC in building the relationship with customers. Moreover, the paper contributed to the BERT-based sentiment analysis scientific area, showing one more way of its application.

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Introduction

The widespread concern of our time is sustainability. Nowadays, people are more worried about whether human progress is moving toward a greener future by creating an eco-friendly environment and caring about the impact on the planet. People care about this as a legacy for future generations and want to take action. The concerns extend to big international companies as, due to their world economic influence and the number of people they employ, the companies' activities play a huge role in sustainability development, affecting the development through their every action. Therefore, companies are under pressure to align their initiatives with people's demands, and they are thoroughly examined to see if their activism contributes to the green transition. If the companies ignore the demands, they will face public criticism and unpleasant consequences.

Being one of the biggest and most powerful banks in the world, HSBC is also under people's surveillance, most precisely its customers, regarding its eco activities and policies. Even though HSBC has put in lots of effort in supporting a sustainable transition, such as financing sustainable projects of its climate partnerships: creating carbon-rich habitats with the National Trust and restoring the wetlands of Scotland with the National Trust for Scotland (HSBC Energy Policy Report, 2022), HSBC questioned about its sincerity in terms of its actions. For customers, it is crucial to know that the bank's intentions are genuine and are not focused only on economic profits.

Announcing the targets by 2030 and 2050 years for reducing financed emissions in two carbon-intensive sectors: oil and gas, power and utilities, HSBC promised not to provide any new finances to clients that can lead to the breakdown of its transition plan (HSBC Energy Policy Report, 2022). Nevertheless, HSBC has met criticism of its dual actions: from one side, the bank sponsors zero net transition as briefly described before and from the other side, it is one of the most prominent investors in fossil fuels in the UK, according to Chris Dorrell's CityAM report on the year 2023. Moreover, pursuing to show the positive impact on the sustainable transition by directly advertising all actions taken and hiding the information of its biggest fossil client, HSBC was banned for greenwashing its name through advertising that hides any details like the partnership with the fossil company (Makortoff, 2022).

HSBC project work

The purpose of the project is to find a way of showing HSBC customers the sincerity of the bank's sustainable initiatives and building the trust relationship, reducing the gap of misunderstanding regarding HSBC's intentions. The desirable result is to achieve the goal by avoiding using direct advertising because of the previous unsuccessful experience of using this. To reach the goal, three strategies for communication with customers are suggested to raise awareness of the bank's eco-friendly activities, demonstrate the sincerity of the initiatives and express the bank's own concern regarding the topic. Each strategy is based on building explicit communication with customers regarding sustainability and without involving any advertisement:

1) Sustainable Investment Showcase and Educational Resources: the strategy suggests integrating additional digital HSBC app sectors aiming to raise awareness of HSBC eco-friendly products and projects along with an educational sector regarding sustainability in general;
2) Green Savings and Checking Accounts: the strategy is about providing an alternative bank account, as an additional option for customers, that transfers a certain amount of money to support sustainable development;
3) Sustainability Event: the strategy offers to run public events that involve the public to contribute to the green future by solving different tasks participating HSBC.

All suggested strategies are based on the theory of planned behaviour (TPB) proposed by Ajzen in 1985. TPB is a social psychology theory that explains human behaviour based on three attributes: attitudes, subjective norms, and perceived behavioural control (Ajzen, 1985). In the project context, attitudes refer to the customer's positive or negative evaluation of HSBC's initiatives that can be comprehended through the survey. By subjective norms, the social influence and other external factors on the customers' attitude are considered. Finally, perceived behavioural control looks at the factors from the customers' point of view that determine HSBC's image. The data from the survey and HSBC's reports regarding current marketing strategies can give an understanding of the attributes mentioned above and find gaps between HSBC's desirable image and the customers' perception.

The reason for choosing TPB as the theoretical framework is preeminent for building strategies and is effectively implemented in diverse domains, such as forecast consumer attitudes in a variety of industries, such as green food and beverage (Wang & Wang, 2016), information technology (Akman & Mishra, 2014) and green products (Shukla, 2019), and has performed successful results.

The analytical part of the project

The suggested strategies should be analytically analysed to determine if a strategy leads to the goal and which performs better. The analytical part of the project is to provide a quantitative estimation regarding the strategies' effectiveness. As the topic is about people's emotions and feelings, sentiment analysis is chosen for application. The method is outstanding for extracting sentiment information from a text and assessing the information numerically using a polar scale, going from negative emotions to positive ones.

Overall, the paper concerns sentiment analysis application for solving the HSBC task. The paper consists of a literature review chapter that includes scientific reviews of the chosen method and brief theoretical explanations of the techniques used to give a reader an overall understanding of the subject, a methodology chapter, which is a detailed description of the analysis application, and a findings and discussion chapter, representing the outcome of the analysis.

Literature Review

The literature review is necessary to provide an understanding of the BERT-based Sentiment Analysis (a sentiment analysis using a deep learning approach) relying on previous scientific papers. The literature review shows the pros and cons of sentiment analysis and the reason for choosing the method, the simple theory of deep learning, which briefly explains the underlying mechanism of all deep learning approaches, the description of Bidirectional Encoder Representations from Transformer (BERT) model, explaining its theory, application, advantages and disadvantages. It is essential to mention that the literature review does not describe the TPB-based suggested strategies due to the paper's primary focus on the BERT-based sentiment analysis.

Sentiment Analysis Literature Review

Sentiment analysis is a computational approach to identifying peoples' "opinions, attitudes and emotions towards an entity" through textual data. An entity can be absolutely anything: a company, an event, a product and so on (Medhat et al., 2014). The fundament of the analysis is dividing textual data into factual and subjective information. Subjective information is the object of analysis, and it is extracted from sentences in different levels: document, sentence and aspect, and used for further polar classifying of attitude: positive, negative and neutral (Feldman, 2013). Overall, sentiment analysis is the classification process of emotional polarities, and the whole process consists of the following stages: data collection, preprocessing, sentiment extraction and classification (Awajan & Mohamad, 2018).

The method is prevalent due to its effectiveness in providing insight into the people's attitude, in this case, towards the company's initiatives and helping make decisions regarding its future actions (Mehta, 2020). However, it always faces problems providing valuable results due to a lack of data, unstructured data, etc. (Li, 2020). Moreover, the method is limited by the strict text categorising with positive, negative or neutral attitudes, it does not identify specific emotions such as anger or happiness (Hajiali, 2019). Despite all the disadvantages, sentiment analysis keeps developing and staying the leading approach for analysing people's emotions through textual data.

According to Mika V. Mäntylä, sentiment analysis's roots in studying public opinion began in the 20th century. However, the method became famous and widely used with technological improvement (Tawunrat & Jeremy, 2015; Matthew et al., 2015). Sentiment analysis has been upgraded by applying artificial intelligence (AI) techniques, such as machine learning (ML) and its subfield deep learning (DL). DL techniques showed the highest results in tackling sentiment analysis tasks (Shahzad et al., 2021).

Theory of Deep Learning Methods

DL methods are based on neural networks, and the first neural network was invented by Frank Rosenblatt in 1958. The neural network contained three main attributes: vector of inputs (x_i) and vector of its weights (w_i), bias (b_i), and activation function (f), which makes the connection between inputs and outputs non-linear, for instance, it can be the sigmoid function. It had several inputs, one neuron and one output (Figure 1). By neuron means the performance of some process for the input data and output production. Neural networks have a layer structure (architecture): the example shows three layers – input, hidden and output. The first one gets the data and passes it to the next layer, called hidden (in Figure 1, there is only one hidden layer, but it could be multiple). The hidden layers are responsible for multiple-function applications, such as the embedding, as mentioned above, and the performance of a neural network. The last layer is the result of the neural network work.

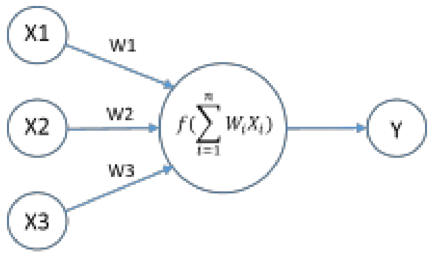

Figure 1. Example of the first neural network architecture: three inputs (X1, X2, X3) as the first layer, inputs weights (W1, W2, W3), one neuron with an activation function (f) as a hidden layer, and one output as the final layer (Mukherjee, 2021).

Learning a neural network has two stages: backpropagation, which computes the gradient of the loss function of different weights and biases, and optimisation, the process of selecting the best weights and biases using parameters like a learning rate (Rosenblatt, 1958).

The training process for any ML model, including neural network, is iterative. It is run using training data until the desired accuracy (the loss function rate) on test data is achieved.

BERT Model Introduction for Natural Language Processing

One of the applications of DL is the Natural Language Processing (NLP) algorithm, which focuses on the interaction between computers and human language. Sentiment analysis is one of the essential tasks in NLP (Hamed, 2023). The critical concept of NLP follows four steps (Adil Rajput, 2020):

- text preprocessing, dividing the text into smaller units called tokens for further analysis;
- lexical analysis, reducing the tokens into lexeme, e.g. words 'depression' and 'depressed' will be reduced to 'depress';
- syntactical analysis, checking if the grammar rules are followed
- semantic analysis, looking at the text's meaning and logic. In this stage, the word embedding technique is widely used to represent words numerically as low-dimensional vectors in a continuous vector space, putting words with similar meanings close (Lebret & Collobert, 2013) and capturing the sentiment meaning of words for sentiment analysis (Faruqui et al., 2015).

The most advanced performance word embedding model in a vast range of NLP tasks is the DL model – Bidirectional Encoder Representations from Transformer (BERT) that is also used for sentiment classifying (Wang et al., 2019). The model BERT was introduced by Devlin et al. in 2018, and according to them, 'BERT is conceptually simple and empirically powerful'. It manifested great metrics results: improved the General Language Understanding Evaluation score by 7.7% and achieved 80.5%. The score shows how well the model performs in solving different tasks of comprehensive understanding of language and got a Multi-Genre Natural Language Inference accuracy of 86.7%, i.e. a high result for the benchmark for NLP (Devlin et al., 2018).

BERT is based on Transformer architecture introduced by Vaswani et al. in 2017 (Figure 2), which is a type of attention-based neural network that looks at entire sentences simultaneously and having the primary purpose – teaching the model to pay attention only to the essential things and not overuse computational resources processing as the human brain does (Lindsay, 2020).

Theory of Transformer Architecture

The Transformer architecture has an encoder-decoder structure that is a bunch of layers, as a neural network example (Figure 2). The encoder and decoder consist of 6 layers, and each has two sublayers: a multi-headed self-attention mechanism and a position-wise feed-forward network. All the sublayers are normalised

$$\mathrm{LayerNorm}(x + \mathrm{sublayer}(x)),$$

here $\mathrm{sublayer}(x)$ is the function of a sublayer and x is a vector of input data (Vaswani et al., 2017).

The structural difference between the encoder and decoder is that the decoder has an additional sublayer – multi-head attention over the encoder output (Vaswani et al., 2017).

The visual representation of the Transformer architecture is given on Figure 2, where the rectangles represent the layers and sublayers described in the 'Theory of Deep Learning Methods' subchapter, Figure 1.

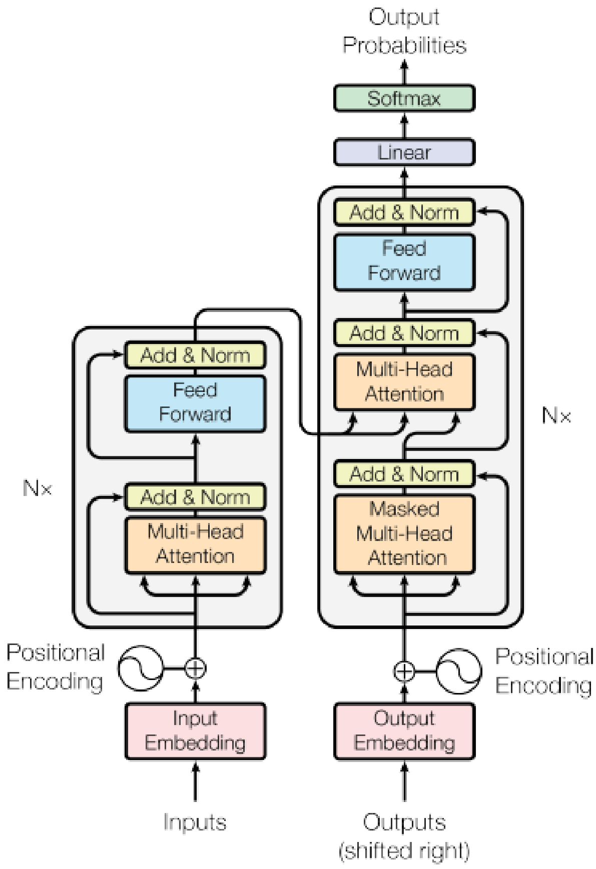

Figure 2. The Transformer model architecture: The left grey rectangle illustrates the sublayers of the encoder right – of the decoder. The architecture also consists of embedding and positional encoding layers for input and output, represented at the bottom of the picture. It can calculate the probabilities of different outputs using softmax and linear layers at the top of the figure (Vaswani et al., 2017).

A brief explanation of the sublayers as mentioned earlier (Vaswani et al., 2017):

1) Multi-Head Attention – the mechanism that assigns the weights for each input data according to its importance. The concept of values (V), the meaning of data, keys (K), the features of data, and queries (Q), the data is looked for, is used for mechanism performance. Q, K and V h times linear project to d_q, d_k, and d_v dimensions, respectively, and each projection performs the attention function (Figure 3):

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V.$$

The results of calculations are concatenated and projected one more time, producing the final value (Figure 3):

$$\text{MultiHead}(Q, K, V) = \text{Concat}(head_1, \ldots, head_h)W^O,$$

$$head_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right).$$

Here the projections are parameter matrices $QW_i^Q \in R^{d_{model} \times d_q}$, $KW_i^K \in R^{d_{model} \times d_k}$, $VW_i^V \in$ R$R^{d_{model} \times d_v}$ and $W^O \in R^{d_v \times d_{model}}$.

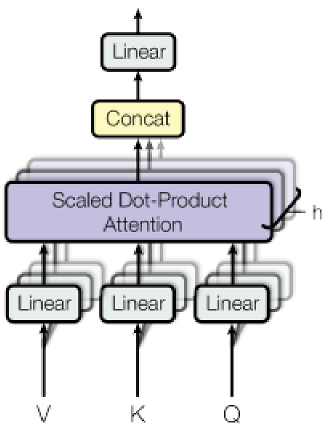

Figure 3. Multi-Head Attention Mechanism: As the input gets values (V), keys (K) and queries (Q) of data, h times calculate the attention function of them and concatenate the result. Rectangles represent layers of the neural network architecture (Vaswani et al., 2017).

2) Position-wise Feed-Forward Network (FNN) allows capturing the positional information effectively using two linear transformations and a ReLU activation between them:

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

As Figure 2 represents, apart from the encoder and decoder layers, the architecture has embedding, input and output tokens transformations to the vectors of model dimension (d_{model}), and positional encoding that gets the information about a token position in a sequence. The positional encoding (PE) uses the cosine functions:

$$PE(pos, 2i) \ = \ sin(pos/10000^{2i/d_{model}}) \ ,$$

$$PE(pos, 2i+1) \ = \ cos(pos/10000^{2i/d_{model}}),$$

where pos is the position and $i \ \in [0, d_{model}/2]$.

BERT Model Literature Review

However, the architecture requires large datasets pre-training (He et al., 2023). From that side, the BERT model is a highly effective tool for sentiment analysis as it is pre-trained on two unsupervised tasks: next-sentence prediction, which divides the text into pairs of sentences with the aim of comprehending the relationship between two consecutive sentences, and masked language modelling, which randomly some of the input tokens and predicts them according to the context (Trivedi, 2019). The model can work in more than 70 languages (Roger, 2019) and is widely used by Google in its algorithms of research that can only emphasise the reliability of the approach (Nayak, 2019).

A vast amount of research shows outstanding results in accuracy and prediction capacity compared with other models in solving NLP tasks. For instance, BERT shows considerable superiority to the following ML and DL models: the unsupervised lexicon-based model, relying on the assumption that the semantic word level-based orientation depends on its polarity based on the known lexicons (databases that contain words with their sentiment scores), the supervised deep learning model and logistic regression model (Shivaji & Manit, 2021; Catelli et al., 2022).

However, the architecture of the BERT is complex and, according to Frankle and Carbin's research, tends to suffer from over-parameterisation and could be reduced in size without a loss in performance. The smaller version of BERT was suggested by Goldberg in 2019 as it got better scores on several syntax tests than the ordinary model. Wu et al. also questioned the necessity of using such complex architecture, giving evidence of the advantages of more lightweight mechanisms (Kovaleva et al., 2019).

Even though BERT is computationally expensive and memory intensive (Hou et al., 2022; Jiao et al., 2020; Zhong et al., 2023), the model is highly accurate in NLP tasks, grasping the context of the sentences and predicting words well and can be used for sentiment extraction and classification in sentiment analysis (Baruah et al., 2020). That explains the reason for choosing the model for the analysis and the procedure of its application.

Methodology

The methodology of the research can be mainly divided into two parts: the BERT-based sentiment analysis application and the statistical method t-test application for analysing the outcome of the sentiment analysis.

The first part applies to the collected data from the online survey to analyse the effectiveness of the suggested strategies, and the whole application procedure has the steps in the following order: the first step is data collection, the second is data cleaning, and the third is the BERT model application.

The second part is essential for the research to comprehend if it is statistically meaningful to differentiate the strategies' sentiment outcomes from each other. That is crucial for comparing the results of strategies performance and distinguishing the most effective one.

Data Collection

The survey collected data on HSBC customers' attitudes regarding the strategies. The survey consists of three questions that ask people to express their opinions and feelings regarding the suggested strategy ideas in a couple of sentences (Appendix A). The first question concerns the strategy of Sustainable Investment Showcase and Educational Resources. Customers are also provided with a visual representation of the possible strategy implementation. The second question represents the 'Green Savings and Checking Accounts' strategy, and the third one – 'Sustainability Event'.

The survey is posted online through social media and requires an HSBC customer older than 18 to fill it. All participants consent to providing data and can withdraw at any stage of the survey. Moreover, participants are not asked for personal information, even demographics, such as age, sex, location, etc. The analysis considers all participants' opinions to contribute equally to the bank's image and does not emphasise HSBC customer focus groups. As a result of data collection, 117 answers (N = 117) were received and used for the following data analysis.

Data Cleaning

The vital step for sentiment analysis implementation is data cleaning. The step influences the reliability of the final result: it reduces the noise from minor and nonessential information, making the classification analysis more accurate.

The cleaning procedure starts with reading a file with the raw data of collected answers (Appendix B). The file in xlsx format, as the survey was published using Google questionnaire form, converts into CSV format for further convenient data analysis on Python programming language in the Jupyter Notebook web-based computer platform. The CSV file is opened to extract the answers and put them in a list matrix. The matrix has one row and three columns, each a list of answers regarding a strategy (Appendix C. Table 4).

After getting a comfortable raw data format, the cleaning part starts, and it includes (Arpita et al., 2020):

1) Data Normalising – putting words in a similar format by removing capitalisation, e.g. the word 'Cat' becomes 'cat'; otherwise, the classification could be wrong due to putting exact words in different classes (Appendix C. Table 5. 1,2);
2) Deleting unnecessary noise, including duplicates and needless symbols, like '\', that surprisingly often has been met in the data (Appendix C. Table 5. 1,2);
3) Removing stopwords, or commonly used words, such as 'the', 'but', 'and' etc., to focus the sentiment analysis only on important information (Appendix C. Table 5. 3);
4) Stemming words to emphasise the meaning of the word, e.g., ' running' and 'runs' are transformed to 'run' (Appendix C. Table 5. 4).

By the end of the cleaning process, the cleaned data is received. The word cloud method is chosen to visually present the cleaning result and get insight into customer feedback on strategies before the primary analysis. The word cloud method shows the most frequently used words in the text. That helps to visibly grasp what words customers rely on when forming their opinions for the three questions and possibly get hints about their emotions regarding strategies.

BERT Model Application

The BERT-based sentiment analysis usually includes the BERT-based model-building process: dividing data into training, testing sub-data, and modifying a model on the sub-data until the desired model accuracy is reached. That is important for accurate results for a specific data type and analysis topic. However, due to the investigation's time limits, the data sample size of 117 feedbacks was achieved, which is relatively small for building a reliable model. Nevertheless, reliable results could still be received using an already-built and pre-trained model.

There are plenty of these models in the public resources. For the research, the 'nlptown/bert-base-multilingual-uncased-sentiment' model was chosen. The model was trained on 150 thousand product reviews (Appendix C. Figure 7). Its accuracy is approximately 95%, and it classifies the answers from 1 to 5, where 1 means a lousy attitude and 5 – an excellent one. The numbers are named sentiment scores as they represent the level of satisfaction with the text. The scores introduce each customer's attitude towards a strategy and rank a strategy's feedback success using a scale (from 1 to 5).

Utilising the chosen model, the sentiment analysis is implemented in three parts (Susnjak, 2023):

1) Embedding – the process of conversation words into the numerical words representation in a lower dimensional space (tokens). In the space, the words with similar meanings are located closer to each other (Appendix C. Table 6.1);
2) Sentiment information extraction and its numerical transformation into sentiment space (Appendix C. Table 6.2);
3) Sentiment classification of the sentiment numerical transformation and sentiment score calculation for each answer, getting the attitude distributions towards the strategies (Appendix C. Table 6.3).

After receiving three distributions of the sentiment scores according to three strategies, the mean and standard deviation values are calculated to comprehend the distributions statistically. The mean values are chosen to represent the distributions for the research because of the small data size. To rank the sentiment score distributions according to their effectiveness, it is essential to understand if the mean values are significantly different for comparison.

Statistical Analysis of the Outcome

To understand whether or not the estimated sentiment scores means are significantly different from each other for comparison, the statistical method two-sided t-test, with the hypotheses (1) and a standard level of significance of 0.05 ($\alpha = 0.05$), is chosen to implement as the most appropriate one for the purpose according to the material of the 'Applied Statistics' course of the first semester. The test calculates t-statistics, the figure on the axe of the t-distribution graph, the p-value, and the area under the t-distribution graph (Figure 4).

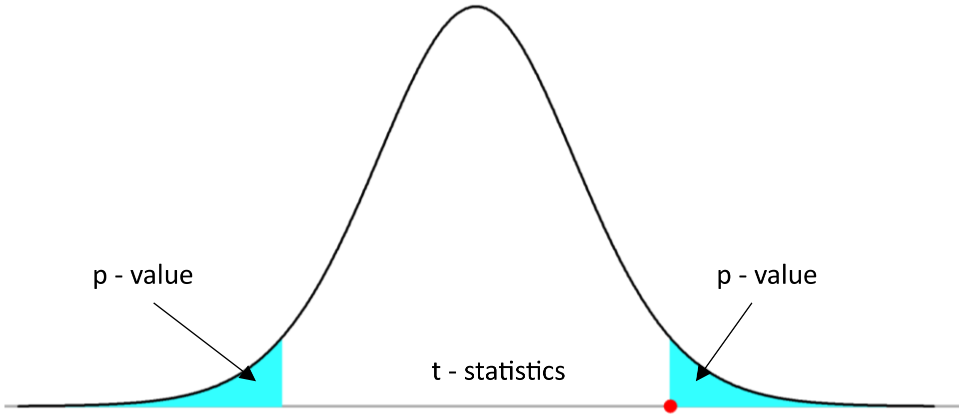

Figure 4. T-distribution with an axe of t-statistics values and a blue area representing the p-value for a two-sided test.

$$\text{Null hypothesis: } m_i = m_j$$
$$\text{Alternative hypothesis: } m_i \neq m_j \tag{1}$$

The last step of the t-test implementation is a comparison of the calculated p-value with α: if the p-value is more than α, then the null hypothesis is not rejected, and the mean values could be considered equal, whereas if the p-value is less, then the mean values are significantly different, and the comparison is possible (Appendix C. Table 7). After statistical test implementation, the differentiation of the mean values is known, and the relevant comparisons are produced to conclude the ranking of the strategies' effectiveness according to the survey could be provided.

Findings and Discussion of Analysis Application

After the methodology application, the results of the research are presented further. Specifically, the input textual data presentation after the cleaning procedure and the outputs of BERT-based sentiment analysis and statistical analysis applications are shown. Finally, the discussion part plays the role of the overview of the research findings.

Cleaned Input Data

The collected customers' answers regarding the strategies are cleaned and represented in word clouds (Table 1). Each word cloud summarises all polished and stemmed textual data of each strategy and puts them into a frame where the most frequently used words are more extensive. It is possible to get some insights into the customers' attitudes towards the strategies by looking at the most often-used words.

Table 1. Stemmed word clouds of customers' answers on the survey for each question.

<table>
<tr><th>Strategy No</th><th>Stemmed word clouds regarding each strategy</th><th>Description</th></tr>
<tr><td>1</td><td>
</td><td>'sustain', 'inform', 'invest', 'commit', and 'demonstr' are some of the most frequently met words.</td></tr>
<tr><td>2</td><td>
</td><td>'sustain', 'save', 'account', 'impact', and 'green' are some of the most frequently met words.</td></tr>
</table>

3		'sustain', 'tournament', 'need', 'affect', and 'event' are some of the most frequently met words.

The third column in Table 1 distinguishes some of the most frequently met words for forming people's opinions about the strategies. Noticeably, the word 'sustain' occurs as the most used one for all three questions, underlying the main topic of the survey. Looking at each word cloud, the following conclusions about the input data for the sentiment analysis could be made:

1) Answers regarding the 'Sustainable Investment Showcase and Educational Resources' strategy consist mainly of non-subjective words that do not help get people's feelings;
2) The 'Green Savings and Checking Accounts' strategy received similar most used words as the first strategy, but some words in the feedback have a clear positive sentiment, e.g. the word 'pleasur';
3) The third strategy – 'Sustainability Event,' produces the same result as the second one.

Overall, it is challenging to grasp people's emotions by looking at their answers. However, word clouds help with the visual representation of the input for the sentiment analysis that numerically can estimate the attitude by DL model – BERT.

BERT-based Sentiment Analysis Output

After the BERT-based sentiment analysis application, each strategy's three sentiment score distributions are received. The scores are numerically represented in Table 2, showing the frequency of each score (from 1, bad attitude, to 5, excellent one) for each strategy, and are visually produced in Figure 5, a histogram of the scores.

Table 2. The frequency of received sentiment scores (from 1 to 5) for each strategy

Strategy 1	5: 45, 4: 43, 3: 26, 1: 3
Strategy 2	3: 44, 4: 30, 5: 23, 1: 16, 2: 4
Strategy 3	3: 47, 4: 35, 5: 32, 1: 3, 2: 2

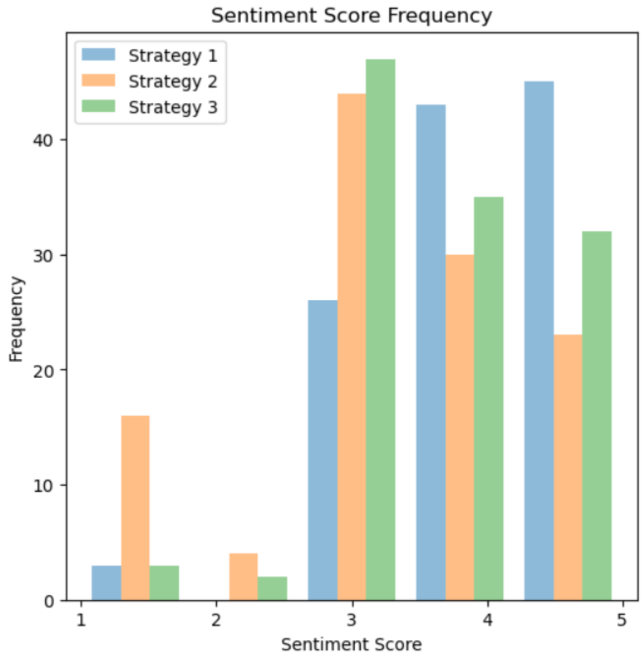

Figure 5. Histogram of the estimated sentiment scores

It is noticeable that the overall sentiment regarding the strategies is positive: on the histogram, the scores higher or equal to '3' occur more than 2 times. For the first strategy, the score '5' is met 45 times, almost 2 times more often than for the second strategy and 1.5 times – for the third one. The most frequently achieved score is '3', 47 times for the third strategy. Moreover, the score '3' is also the most prevalent score for the second strategy, 44 times. That means the first strategy got the best emotional feedback, and the other two are estimated as neutral-positive strategies from customers' perspective. As the output of the sentiment analysis is distributions, it is essential to implement statistical analysis to check the right of the statement in the above conclusion.

Statistical Analysis of the Output

The distributions mentioned above are visually presented as a box plot to apply the statistical analysis, showing the distribution shape (Figure 6). The mean values are chosen as the fundamental parameters for representing and comparing the score distributions and calculated for ranking the strategies' effectiveness accordingly (their values are shown at the top of Figure 6). According to the calculated mean values, the hierarchy of the possible strategies' effectiveness is built: the first strategy with a mean of 4.09 (m_1), the third one – 3.76 (m_2) and the second one – 3.43 (m_3).

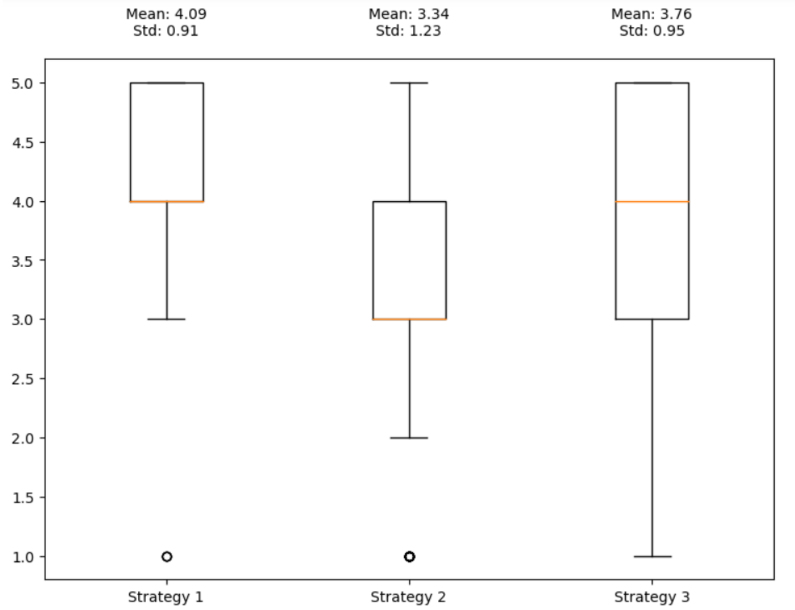

Figure 6. Box plot for the sentiment scores with calculated means and standard deviations at the top of the figure.

To statistically prove that the hierarchy of strategies' effectiveness is correct, a statistical t-test was conducted with relevant hypotheses (Table 3). The hypotheses are based on the original one (1) described in the methodology chapter.

Table 3. The t-test hypotheses comparing different mean values

For m_1 and m_3	Null hypothesis: $m_1 = m_3$ Alternative pothesis: $m_1 \neq m_3$	(2)
For m_2 and m_3	Null hypothesis: $m_2 = m_3$ Alternative pothesis: $m_2 \neq m_3$	(3)

The result of the test is a p-value calculation that, in its turn, is compared with a chosen standard significance level ($\alpha = 0.05$):

1) For m_1 and m_3, p-value equals 0.0089 (Table 3. 2). As the p-value is less than α, the null hypothesis is rejected. The mean values are considered significantly different to compare them. Overall, the first strategy's sentiment rank is the highest;
2) For m_2 and $m_3$the received p-value is 0.0035, less than α, so the values are comparable. The third strategy is considered the second sentiment rank.

The findings of the research are the statistically proven strategies ranking according to the estimated sentiment scores calculated by the DL model in sentiment analysis: the 'Sustainable

Investment Showcase and Educational Resources' strategy has the highest survey participants' satisfaction, and the 'Green Savings and Checking Accounts' strategy - the lowest.

Discussion

The survey sentiment analysis result shows that all three suggested strategies have positive feedback from HSBC customers, and the first one ('Sustainable Investment Showcase and Educational Resources'), which is about raising awareness of the bank's sustainable initiatives and increasing the education level of its customers through app modification, has the highest level of the survey participants satisfaction. The other strategies that offer to create an alternative green HSBC bank account ('Green Savings and Checking Accounts') and conduct sustainability events have lower sentiment scores ('Sustainability Event'), getting more neutral customer feedback.

The sentiment analysis is limited by the relatively small data sample and an absence of weighting participants' answers mechanism according to the influence it has on building the HSBC image: customers that represent the main bank's focus group could have a more significant impact towards HSBC brand shaping, so it is reasonable to accord a degree of preferences to their answers. Moreover, the statistical analysis is constricted by estimating sentiment score distributions relying only on mean values, and this can be updated by involving other parameters like standard deviation.

Overall, the analyses provide some insights regarding the possible directions for HSBC brand improvement to build trust with its customers regarding the sincerity of the bank's sustainable initiatives. All strategies can be implemented, so it is meaningful to investigate further with a more significant data sample and weight system, getting a broader picture of the strategies. Moreover, the more significant data sample can be used for building the BERT model, specifically for this task, increasing the accuracy of the sentiment classification and not using the built model implemented in this research. That would allow HSBC to make the right decision regarding the choosing strategy for effective communication with customers.

Conclusion

To fit HSBC to the modern people's standard demands regarding sustainability and green transition, HSBC is required to find a way of building a trust-based relationship with its customers and expressing the sincerity of its sustainable initiatives. Seeking to achieve the goal, three following TPB-based strategies were suggested: 'Sustainable Investment Showcase and Educational Resources', raising awareness of HSBC's activities through the app, 'Green Savings and Checking Accounts', allowing customers to invest in sustainable development, and 'Sustainability Event', giving an opportunity to contribute in eco transition by taking part in the events.

Willing to assess whether or not the strategies are suitable, the survey was conducted, and the collected textual data was analysed by BERT-based sentiment analysis. As a result of the analysis, all three suggested strategies showed good results according to the survey participants' feedback and could be considered possible solutions to the problem. Moreover, the 'Sustainable Investment Showcase and Educational Resources' strategy received the best results among others and is recommended as the most effective to apply.

According to past papers, the method of analysis is reliable and valuable for a vast range of problems. However, the research in the paper can be upgraded to get more accurate results regarding the strategies' effectiveness by expanding the sample size to build the unique BERT model for the problem and distinguishing the focus groups of the bank to weigh the importance of the collected data. These upgrades would demand the application of deeper statistical analysis, making results better grounded. The research of the article was limited to the time frame and could not implement the actions above. Specifically, data collection was the most challenging part, as it was conducted through direct online communication with customers.

Nevertheless, the research gave recommendations for the HSBC problem solution, providing ideas for further investigation and some new insights into the ways of communicating with customers and their sentiments regarding building trust-relationship actions with them.

Overall, the importance of the research can be estimated pretty high due to it being innovative in terms of the strategies themselves and the approach used to analyse them. There are plenty of papers regarding BERT-based sentiment analysis about banking. However, none of them considers the analysis for estimating strategies' effectiveness regarding sustainability initiatives, which makes the article unique and valuable as a contribution to the diversity of the AI-based sentiment analysis application.

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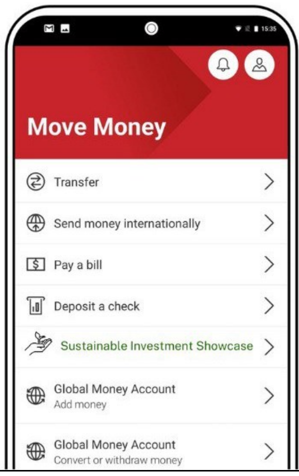
Appendix A: Online survey questions (from the group report)

1	Question	To what extent would more education about our sustainable investment products and as well as a more educational section about sustainability in general (both within our app) influence your satisfaction regarding HSBC's sustainability efforts as well as credibility in this regard? Please provide reasons for your opinion. Here's an idea of what it could look like. what do you think about it?
	Picture	
2	Question	There is an idea to set up a Green Savings Account. This is a customer account where a part of your interest is donated to one of our sustainability projects. The account holder can choose from a number of projects. In addition, CO2 emissions are saved with each transaction, which is also displayed to the customer. To what extent would a Green Savings Account influence your satisfaction with HSBC's sustainability efforts and credibility? Please give reasons for your opinion.
3	Question	The idea is to organise an event called the "Sustainability Tournament".The event should take place throughout the year in different cities of the United Kingdom and include a competition in which teams consisting of the entire population develop and present their ideas regarding a previously set sustainability theme, for example: "Green Finance for a Better Future". The idea that has prevailed is to be implemented by HSBC. To what extent would such an event affect your feelings about HSBC's sustainability efforts and its credibility?

Appendix B: Answers on the questions in Excel spreadsheet (first and last 20 answers on three questions):

	A	B	C	D	E	F	G	H	I	J
1	#	**Answers1**	**Answers2**	**Answers3**						
2	1	Including a dedicated section on sustainable investment o	A Green Savings Account is an ingenious concept, truly highlighting HSBC'	Organizing such an event could provide HSBC with a valuable opportunity to engage with clients and the gener						
3	2	I believe that educating clients about HSBC's sustainable in	The thought of contributing my savings to environmental causes has me	The idea of the "Sustainability Tournament" resonates with me. It's a tangible way for HSBC to showcase its de						
4	3	Introducing a segment focused on environmental educatic	HSBC's introduction of a Green Savings Account sets it apart – it's not just	Before assessing the potential influence of the "Sustainability Tournament" on HSBC's credibility, I would need						
5	4	Gaining a better understanding of HSBC's sustainable inves	The very idea of a Green Savings Account resonates deeply with my value	Anticipation grows for the upcoming "Sustainability Tournament." This event has the potential to significantly						
6	5	Providing comprehensive sustainability education marks a	I'd be genuinely happier with HSBC if I knew my money was directly fuelin	The "Sustainability Tournament" concept intrigues me. However, I'm awaiting more information about its ther						
7	6	I appreciate the idea of educating clients about both sustai	By offering a Green Savings Account, HSBC is making a bold statement ab	The prospect of the "Sustainability Tournament" would instill a sense of pride in my association with HSBC. It's						
8	7	I would feel more informed and content with HSBC's sustai	A Green Savings Account serves as a clear testament to HSBC's unwaverin	I'm genuinely excited about the "Sustainability Tournament" idea. It would undoubtedly shape my view of HSB						
9	8	Incorporating a sustainability education section would unc	The assurance that my money contributes to environmental programs ali	Implementing the "Sustainability Tournament" would positively influence my perspective on HSBC's environm						
10	9	I'm eagerly anticipating the inclusion of a dedicated app se	The innovative idea of reducing CO2 emissions with each transaction is a f	HSBC's forward-looking stance in launching the "Sustainability Tournament" pleases me. It would undoubtedl						
11	10	Educating clients about sustainable investment products t	A Green Savings Account solidifies my belief that HSBC is forward-looking	The concept behind the "Sustainability Tournament" is groundbreaking. It would effectively showcase HSBC's						
12	11	HSBC's initiatives aimed at educating consumers about sus	The idea of a Green Savings Account is a win-win for me because it lets me	I'm really enthusiastic about how the "Sustainability Tournament" could positively shape HSBC's image as a re						
13	12	The inclusion of environmental education within the app is	Having the choice to support specific sustainability projects empowers me	The "Sustainability Tournament" is a commendable endeavor that would further solidify my trust in HSBC's de						
14	13	I'm eagerly anticipating the opportunity to delve into susta	To me, a Green Savings Account would be a game-changing concept. It sh	There's a sense of anticipation for what the "Sustainability Tournament" could bring. It's an impressive display						
15	14	Providing insights on sustainable investing via the app wou	With a Green Savings Account, I would feel more connected to HSBC's env	No doubt, the "Sustainability Tournament" has the potential to strengthen my belief in HSBC's reputation and						
16	15	Embedding sustainability education within the app is an in	The Green Savings Account idea underscores HSBC's commitment to bein	HSBC's forward-thinking approach in arranging the "Sustainability Tournament" leaves me truly impressed. Th						
17	16	Should HSBC incorporate instructional segments on sustai	I would be proud to hold an HSBC Green Savings Account. It reaffirms my	The "Sustainability Tournament" effectively showcases HSBC's determination to engage the community in thei						
18	17	Utilizing the app as a platform to learn about sustainable ir	A Green Savings Account presents a wonderful opportunity to give back a	The concept of the "Sustainability Tournament" captivates my interest. It serves as a tangible step by HSBC to						
19	18	The integration of a sustainability education component w	Seeing tangible results from my Green Savings Account activities would gr	The "Sustainability Tournament" is a standout project that would notably reinforce my confidence in HSBC's su						
20	19	Incorporating sustainability education would elevate HSBC	The Green Savings Account concept showcases HSBC's dedication to align	I'm eagerly awaiting how the "Sustainability Tournament" will impact HSBC's reputation as an environmentally						

98	97	Learning about HSBC's sustainable investing solutions via t	While this novel idea might enhance my happiness, my assessment of HS	A year-long event with a focus on sustainability reflects HSBC's commitment to fostering public enga
99	98	The HSBC client app is a great idea because it includes a sec	The notion of aligning with sustainability is appealing, yet its influence on	The notion of involving the public in a tournament centered around sustainability themes is intriguin
100	99	I'm quite pleased by HSBC's innovative strategy for adding	Although intriguing, the actual impact of this initiative on my perception c	This initiative aligns with HSBC's objective of involving the community in sustainable projects. Its cred
101	100	The move by HSBC to include educational materials on sus	While the idea is captivating, the real influence of this initiative on my sati	An event like this provides an opportunity for HSBC to interact with its clients and the public on matt
102	101	It's an impressive move by HSBC to include a sustainability	This initiative might bring joy, but its effect on HSBC's trustworthiness is a	It sounds interesting to involve the entire public in a tournament with a sustainability theme. If HSBC
103	102	The initiatives made by HSBC to inform its consumers abou	The concept's potential is captivating, yet my judgment of HSBC's depend	The "Sustainability Tournament" supports HSBC's endeavors to engage the neighborhood in sustain
104	103	The updated HSBC customer app now includes sections th	Although tempting, I'm concerned about the actual impact of this initiativ	Such a gathering might give HSBC a chance to interact with its clients and the general public on sustai
105	104	A clear indication of HSBC's sincere commitment to a green	In light of broader environmental concerns, this initiative might seem a sn	The initiative aimed at promoting sustainability reflects HSBC's commitment to engaging the commu
106	105	With the addition of these educational portions to the app	I'm unconvinced that this initiative will counterbalance any environmenta	This event provides a platform for HSBC to connect with its clients and the public regarding sustainab
107	106	It says a lot about HSBC's commitment to both financial su	While the concept is appealing, I doubt if the impact on CO2 emissions fro	Seen as HSBC's proactive step towards advancing sustainability, the effectiveness of integrating the v
108	107	Congratulations to HSBC for adopting sustainable practices	While this approach holds appeal, I remain skeptical about the accuracy a	The captivating idea of fostering sustainable practices resonates with HSBC's ethical investment focu
109	108	I'm thrilled to see HSBC going above and above by informir	This initiative may not fully address the larger sustainability concerns I ass	While the sustainability-related effort is admirable, I'm uncertain about its potential to substantially
110	109	The app's instructional parts clearly demonstrate HSBC's de	Though enticing, if HSBC's overall policies remain unchanged, it might not	While intriguing, I'm unsure if this endeavor will greatly impact how I perceive HSBC's sustainability in
111	110	The app's inclusion of sustainable investment and sustaina	I'm not entirely confident that this initiative would substantially enhance	Although commendable, I have reservations about how much this initiative will reshape my understa
112	111	The initiative by HSBC to inform clients about sustainable ir	This is a positive step forward, yet it might not fully restore my confidence	The approach of promoting sustainability efforts is interesting, but its influence on my view of HSBC's
113	112	I sincerely appreciate the efforts made by HSBC to inform c	While this concept is intriguing, I'm cautious about relying solely on it to n	While a compelling notion, I'm not entirely convinced this initiative will significantly change my opinic
114	113	The newly added sections in the client app that showcase s	While the concept of a Green Savings Account is tempting, if HSBC's overa	This initiative piques my curiosity, but I'm not fully convinced it will dramatically shift my perception
115	114	I doubt that knowledge in these areas would alleviate my c	I'm not confident that a Green Savings Account would improve my experi	I'm curious about this endeavor, but its transformative impact on my perception of HSBC's sustainab
116	115	These components may not have a significant impact on m	A Green Savings Account is a step in the right direction, but it's not enoug	The approach taken towards promoting sustainability is intriguing, yet its ability to significantly alter
117	116	Education on sustainability will not compensate for any de	A Green Savings Account is a fantastic idea, but it may not completely ans	While potentially impactful, I'm skeptical if this effort will be decisive in shaping my judgment of HSBC
118	117	I am skeptical that these sections will address the underlyir	I'm hesitant to place too much faith in a Green Savings Account as a meas	The endeavor focused on sustainability may hold promise, but its ability to change my perspective o

Appendix C: Coding part of Sentiment Analysis

Table 4. Opening survey answers in CSV file

<table>
<tr><td>Code part</td><td>
# After downloading answers from google questionnaire, open excel file
df = pd.read_excel('D://BIRMINGHAM//PROJECT//HSBC//second_start.xlsx')
# Convert excel file to csv file
df.to_csv('D://BIRMINGHAM//PROJECT//HSBC//answers_new.csv', index=False)
# Read the new csv file for further work process
df = pd.read_csv('D://BIRMINGHAM//PROJECT//HSBC//answers_new.csv', index_col=0)
# Get the answers from the document
list_of_all_answers = []
for i in range(1, 4):
    answers_list = df['Answers'+str(i)].tolist()
    list_of_all_answers.append(answers_list)
</td></tr>
<tr><td>Part of the code output</td><td>
[["Including a section on sustainable investing options in the HSBC client app is
k's commitment to responsible investment practises.", "I feel that teaching clien
ilities via the app will increase my satisfaction with the bank's sustainability
adiness to provide us with ethical investing options.", "The addition of a sectic
</td></tr>
</table>

Table 5. The cleaning data procedure

<table>
<tr><td>(1,2)</td><td>Code part of normalising data and removing unnecessary information</td><td>
# Flatten the matrix into a single list
flat_matrix = [item for sublist in list_of_all_answers for item in sublist]

# Count occurrences of each item in the list
item_counts = Counter(flat_matrix)

# Normilising and Deleting duplicates and unnecessary symbols
cleaned_data_fisrt_stage = []
for sublist in list_of_all_answers:
    new_sublist = [sentence for sentence in sublist if item_counts[sentence] == 1 or sentence == "NaN"]
    new_sublist = [re.sub(r"(@\[A-Za-z0-9]+)|([^0-9A-Za-z \t])|(\w+:\/\/\S+)|^rt|http.+?", '', sentence)
                   for sentence in new_sublist]
    new_sublist = [sentence.lower() for sentence in new_sublist]
    cleaned_data_fisrt_stage.append(new_sublist)
</td></tr>
<tr><td>(3)</td><td>Code part of removing stop words</td><td>
# Remove stopwords from each sentence
stop_words = set(stopwords.words('english'))

cleaned_data_second_stage = []
for sublist in cleaned_data_fisrt_stage:
    cleaned_sublist = []
    for sentence in sublist:
        words = sentence.split()
        cleaned_words = [word for word in words if word.lower() not in stop_words]
        cleaned_sublist.append(' '.join(cleaned_words))
    cleaned_data_second_stage.append(cleaned_sublist)
</td></tr>
<tr><td>(4)</td><td>Code part of the steaming process</td><td>
# Steamming process
stemmer = PorterStemmer()

cleaned_data = []
for sublist in cleaned_data_second_stage:
    stemmed_sublist = []
    for sentence in sublist:
        words = word_tokenize(sentence)
        stemmed_words = [stemmer.stem(word) for word in words if word.lower() not in stop_words]
        stemmed_sublist.append(' '.join(stemmed_words))
    cleaned_data.append(stemmed_sublist)
</td></tr>
<tr><td colspan="2">Part of the code output</td><td>
['includ section sustain invest option hsbc client app wonder idea demonstr bank commi
ient hsbc sustain invest possibl via app increas satisfact bank sustain initi signific
ption', 'addit section environment educ app wonder would strengthen connect hsbc large
</td></tr>
</table>

```
tokenizer = AutoTokenizer.from_pretrained('nlptown/bert-base-multilingual-uncased-sentiment')

model = AutoModelForSequenceClassification.from_pretrained('nlptown/bert-base-multilingual-uncased-sentiment')
```

Figure 7. The downloading BERT-based model process

Table 6. Sentiment analysis procedure. BERT-model application

(1) Code part of the embedding process

```
# Embedding process
def Embedding (answers_list: list):
    tokens_list = []
    for i in range(0, len(answers_list)):
        tokens = tokenizer.encode(answers_list[i], return_tensors='pt')
        tokens_list.append(tokens)
    return tokens_list

list_Embedding = []
for i in range(0,3):
    list_Embedding.append(Embedding(cleaned_data[i]))
```

Part of the code output

```
[[tensor([[  101, 13565, 11567, 10163, 13905, 10877, 41722, 10104, 39368, 28961,
         53798, 33160, 31512, 35821, 28261, 14653, 66264, 35176, 12638, 10241,
         16378, 49159, 14389, 10104, 39368, 49411, 13442,   102]]), tensor([[  101
```

(2) Code part of the model application process

```
# Model application
def BERTmodelapplication (tokens_list: list):
    result_list = []
    for i in range(0, len(tokens_list)):
        result = model(tokens_list[i])
        result_list.append(result)
    return result_list

list_BERTmodelapplication = []
for i in range(0,3):
    list_BERTmodelapplication.append(BERTmodelapplication(list_Embedding[i]))
```

Part of the code output

```
[[SequenceClassifierOutput(loss=None, logits=tensor([[-1.0522, -1.0749,  0.1196,  0.7906,  1.0023]]
       grad_fn=<AddmmBackward0>), hidden_states=None, attentions=None), SequenceClassifierOutput(lo
1.4303, -1.2879, -0.0190,  0.9996,  1.2371]],
```

(3) Code part of the sentiment score calculation

```
# Sentiment score distributions calculation
def Sentiment_score (result_list: list):
    sentiment_score_list = []
    for i in range(0, len(result_list)):
        sentiment_score = int(torch.argmax(result_list[i].logits))+1
        sentiment_score_list.append(sentiment_score)
    return sentiment_score_list

list_scores = []
for i in range(0,3):
    scores = Sentiment_score(list_BERTmodelapplication[i])
    list_scores.append(scores)
```

Part of the code output

```
[[5, 5, 4, 5, 5, 5, 3, 4, 4, 4, 5, 5, 5, 5, 4, 5, 4, 3, 4, 5, 3, 4,
4, 5, 3, 5, 5, 4, 4, 5, 4, 4, 5, 5, 5, 4, 3, 3, 4, 5, 5, 5, 3, 4, 5,
3, 3, 3, 4, 3, 4, 4, 5, 4, 3, 4, 4, 5, 5, 5, 5, 5, 5, 4, 4, 5, 5, 4,
```

Table 7. t-test conduction. P-value calculation

Code part of the t-test

```
t_statistic, p_value = stats.ttest_ind(list_scores[0], list_scores[2])

# Display the results
print("T-Statistic:", t_statistic)
print("P-Value:", p_value)

# Interpret the results
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: Means are significantly different.")
else:
    print("Fail to reject the null hypothesis: No significant difference in means.")
```

Output

```
T-Statistic: 2.63509934906849
P-Value: 0.008973227958755403
Reject the null hypothesis: Means are significantly different.
```