The Influence of Mimicry in Entrepreneurial Pitches

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Success of entrepreneurs is affected by decision making in social interactions, where not only speech but also facial expressions are of great importance. Mimicry of emotions and facial expressions is the copying of someone's behavior and expressions, which can even happen unconsciously. In facial expressions, smiling tends to express happiness, smiles are perceived as friendly, and people who tend to be liked smile more. To find out whether mimicry in smiling has a positive influence on the ranking of the pitches, the main research question is stated as: "Is there a positive influence on the ranking of entrepreneurial pitches through mimicry of facial action units involved in smiling, between the pitcher and investor?". To answer this question, the degree of mimicry between Action Units involved in smiling of the entrepreneurs and investors needs to be computed by using Pearson correlation coefficients. Next, the Spearman's rho and Kendall's tau correlation are computed between the degree of mimicry of Action Units and the rankings of the pitches. To look into classification of the degree of mimicry onto the ranking of the pitches, three classifiers are used and compared: Logistic Regression, K-Nearest Neighbors, and Support Vector Machine. The dataset used consists of 25 pitches, which all consist of one video of a pitcher and three videos of investors. The main findings are that mimicry in smiling has no (positive) influence on the ranking of the entrepreneurial pitches.

1. Introduction

In this thesis, the main goal is to find out whether there is a positive influence on the ranking of entrepreneurial pitches through mimicry of facial action units that are involved in smiling. The mimicry should be between the pitcher and the investors. Mimicry of emotions and facial expressions is the imitation of someone's facial expressions, this copying of behavior can already happen unconsciously when only talking to someone (Klerk et al., 2019).

The research domain consists of entrepreneurship and mimicry. Both are very different areas, and especially mimicry is important in this thesis because the research exists partially of detecting mimicry in the entrepreneurial pitches. The success of an entrepreneur is affected by decision making in several types of social interactions, with for instance stakeholders or resource providers. In entrepreneurial pitches, the entrepreneurs pitch their business ideas to get an investment from an investor (Ciuchta et al., 2018). In these pitches, not only speech but also non-verbal signals like body language and facial expressions are very important (Adolphs, 1999). Huang and Knight (2015) mentioned that entrepreneurs convey interpersonal and informational signals to potential investors, wherefrom investors decide whether or not to invest. Thus the investors are not only influenced by what the pitchers say, but also by their body language and facial expressions (Clarke, 2011). Because facial expressions are important in pitches, it is interesting to look at the influence of facial mimicry in pitches. According to Paxton and Dale (2013) and Liebregts et al. (2019),interesting research would be to find out whether mimicry positively affects investment decisions made by investors, in entrepreneurial pitches.

Since mimicry of the facial expressions in the entire face consists of a large number of facial Action Units that show movements of muscles in the face (Tian, Kanade & Cohn, 2001), a decision had to be made in what facial expression is most interesting to look at. Dimberg and

Thunberg have shown that showing people pictures of happy people results in spontaneously increased zygomatic major muscle activity to form a smile, after 500 ms of exposure (1998). Smiles are often perceived as friendly and therefore should lead to positive intentions (Mussel, Göritz, & Hewig, 2013). Research in psychology has shown that people who are trying to be liked by others, tend to mimic all kinds of positive emotions (Bilakhia et al., 2015). Finally, in a study of a two-person game, where the proposer divides a certain amount of money into two parts and proposes to divide the money, the offers of smiling proposers tend to get accepted more often (Balachandra et al., 2013). For these reasons, the Action Units involved in smiling are used to detect mimicry. These are the Action Units 6, 7, 12 and, 14, also known as the cheek raiser, the lid tightener, the lip corner puller, and the dimpler (Baltrusaitis, Robinson & Morency, 2016; Rogers, 2018).

To find out if mimicry in entrepreneurial pitches positively affects the ranking of the pitches, and therefore probably the willingness to invest, several methods will be used. First, the opensource program OpenFace will be used to analyze the videos. After detecting mimicry with Pearson's R correlation method, Spearman's rho and Kendall's tau correlation methods are used to find out if mimicry has a positive effect on the ranking of the pitches. To see if it is possible to predict the ranking with mimicry, several machine learning classifiers are used. The used machine learning models are Logistic Regression, K-Nearest Neighbor, and Support Vector Machine. In most previous studies not only correlation methods are used to detect mimicry and the influence of mimicry on other aspects, but also other methods are used (more information in section 2 Related Work). For instance, in this study multiple regression, cross-correlation, or programs like SPSS and Matlab are used. This study is scientifically relevant because of the use of a small set of relevant data, consisting of real pitches and real investors. The influence of mimicry on a ranking will be studied, while rankings are not very common in research in the field of mimicry. Ranking is different from knowing whether or not an investor would consider an investment. Using correlations to name the degree of mimicry and then use other correlation coefficients to study the influence of the degree of mimicry on the ranking of the pitches is a new approach to detecting mimicry and the influence of it. The classifiers that are also used to see if mimicry has an influence on the rankings of the pitches will be evaluated and compared based on their Accuracy, Precision, Recall, and F1-score.

The main research question in this thesis is stated as: “Is there a positive influence on the ranking of entrepreneurial pitches through mimicry of facial action units involved in smiling, between the pitcher and investor?”. The null hypothesis in this thesis states that there is no influence of mimicry on the ranking of the pitches, whereas the alternative hypothesis states that mimicry does influence the ranking of the pitches positively. To answer this question, several steps have to be taken. First of all, the videos have to be analyzed and transformed into a dataset that contains information about the Action Units. Second, the corresponding rows between pitcher and investor files have to be combined, so that in the next step, the mimicry between these two can be found. Third, the correlation between the mimicry and ranking of the pitches needs to be calculated to see if there is a correlation between the degree of mimicry and the rankings of the pitches. Then the ranking of the pitches will be predicted by using the degree of mimicry.

The main findings in looking for the influence of mimicry in smiling on the ranking of entrepreneurial pitches is that there is no (positive) influence on the ranking of the pitches because the null hypothesis fails to be rejected. The null hypothesis states that there is no influence of mimicry on the ranking of the pitches.

2. Related work

The process of decision making in social interactions is very important for entrepreneurs to get investments of investors (Ciuchta et al., 2018). To help with those social interactions, facial expressions are of great importance. Smiling is a facial expression that shows happiness, which often leads to positive intentions (Mussel, Göritz, & Hewig, 2013). According to Bilakhia et al., research has also shown that people who are trying to be liked by others, tend to mimic all kinds of positive emotions (2015).

A well-known topic in entrepreneurship research is decision-making (Shepherd, 2011; Shepherd et al., 2015). According to Ciuchta et al. coachability is very important in entrepreneurship for investors, mimicry or eye attention could for instance influence what an investor thinks of the entrepreneur's coachability (2018). Postma and Nilsenová state that with data science methods it could be possible to find mimicry and see who is leading (2016).

Postma and Nilsenová use visual analysis to find signs of mimicry in emotional facial expressions (2016). The data consists of videos, where with the Computer Expression Recognition Toolbox (CERT) the video sequences are analyzed automatically. CERT automatically processes seven emotional facial expressions, namely anger, contempt, disgust, fear, happiness, sadness, and surprise. These emotional facial expression scores are based on the estimated presence of Action Units. According to Postma and Nilsenová, the analysis of the separate Action Units using the Computer Expression Recognition Toolbox achieved an average estimation accuracy of around 80%. For the seven emotional facial expressions, the CROSS-CORR function in Matlab is used. This function is used to find mimicry. The delay that is measured for mimicry is 500-1500 ms, wherein the peaks in sample cross-correlation are defined. Then, for each emotion, the cross-correlation coefficient and lag are calculated from the average sample cross-correlations (Postma and Nilsenová, 2016).

Wu, Liu, and Calvo studied the influence of nonverbal behavior mimicry on the quality of medical consults in a video conference using IBM SPSS Statistics (2020). This four-month study used undergraduate medical students and volunteers to investigate the relationship between mimicry and the communication skills in videos. After the video data was collected, the videos were processed by the open-source toolkit OpenFace. The Action Units in OpenFace are calculated using the Facial Action Coding System. In this study, smile and frown are the measured facial expressions. Action units 12 and 17 are used to detect a smile and a frown. To name a movement in the face a smile, the intensity of AU 12 had to be larger than 1 for at least 0.2 seconds, as soon as the intensity is lower than 1, the smiling period is over. For a frown, the period had to be at least 0.4 seconds. After this, the mimicry was detected by matching the features of the students and the volunteers. Within a certain timeframe, the behavior of the two was compared. First, they looked at the starting point of when certain behavior of the medical student happened, after that the starting point of the mimicked behavior of the volunteer was calculated. With this method, there were several types of mimicry, all depending on the start and end time of the smiling or frowning. To analyze the effect of mimicry on the communication skill on video, the correlations between nonverbal behavior mimicry and the students' performance are analyzed. A multiple regression model is applied to investigate the influence of the nonverbal behavior mimicry on the ratings of the communicational skills. Also, unsupervised clustering was used to see the difference between the different forms of mimicry (Wu, Liu, & Calvo, 2020).

In the third example of a study in mimicry, participants had to watch videos of facial expressions and had to watch closely (Pavarini et al., 2019). To keep them focused on the video, the participants had to rate the expression that they had seen on a 5 point Likert scale. Afterward their ratings are also used in analyzing mimicry. After filming the participants, the videos were analyzed with OpenFace. In this study, the Facial Action Units are used to detect mimicry. Here the participants' expressions were divided into blocks per facial expression. Each Action Unit was categorized into the emotional facial expression that belongs to it, and each image of the participants received a score corresponding to these emotions. R is used to average all the scores per Action Unit across all frames. Then the scores between 0 and 1 indicated if a specific facial expression was shown when watching the video of the facial expressions (Pavarini et al., 2019).

The effect that mimicry in facial expressions, tone of voice, mood, and physical mannerisms have on the bond between two people is also called 'the Chameleon Effect' (Verberne et al., 2013). In a study about the chameleon effect, the main hypothesis is that a mimicking computer-controlled representation of a human, also called 'agents', will be trusted more than a non-mimicking one. To prove this, participants were paid to play an investment game and route planner game (Verberne et al., 2013). The head movements of the participants were tracked during the games with a magnetic field sensor attached to a cap that they were wearing. The agents mimicked the head movements of the participants with a delay of 4 seconds. In both games, behavioral trust was measured. In the investment game, trust is measured by the number of credits that participants gave to the agent. In the route planner game, trust was measured by people who chose to follow the route that the agent gave, instead of planning a route by themselves. To test the main hypothesis, one-way MANOVA is conducted. Here, mimicry is the independent variable and trust, liking, and the investment game decision are dependent variables. As exploratory analysis, separate one-way ANOVA's were conducted with mimicry as independent measure and measures like expected credits, IQ, and perceived risk as dependent measures. For both games, these methods are the same. The route planner game also had a mediation analysis, where a Sobel test was used to test whether increased liking mediated the effect of mimicry on the decision made by the participants (Verberne et al., 2013).

These examples show that mimicry has already been studied before but in all kinds of ways. OpenFace has been used in the past, but also here the approach in detecting mimicry differs. Different programs like R, SPSS, and Matlab are used. The methods differ from the time range in which mimicry is detected. The datasets are very different in structure and setup, for instance the difference between the entrepreneurial pitches and short videos where participants had to watch the facial expressions of others. A difference can be made by looking at mimicry for not only the one Action Unit per time, but also combined Action Units. Also, the time ranges within mimicry is analyzed are quite different between the previous studies.

3. Experimental setup

3.1. Data

The provided data (Liebregts, Urbig & Jung, 2018-2020) consists of videos of pitchers and videos of investors, filmed in a timeframe of three years. Each pitcher presents their business ideas to three investors, who then rank the pitches from that certain year. This means that each pitch gets ranked by three different judges. Each pitch consists of four separate videos, where the pitcher and judges are filmed separately.

Not all videos of the investors were filmed in a properly, meaning that sometimes, another investor was visible in the video. To make sure that each video only contained one face, the program iMovie was used to crop the videos into a smaller format (Hastings & Mansel-Pleydell, 2001). The videos are cropped because while analyzing, the open-source program that is used only analyzes the largest face that it can detect per frame.

To be able to analyze the four separate videos of pitchers and investors, the open-source program OpenFace is used (Baltrusaitis, Robinson & Morency, 2016). OpenFace is the first open-source tool capable of recognition of facial action units, landmark detection, eye-gaze, and head pose estimation. The program does not need any specialistic hardware. For Windows, a user interface is available, for other operation systems such as Mac OS the tool works as a command line tool. OpenFace uses several technologies for the analysis of facial expressions and behavior. For this thesis only the Action Units are used, therefore only the technology behind the Action Unit detection will be explained. Action Units are used because they make it possible to describe all visual detectable facial changes (An, Yang, & Bhanu, 2015).

The OpenFace Action Unit intensity and presence detection are based on existing AU recognition (Baltrusaitis, Banda & Robinson, 2013). Over- or under-estimating happens in existing AU predictors (Afzal, Robinson, 2009), to correct for such errors in AU prediction, OpenFace takes the lowest percentile of validation data on a specific person and subtracts it from all predictions. OpenFace also uses hyperplane of the trained SVM model as a feature for the SVR regressor, which allows the tool to train a single predictor while using the intensity and presence datasets instead of other datasets who contain only labels for AU presence or intensity (Baltrusaitis, Robinson & Morency, 2016). OpenFace uses a similarity transform from detected landmarks to a representation of frontal landmarks known from a neutral facial expression to extract facial expression features, leading to a 112 by 112 pixel image. In this image, the distance between the centers of the pupils of the eyes is 45 pixels. HOGs features (Histogram of Oriented Gradients) are extracted from the aligned face. Blocks of 2 by 2 cells are used, which lead to a 4464 dimensional vector which describes the face (12 by 12 blocks of 31 dimensional histograms). A PCA model trained on facial expression datasets is applied to the images, where keeping 95% of the explained variability reduces the basis to 1391 dimensions. Linear kernel SVM is used for presence predicting and a linear kernel SVR is used for intensity prediction (Baltrusaitis, Robinson & Morency, 2016). OpenFace recognizes the following AUs: AU1, AU2, AU4, AU5, AU6, AU7, AU9, AU10, AU12, AU14, AU15, AU17, AU20, AU23, AU25, AU26, AU28, and AU45.

After the videos are processed by OpenFace, three types of files are given by the opensource tool as output, namely, comma-separated files, text files, and AVI files. The csv files are used to analyze the four Action Units. There is a row for every 0.04 seconds in the video (Baltrusaitis, Robinson & Morency, 2016). Since only four of the action units are used to look into mimicry in the dataset, the unnecessary columns are deleted in R (the link to the Github repository is in Appendix C). The Action Units 6, 7, 12 and 14 are used, these are also known as the cheek raiser, the lid tightener, the lip corner puller, and the dimpler. In Appendix A, information about the mean, standard deviation, median, the minimum and maximum value of these AUs from each pitch are displayed. The values per AU lie between 0 and 5.00 and the mean is in most cases under 1.00. These values show the intensity of the Action Units (Baltrusaitis, Robinson & Morency, 2016). Higher values indicate a higher intensity (Wu, Liu, & Calvo, 2020).

In R, two libraries were used. First to access the data easier and use functions to clean the data or access specific columns the library dplyr is used (Wickham et al., 2019). Second, the library psych is used to get more information about the data, for instance, the mean, median, kurtosis, and skewness (Revelle & Revelle, 2015).

The Action Unit variables are independent variables, whereas the rankings of the pitches are dependent variables. The degree of mimicry is also an independent variable. This means that the correlation between the Action Units is unsupervised learning, whereas the methods to predict and classify mimicry to the ranking of the pitches are supervised learning.

3.2. Method

The method that is described in this paragraph is based on answering the main research question: "Is there a positive influence on the ranking of entrepreneurial pitches through mimicry of facial action units involved in smiling, between the pitcher and investor?". To answer this question, first, the degree of mimicry needs to be calculated. The ranking of the pitch is chosen, because this says something about how good the investors think that the pitch is. Also, the ranking somehow says something about the probability to invest, compared to other pitches. For instance, when investors see multiple entrepreneurs and need to decide in which of the entrepreneurs they want to invest. By using several machine learning classifiers and correlation methods, the main research question will be answered.

3.2.1. Degree of Mimicry

The data that has been cleaned will be used to detect mimicry. The loop to detect mimicry is made with SQL, using Microsoft Access (link to Github repository is in Appendix C). All four data files per pitch are combined into one file per pitch. The loop compares each AU value per row of the pitch file with the AU values in the investor files with timestamps between 0.48 and 1.00 further than the timestamp in the row of the pitch file. This is to take the delay of 500 ms to 1000 ms into account, this delay in time is normally used when detecting mimicry, because mimicry tends to happen between 500 ms and 1000 ms (Moody et al., 2007). The maximum value within the range of 500 ms to 1000 ms is then added to a new column, which will be used to calculate the degree of mimicry. To show an example of the file after creating the extra column with the highest values within every delay in time, a short part of a file is shown in Appendix B.

The degree of mimicry is calculated in R, using Pearson's r correlation method, using the packages dplyr and psych (dplyr version 0.8.5, psych version 1.9.12.13). The Pearson's r correlation method is chosen because it is used for normally distributed data and continuous variables (Akoglu, 2018). It is also the most commonly chosen correlation coefficient. The Pearson's r correlation is calculated between the Action Units column and column with the maximum values of the Action Units (where the time delay was used to find the maximum values), to display the degree of mimicry. After calculating the degree of mimicry per Action Unit, the average degree of mimicry per pitch will be calculated. The equation for the Pearson's r is displayed below (BYJU's, 2018).

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

3.2.2. Spearman rho and Kendall's tau correlation

To see if there is a positive influence of mimicry on the ranking of the pitches, the Spearman rho correlation method is used to compare degrees of mimicry with the ranking of the pitches (Akoglu, 2018). The Spearman rho can be used in non-normal distributions and with ranks from the data. However, when the same rank is repeated too many times the Kendall's tau correlation coefficient is advised (Akoglu, 2018). In this dataset, the rankings do appear three times per pitch, but it is not known when a ranking appears too many times. For this reason, both the Spearman rho and Kendall's tau are calculated in R with the dplyr and psych package (dplyr version 0.8.5, psych version 1.9.12.13). The pitches are split up per session, because that is what the rankings are based on. This means that there are four different Spearman and Kendall correlations calculated for the average degree of mimicry, and also four Spearman rho and Kendall's tau correlations for every Action Unit.

3.2.3. Classification Models

The following algorithms are used for classification, K-Nearest Neighbors, Logistic Regression, and Support Vector Machine. The rankings are not equally distributed, because the number of pitches per session was different. This means that ranking 1 occurs more often than ranking 8. To solve this problem, the rankings are split up in three classes: 1 (high), 2 (middle), and 3 (low), whereas rankings 1 and 2 belong to 1, rankings 3 and 4 belong to the middle class, and rankings

5, 6, 7 and 8 belong to class 3. The classes are still not completely equally distributed, but this way there are fewer and more meaningful classes. K-fold cross-validation is used in all models to get a more accurate evaluation of the model (Sanjay, 2018). The K-fold is set on 3 in the sklearn KFold function, random_state is set to 0, and the other parameters are set to default (sklearn version 0.0). For opening the file in Python, pandas is used (pandas version 0.25.1). The link for the github page with the Python code for all of the classifiers is mentioned in Appendix C.

3.2.4. K-Nearest Neighbors

K-Nearest Neighbor classifier is a model which, just as the name says, classifies labels based on the neighbors (Cunningham, & Delany, 2020). The *k* in K-Nearest Neighbors stands for the number of neighbors, which is mostly more than one. KNN is considered a lazy learning technique because induction is delayed to run time. In Python, the KNeighborsClassifier function from sklearn.neighbors is used (sklearn version 0.0). This function has several parameters, where the most important *n_neigbors* is, this is the number of neighbors. The *weights* parameter is set to both '*uniform'* and *'distance'*, but in the end *'uniform'* was chosen because all neighbors are weighted equally. The *leaf_size* is set to default, just like the *p* parameter. This last parameter has been set to 1 to try out.

To see which number of neighbors is worth trying in the model, the error rate is measured by calculating the mean difference between prediction of the test labels and the real test labels. This error loop also uses the sklearn KneighborClassifier, matplotlib pyplot (matplotlib version 3.1.1.), and numpy (numpy version 1.17.2).

3.2.5. Logistic Regression

The Logistic Regression model is widely used in statistics and machine learning. In Logistic Regression, the independent variables do not have to be normally distributed or linearly related (de Souza et al., 2008). A multi-class Logistic Regression model is based on a log-linear relationship between the input variables and the labels, in this thesis the classes of the rankings (Memisevic et al., 2010). The training data helps the model to find a classification rule. This model will be trained using K-Fold Cross-Validation. The Logistic Regression function from the package sklearn.linear_model is used (sklearn version 0.0). Logistic Regression has a wide variety of parameters. The *solver* parameter is set to *'newton-cg', 'sag', 'saga',* and *'lbfgs'*, because these are for multiclass problems. Eventually, *'newton*-cg' is chosen. The *penalty* has been set to *'l2'*, this is the regularization because this fits best with the *newton-cg* parameter. The *random_state* is set to 0, so that the results will be the same every time the model runs. The other parameters are al set to default.

3.2.6. Support Vector Machine

Support Vector Machine is based on the statistical learning theory (Vapnik, 1998). It uses a kernel function to map the input vectors into a feature space (Cai et al., 2002). The goal of the SVM is to produce a model based on the training data which predicts the target values of the test data (Hsu, Chang, & Lin, 2003). Support Vector Machine can be used for several types of learning problems, for instance for binary classification, (non-) linearly separable problems, and multiclass classification. SVM has four basic kernels: linear, polynomial, radial basis function, and sigmoid. Kernels can also be self-made functions. In this study, the RBF kernel is used in the SVC function of the sklearn svm package in Python (sklearn version 0.0), this function is for multiclass classification. The SVC function has several parameters, like the *class_weight,* *gamma, kernel,* and *random_state*. The *kernel* parameter is set to ‘RBF’, and the *random*_state is set to 0. For all the other parameters the default values are chosen.

3.2.7. Evaluation Methods

The performance of the Spearman rho and Kendall’s tau correlations will be evaluated by using the p-value (Statistics How To, 2018). Here, the goal is to get a p-value smaller than 0.05.

The performance of the classifiers will be evaluated by the accuracy, by which the same classifiers are optimized. Not only the accuracy of the model itself is important to be as high as possible, but also the accuracy should be higher than the baseline model. The formula for accuracy is as follows:

Accuracy = (True positives + True negatives) / N

A baseline model is created using the DummyClassifier from the sklearn.dummy package (sklearn version 0.0). This DummyClassifier is trained on the data that has been split by the train_test_split function (test size set at 1/3). This score is rounded at 0.316. The goal is for the other classifiers to score an accuracy above *0.316*.

The dataset is small and the classes are not equally balanced, therefore looking at precision, recall, and f1-score is also necessary after comparing the models (Brownlee, 2018). To see the precision and recall, confusion matrices are made for the best performing algorithms. Precision is the proportion of positive predicted cases that are predicted correctly, it is calculated with the following formula:

Precision = True Positive / Total Predicted Positive

Recall is the proportion of real positive cases that are predicted as positive cases. Recall is calculated with the following formula:

Recall = True Positive / Total Actual Positive

To make a good decision about what model fits the data best and for answering the main research question: all the measures mentioned will be taken into account. However, the classifiers are optimized using the accuracy.

The F1-Score shows a harmonic mean between the precision and recall. If the F1 is around 1, this shows a perfect precision and recall. F1-score is calculated by the following formula:

*F1 = 2 * (Precision * Recall) / (Precision + Recall)*

4. Results

In this section the results will be split into three different parts. First, the degree of mimicry is calculated by using the Pearson's r correlation coefficient, and next, the correlation between the degree of mimicry and the rankings of the pitches are calculated. Last, the three different classifiers will be compared.

4.1. Degree of mimicry

First of all, the Pearson r correlation coefficient is calculated for all corresponding AU values between the pitcher and judge files. These results show the degree of mimicry. Almost all of the degrees show a value between -13.0 and 50.0. The tables with all of the correlations and the significance level are to be found in Appendix C. Most correlations are below 0.30, which means that there is a weak positive relationship, and therefore a low degree of mimicry (Akoglu, 2018). In a few cases there is a negative weak relationship, and in some cases there is a moderate positive relationship between the compared pitcher and judge Action Units. Also, correlations of between 0 and 0.10 appear, which means that there is no relationship at all. Most of the Pearson's r correlations have a probability of less than 5% ($p < 0.05$) and mostly even smaller than 0.1% ($p < 0.001$), which means that the null hypothesis stating that there is no mimicry between the entrepreneur and the investor.

4.2. Spearman rho and Kendall's tau correlations

The Spearman rho and Kendall's tau correlations between the degrees of mimicry and the ranking of the pitches are calculated to see if the mimicry has a positive influence on the ranking of the pitches. In table 1 on the next page, the Spearman's rho correlation between the Action

Units and the ranking of the pitches is shown. The pitches are combined per session, because the rankings are based on these four sessions.

Table 1

Spearman rho correlations of the degree of mimicry from each AU per pitch and the average degree of mimicry, with the ranking of the pitches

Sessions	AU06	AU07	AU12	AU14	Average
DEiA	0.19	0.39	0.21	-0.11	0.28
Startups 2018-2019	0.21	0.06	0.10	0.00	0.21
Startups 2019-2020 1	0.12	0.08	-0.27	-0.04	-0.11
Startups 2019-2020 2	-0.13	0.12	-0.38	-0.54	-0.31
All pitches	0.06	0.16	-0.11	-0.11	-0.01

*p < .05. **p < .01.***p < .001

First of all, the most outstanding result is that most of the Spearman's rho correlations are the moderate negative correlation of -0.54, which shows exactly the opposite of what the main research question indicates. The Spearman's rho correlations are all very different, and none of the correlations show a strong or perfect positive correlation (Akoglu, 2018). Most importantly, the correlations do not say much about the influence of mimicry on the rankings of the pitches, because the null hypothesis cannot be rejected ($p > 0.05$). The null hypothesis, in this case, is that mimicry has no (positive) influence on the ranking of the pitches.

In table 2, the Kendall's tau correlation between the degree of mimicry per Action Unit and the ranking of the pitches are computed. Here, the most outstanding value is the negative moderate correlation between the ranking of the pitches in the second session of Startups 2019-

2020 and the degree of mimicry in Action Unit 14 ($p < 0.05$). This is also the only correlation that does not fail to reject the null hypothesis. The other Kendall's tau correlations all have weak positive and negative effects, and fail to reject the null. This means that there is no influence of mimicry on the rankings of the pitches.

Table 2

Kendall's tau correlations of the degree of mimicry from each AU per pitch and the average degree of mimicry, with the ranking of the pitches

Sessions	AU06	AU07	AU12	AU14	Average
DEiA	0.14	0.32	0.16	-0.10	0.21
Startups 2018-2019	0.16	0.08	0.07	-0.02	0.13
Startups 2019-2020 1	0.09	0.04	-0.18	-0.06	-0.08
Startups 2019-2020 2	-0.05	0.08	-0.19	-0.43*	-0.16
All pitches	0.05	0.12	-0.07	-0.09	-0.01

*p < .05. **p < .01.***p < .001

The difference between Kendall's tau and Spearman's rho is visible in the correlations, which all show different values. One similarity is that both of the correlation methods fail to reject the null, except for one single Kendall's tau correlation.

4.3. Performance of the Classifiers: K-Nearest Neighbor, Linear regression, and Support Vector Machine

The classifiers K-Nearest Neighbor, Linear Regression, and Support Vector Machine are trained using several different parameters, and picking the best for the final result. In table 3, the models and the used hyperparameters are mentioned. If more than one value for the hyperparameter was used to see what hyperparameter works best for the model, the bold value is the value that is used in the optimized model.

Table 3

Models with the hyperparameters used for classification. The bold values are the values that are used.

Models	Hyperparameters	Values
K-Nearest Neighbors	Number of neighbors	12, **25**, 49, 50
	P	1, **2 (default)**
	Weights	**Uniform**, distance
	Leaf_size	5, 10, 20, **30 (default)**, 50
Logistic Regression	Regularization	**L2**
	Solver	**Newton-cg**, sag, saga, lbfgs
	Random state	**0**
	Multi class	**Auto**, multinomial
Support Vector Machine	Kernel	**Rbf**
	Random state	**0**

To see if the models can prove that mimicry does have a positive influence on the ranking of the pitches, the models will be evaluated separately by looking at the baseline. Then, the accuracy, precision and recall of the models will be compared against each other to see which of the models performed best.

The K-Nearest Neighbor classifier scores an average accuracy of *0.293* with 3-fold cross-validation, where the three accuracies score *0.24*, *0.24*, and *0.40.* This means that the average accuracy does not beat the baseline of *0.316*. In table 4, the confusion matrix of the optimized KNN is displayed. Here it is clear that class 3, which stands for the low chance of investment is predicted most often. Precision is the proportion of positive predicted cases that are predicted correct, while recall is the proportion of real positive cases that are predicted as positive cases. The values of precision and recall are not very high, only class 3 stands out with a slightly higher precision and a quite large recall value of *0.625.* When looking at the F1-scores, it shows that the relationship between precision and recall is not very high. A F1-score of around 1 shows a perfect precision and recall, a score of 0 shows the lowest precision and recall.

Table 4

Confusion matrix of optimized K-Nearest Neighbor Classifier

	Predicted 1	Predicted 2	Predicted 3	Precision	Recall	F1
Class 1	3	0	19	0.214	0.136	0.166
Class 2	2	1	18	0.250	0.048	0.080
Class 3	9	3	20	0.351	0.625	0.080

The Linear Regresssion Model scores an average accuracy of *0.280.* The cross validated sections of the model score an accuracy of *0.240, 0.160,* and *0.440.* This means that this model also does not score higher than the baseline level. In table 5, the confusion matrix, precision, recall, and f1-scores are displayed. Here too, only the third class seems to score a higher precision and recall. The f1-score however is still very close to 0. The F1-score of class 2 gives an error, because both Precision and Recall are values of 0.

Table 5

Confusion matrix of optimized Linear Regression

	Predicted 1	Predicted 2	Predicted 3	Precision	Recall	F1
Class 1	1	0	21	0.077	0.045	0.057
Class 2	2	0	19	0.000	0.000	error
Class 3	10	1	21	0.344	0.656	0.080

The Support Vector Machine scores an average accuracy of *0.280*, which is also below the baseline of *0.316*. With 3-fold cross-validation, the accuracies are: *0.240, 0.160*, and *0.440*. The confusion matrix, and values for precision, recall, and F1-score are displayed in table 6 below. Here it is remarkably that class 2 is not predicted at all. The Precision and Recall values are both higher for class 3, and are 0 or give an error for class 2. The F1-score is again very close to zero, but for class 1 and class 3, the F1-score scored higher than in Logistic Regression or K-Nearest Neighbors.

Table 6

Confusion matrix of optimized Support Vector Machine

	Predicted 1	Predicted 2	Predicted 3	Precision	Recall	F1
Class 1	4	0	18	0.160	0.182	0.170
Class 2	6	0	15	error	0.000	error
Class 3	15	0	17	0.340	0.531	0.170

When looking at the accuracies of the three classifiers, it seems that the K-Nearest Neighbor is the best method to use. However, none of the models seem to score above baseline with the average accuracy. The F1-score of the models also is closer to 0 thank to 1, which means that the precision and recall are very low. What does stand out, is that the third class, thus the low score on ranking, seems to be predicted most often. This also is the class that appears most in the dataset.

5. Discussion

The goal of the study was to see if there is a positive influence of mimicry on the ranking of the pitches. First of all, mimicry had to be detected in the pitches. Second, the correlation between the degree of mimicry and the rankings of the pitches had to be calculated to see if mimicry has a positive influence on the ranking of the pitches. Third, three models of classifiers are used to see if classification can prove that mimicry in smiling has an effect on the ranking of the pitches. This section looks at the findings of these three steps, and relates them to what was already known from the literature.

5.1. Detecting Mimicry

The degree of mimicry is formed by the Pearson r correlation between each timeframe from the Action Units in the pitcher files and the highest values in a time range of 500 ms to 1000 ms later in the investor files. The 500 to 1000 ms delay in time for mimicry was proven in several studies (Postma and Nilsenová, 2016; Thunberg, 1998). These degrees of mimicry did not have a strong or perfect correlation, which shows that there is no high level of mimicry, but there is a small amount of mimicry present. When looking at the previous research that is done in this area, it would make sense to look into the mimicry between pitcher and investor more deeply. For instance, by looking at how long mimicry takes place, and therefore take the time more into account in the detecting of mimicry in smiling. An example of looking at how long mimicry takes place is the study from Wu, Lin and Calvo (2020). Looking at the values closest to the Action Unit values in the pitcher files, instead of using the maximum values in the investor files. In that case, the correlations could be higher and therefore the degree of mimicry would be higher. Another option would be to look at the meaning of the mimicry. Here it would be interesting to look at the difference of different values that can be used to express mimicry, and looking at the intensity of the Facial Action Units involved in smiling or the time that the smile takes (Wu, Liu, & Calvo, 2020).

5.2. Correlations

The Spearman's rho and Kendall's tau correlation between the degree of mimicry and the rankings of the pitches overall fail to reject the null hypothesis, which means that there is no influence of mimicry on the rankings of the pitches. This can have several reasons. For starters, it can be caused by having too little data to really have significant results. However, it can also show that mimicry does not have such a large impact on the ranking of the pitches, because verbal behavior or gestures also play an important role in entrepreneurial pitches (Adolphs, 1999). The correlation coefficients are also

5.3. Classifiers

The three classifiers K-Nearest Neighbors, Logistic Regression, and Support Vector Machine all show an average accuracy lower than the baseline. The average accuracies are *0.28*, *0.28* and *0.293.* The baseline was stated at *0.316.* The baseline was already quite low, but the classifiers cannot reach that accuracy. Not only the accuracies are low, also Precision, Recall, and F1-score have very low scores. The three classifiers that are used where chosen because there is very little data available, so the first improvement on this research would be to gather more data or use the data in a different way. Not only more data, but also different analysis could probably give a different result. Methods for large datasets like a Convolutional Neural Network can also be trained for classification on a smaller dataset (Liu, & Deng, 2015). A Convolutional Neural Network can be trained to see more detailed features. As mentioned by Louwerse (2011), a Cross-Recurrence Analysis seems to be an option for future research too. For instance, a Cross-

Recurrence Analysis can be used for classification of ECG signals (Saraswat, Srivastava & Shukla, 2018).

The contribution of this study within the existing framework, is to state that mimicry in smiling has no influence on ranking of the pitches in these four sessions of entrepreneurial pitches. However, to really be sure that there is no influence of mimicry in smiling on the chances of getting a certain investment through entrepreneurial pitches is not studied, it would be interesting to further research the effectiveness of the pitches influenced by mimicry.

6. Conclusion

In this study the main goal was to find out if mimicry in smiling has a positive influence on the ranking of entrepreneurial pitches. The research question was stated as follows: “Is there a positive influence on the ranking of the entrepreneurial pitches through mimicry of Facial Action Units involved in smiling, between the pitcher and investor?”

To answer this research question, first mimicry had to be detected between the Action Units involved in smiling of the pitchers and investors. The degrees of mimicry are calculated using Pearson’s r correlation coefficient, and show the correlation between the Action Units of the pitcher and the Action Units of the investor. The Action Units of the investor are measured with a time delay of 500 ms to 1000 ms.

The main research question is be answered by applying the Spearman’s rho and Kendall’s tau correlation coefficients on the degree of mimicry and the rankings of the pitches. Unfortunately, the null hypothesis cannot be rejected. Only one of the correlations between the degree of mimicry in one pitch session for Action Unit 14 and the ranking of those pitches can be called significant, which means that only for that specific Action Unit, in that specific pitch, mimicry in smiling has a negative influence on the ranking of the pitches instead of positive.

The Logistic Regression, K-Nearest Neighbor and Support Vector Machine are optimized using 3-fold cross validation. These three models were optimized to classify the degree of mimicry on to the classes of the rankings. The average accuracies that these classifiers scored are not enough to score above the baseline. This means that these models also cannot classify the degree of mimicry to the rankings of the pitches. Not only the accuracies, but also the Precision, Recall, and F1-score have very low values. Therefore it can be concluded that mimicry in smiling has no (positive) influence on the ranking of the pitches when using these classifiers or correlation methods.

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Appendix A

Table A1

Information on the data from pitch Ziggurat

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	20645	0.18	0.45	0.00	0.00	3.37	3.81	16.72	0.00
AU07	20645	0.26	0.49	0.00	0.00	3.13	2.48	6.64	0.00
AU12	20645	0.25	0.55	0.00	0.00	3.22	3.02	9.61	0.00
AU14	20645	0.35	0.42	0.17	0.00	2.37	1.33	1.17	0.00
Judge 1									
AU06	20645	0.25	0.40	0.01	0.00	2.62	1.98	4.05	0.00
AU07	20645	0.13	0.35	0.00	0.00	3.45	4.24	22.45	0.00
AU12	20645	0.24	0.44	0.00	0.00	3.57	2.47	7.01	0.00
AU14	20645	0.32	0.52	0.01	0.00	3.14	1.95	3.46	0.00
Judge 2									
AU06	20645	1.00	0.37	0.99	0.00	2.77	0.32	0.13	0.00
AU07	20645	1.16	0.69	1.23	0.00	3.96	0.10	-0.66	0.00
AU12	20645	0.90	0.41	0.77	0.00	3.49	1.38	2.82	0.00
AU14	20645	1.11	0.77	0.98	0.00	3.31	0.43	-0.75	0.01
Judge 3									
AU06	20645	0.18	0.38	0.00	0.00	3.09	2.22	4.37	0.00
AU07	20645	0.25	0.40	0.05	0.00	3.04	2.28	6.12	0.00
AU12	20645	0.03	0.16	0.00	0.00	2.45	8.96	97.01	0.00
AU14	20645	0.71	0.42	0.71	0.00	2.87	0.55	1.26	0.00

Table A2

Information on the data from pitch PREA

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	20180	0.15	0.29	0.00	0.00	1.98	2.61	7.86	0.00
AU07	20180	0.16	0.26	0.03	0.00	2.28	2.27	5.85	0.00
AU12	20180	0.26	0.41	0.04	0.00	2.56	2.01	4.17	0.00
AU14	20180	0.16	0.30	0.00	0.00	1.78	2.07	3.79	0.00
Judge 1									
AU06	20173	0.21	0.41	0.00	0.00	2.95	2.52	6.94	0.00
AU07	20173	0.27	0.57	0.00	0.00	3.48	2.36	5.06	0.00
AU12	20173	0.14	0.42	0.00	0.00	3.23	4.16	18.74	0.00
AU14	20173	0.36	0.63	0.02	0.00	3.97	2.31	5.12	0.00
Judge 2									
AU06	20173	0.34	0.39	0.23	0.00	2.24	1.43	1.37	0.00
AU07	20173	0.50	0.53	0.34	0.00	3.35	1.54	2.32	0.00
AU12	20173	0.62	0.41	0.58	0.00	2.92	1.11	2.53	0.00
AU14	20173	0.34	0.55	0.04	0.00	4.35	2.12	4.70	0.00
Judge 3									
AU06	20180	0.18	0.41	0.00	0.00	2.94	2.70	7.32	0.00
AU07	20180	0.41	0.53	0.16	0.00	2.92	1.51	1.93	0.00
AU12	20180	0.08	0.29	0.00	0.00	2.63	5.52	33.98	0.00
AU14	20180	0.67	0.43	0.64	0.00	2.85	0.71	0.96	0.00

Table A3

Information on the data from pitch Young Boosters

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	25975	0.18	0.45	0.03	0.00	3.59	2.60	7.67	0.00
AU07	25975	0.26	0.49	1.03	0.00	3.47	0.30	0.33	0.00
AU12	25975	0.25	0.55	0.00	0.00	3.29	3.10	9.69	0.00
AU14	25975	0.35	0.49	0.07	0.00	2.69	1.60	1.99	0.00
Judge 1									
AU06	25968	0.27	0.46	0.02	0.00	3.24	2.49	7.91	0.00
AU07	25968	0.38	0.69	0.00	0.00	4.10	1.96	3.11	0.00
AU12	25968	0.22	0.52	0.00	0.00	3.97	3.21	12.01	0.00
AU14	25968	0.48	0.71	0.09	0.00	3.84	1.69	2.48	0.00
Judge 2									
AU06	25968	0.75	0.64	0.62	0.00	3.51	0.58	-0.60	0.00
AU07	25968	1.19	0.83	1.21	0.00	4.65	0.25	-0.65	0.01
AU12	25968	0.59	0.57	0.46	0.00	3.87	1.34	2.42	0.00
AU14	25968	0.81	0.70	0.66	0.00	3.30	0.63	-0.58	0.00
Judge 3									
AU06	25975	0.12	0.33	0.00	0.00	2.64	3.36	12.55	0.00
AU07	25975	0.35	0.54	0.05	0.00	3.52	1.87	3.39	0.00
AU12	25975	0.05	0.23	0.00	0.00	2.64	6.69	52.47	0.00
AU14	25975	0.57	0.44	0.51	0.00	3.29	0.87	0.94	0.00

Table A4

Information on the data from pitch Whitebox

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	20758	0.11	0.27	0.00	0.00	2.79	4.46	26.17	0.00
AU07	20758	0.20	0.33	0.04	0.00	2.5	2.39	6.68	0.00
AU12	20758	0.05	0.26	0.00	0.00	3.30	6.96	57.49	0.00
AU14	20758	0.09	0.24	0.00	0.00	2.93	4.20	23.70	0.00
Judge 1									
AU06	20751	0.33	0.53	0.04	0.00	4.41	2.04	4.36	0.00
AU07	20751	0.31	0.60	0.00	0.00	3.66	1.97	2.92	0.00
AU12	20751	0.30	0.58	0.00	0.00	4.05	2.34	5.11	0.00
AU14	20751	0.47	0.72	0.08	0.00	3.56	1.85	1.43	0.00
Judge 2									
AU06	20751	0.20	0.35	0.01	0.00	2.99	2.24	5.27	0.00
AU07	20751	0.71	0.60	0.59	0.00	3.59	0.85	0.34	0.00
AU12	20751	0.41	0.41	0.31	0.00	3.37	1.24	1.75	0.00
AU14	20751	0.70	0.76	0.43	0.00	3.83	0.87	-0.65	0.01
Judge 3									
AU06	20758	0.12	0.36	0.00	0.00	2.92	3.94	16.95	0.00
AU07	20758	0.54	0.58	0.35	0.00	3.10	1.12	0.68	0.00
AU12	20758	0.07	0.28	0.00	0.00	2.78	6.16	42.45	0.00
AU14	20758	0.58	0.49	0.51	0.00	3.64	1.10	1.54	0.00

Table A5

Information on the data from pitch Soccer Academy

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	32665	0.04	0.21	0.00	0.00	2.94	9.19	97.06	0.00
AU07	32665	0.03	0.15	0.00	0.00	2.96	7.84	77.97	0.00
AU12	32665	0.03	0.20	0.00	0.00	3.01	10.70	124.66	0.00
AU14	32665	0.39	0.42	0.27	0.00	3.00	1.61	3.36	0.00
Judge 1									
AU06	23647	0.29	0.50	0.00	0.00	3.54	2.15	5.04	0.00
AU07	23647	0.31	0.64	0.00	0.00	4.01	2.49	6.23	0.00
AU12	23647	0.26	0.53	0.00	0.00	3.69	2.58	6.94	0.00
AU14	23647	0.39	0.65	0.00	0.00	5.00	1.96	4.11	0.00
Judge 2									
AU06	32665	0.17	0.34	0.00	0.00	3.73	3.37	16.92	0.00
AU07	32665	0.42	0.43	0.30	0.00	3.29	1.78	4.18	0.00
AU12	32665	0.28	0.41	0.04	0.00	3.46	2.07	6.97	0.00
AU14	32665	0.62	0.69	0.44	0.00	3.37	1.50	2.02	0.00
Judge 3									
AU06	32658	0.27	0.56	0.00	0.00	3.46	2.55	6.69	0.00
AU07	32658	0.59	0.65	0.36	0.00	3.69	1.09	0.47	0.00
AU12	32658	0.09	0.30	0.00	0.00	3.58	4.88	27.40	0.00
AU14	32658	0.69	0.50	0.68	0.00	4.42	1.03	3.30	0.00

Table A6

Information on the data from pitch Little Sister

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	23739	0.07	0.27	0.00	0.00	2.32	4.53	21.68	0.00
AU07	23739	0.25	0.45	0.00	0.00	3.35	2.42	6.53	0.00
AU12	23739	0.11	0.34	0.00	0.00	2.36	3.96	16.67	0.00
AU14	23739	0.09	0.27	0.00	0.00	2.63	3.81	16.07	0.00
Judge 1									
AU06	23732	0.47	0.42	0.40	0.00	3.27	2.07	7.75	0.00
AU07	23732	0.47	0.50	0.35	0.00	4.94	1.97	7.34	0.00
AU12	23732	0.57	0.44	0.53	0.00	2.62	0.96	1.54	0.00
AU14	23732	0.35	0.48	0.14	0.00	2.55	1.78	2.82	0.00
Judge 2									
AU06	23732	0.37	0.32	0.34	0.00	2.31	1.96	6.21	0.00
AU07	23732	0.17	0.36	0.00	0.00	3.60	3.06	12.28	0.00
AU12	23732	0.05	0.17	0.00	0.00	2.49	4.70	30.26	0.00
AU14	23732	0.32	0.62	0.00	0.00	4.25	2.23	4.97	0.00
Judge 3									
AU06	23732	0.37	0.35	0.29	0.00	2.00	1.17	1.23	0.00
AU07	23732	0.70	0.58	0.66	0.00	4.11	0.77	0.79	0.00
AU12	23732	0.23	0.33	0.08	0.00	2.41	2.02	4.53	0.00
AU14	23732	0.75	0.59	0.72	0.00	3.00	0.65	0.16	0.00

Table A7

Information on the data from pitch FLIPR

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	18524	0.05	0.17	0.00	0.00	1.72	4.85	27.08	0.00
AU07	18524	0.07	0.19	0.00	0.00	2.19	4.55	28.32	0.00
AU12	18524	0.02	0.12	0.00	0.00	1.83	9.72	107.81	0.00
AU14	18524	0.14	0.26	0.00	0.00	2.15	2.85	10.05	0.00
Judge 1									
AU06	18517	0.77	0.41	0.80	0.00	2.25	-0.32	-0.06	0.00
AU07	18517	0.69	0.96	0.34	0.00	4.86	2.10	4.05	0.00
AU12	18517	0.78	0.54	0.91	0.00	2.77	-0.23	-0.87	0.00
AU14	18517	0.62	0.53	0.55	0.00	2.85	0.73	0.00	0.00
Judge 2									
AU06	18020	0.44	0.32	0.44	0.00	2.61	1.58	5.93	0.00
AU07	18020	0.27	0.42	0.11	0.00	4.48	3.97	24.99	0.00
AU12	18020	0.06	0.21	0.00	0.00	2.38	6.11	45.40	0.00
AU14	18020	0.21	0.49	0.00	0.00	3.52	2.78	7.98	0.00
Judge 3									
AU06	18524	0.30	0.40	0.16	0.00	2.57	2.13	4.87	0.00
AU07	18524	0.53	0.47	0.48	0.00	3.46	0.71	0.12	0.00
AU12	18524	0.21	0.33	0.05	0.00	2.66	2.25	6.36	0.00
AU14	18524	0.90	0.49	0.93	0.00	2.48	0.06	-0.37	0.00

Table A8

Information on the data from pitch Bubble Pop

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	20871	0.11	0.22	0.00	0.00	2.73	3.18	14.23	0.00
AU07	20871	0.23	0.31	0.09	0.00	2.26	1.60	2.83	0.00
AU12	20871	0.02	0.12	0.00	0.00	1.96	9.62	110.80	0.00
AU14	20871	0.08	0.21	0.00	0.00	2.70	4.27	24.11	0.00
Judge 1									
AU06	20859	0.65	0.37	0.72	0.00	2.49	-0.18	0.29	0.00
AU07	20859	0.26	0.39	0.09	0.00	4.36	2.30	6.69	0.00
AU12	20859	0.62	0.39	0.68	0.00	2.41	-0.04	-0.36	0.00
AU14	20859	0.58	0.48	0.60	0.00	2.62	0.68	0.52	0.00
Judge 2									
AU06	20864	0.39	0.29	0.42	0.00	3.55	1.43	7.88	0.00
AU07	20864	0.30	0.45	0.16	0.00	3.85	3.36	16.31	0.00
AU12	20864	0.04	0.18	0.00	0.00	4.14	10.78	157.69	0.00
AU14	20864	0.29	0.52	0.02	0.00	4.76	2.46	6.41	0.00
Judge 3									
AU06	20298	0.32	0.29	0.30	0.00	2.77	0.99	1.62	0.00
AU07	20298	0.79	0.65	0.76	0.00	3.39	0.34	-0.91	0.00
AU12	20298	0.28	0.29	0.21	0.00	1.98	0.94	0.55	0.00
AU14	20298	1.00	0.72	0.99	0.00	2.83	0.09	-1.20	0.01

Table A9

Information on the data from pitch RecognEyes

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	17275	0.26	0.36	0.03	0.00	2.22	1.55	2.09	0.00
AU07	17275	0.20	0.30	0.05	0.00	3.02	2.28	8.18	0.00
AU12	17275	0.23	0.28	0.13	0.00	2.14	1.78	4.25	0.00
AU14	17275	0.43	0.45	0.30	0.00	2.93	1.24	1.48	0.00
Judge 1									
AU06	17268	0.61	0.40	0.61	0.00	2.46	0.82	2.17	0.00
AU07	17268	0.45	0.50	0.30	0.00	3.37	1.70	3.88	0.00
AU12	17268	0.64	0.38	0.70	0.00	2.16	-0.13	-0.60	0.00
AU14	17268	0.67	0.59	0.55	0.00	2.59	0.64	-0.59	0.00
Judge 2									
AU06	17268	0.34	0.38	0.29	0.00	3.91	4.22	28.34	0.00
AU07	17268	0.36	0.56	0.17	0.00	4.99	3.68	19.44	0.00
AU12	17268	0.06	0.26	0.00	0.00	3.96	7.84	71.23	0.00
AU14	17268	0.32	0.64	0.00	0.00	5.00	2.70	8.58	0.00
Judge 3									
AU06	17275	0.26	0.30	0.16	0.00	1.74	1.46	1.96	0.00
AU07	17275	0.46	0.49	0.33	0.00	3.11	1.13	1.11	0.00
AU12	17275	0.18	0.26	0.07	0.00	1.56	2.19	5.57	0.00
AU14	17275	0.81	0.60	0.82	0.00	2.77	0.24	-0.85	0.00

Table A10

Information on the data from pitch HOTIDY

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	21345	0.08	0.22	0.00	0.00	2.00	3.84	17.15	0.00
AU07	21345	0.84	0.50	0.81	0.00	3.08	0.37	-0.18	0.00
AU12	21345	0.05	0.15	0.00	0.00	2.02	5.13	34.40	0.00
AU14	21345	0.14	0.29	0.00	0.00	4.33	2.89	12.17	0.00
Judge 1									
AU06	21345	0.62	0.35	0.63	0.00	2.60	0.13	0.13	0.00
AU07	21345	0.24	0.41	0.01	0.00	2.75	2.16	4.64	0.00
AU12	21345	0.43	0.32	0.45	0.00	2.45	0.57	0.78	0.00
AU14	21345	0.52	0.45	0.49	0.00	3.42	0.61	-0.09	0.00
Judge 2									
AU06	21345	0.39	0.28	0.37	0.00	1.90	0.79	1.46	0.00
AU07	21345	0.23	0.39	0.06	0.00	3.10	2.98	11.21	0.00
AU12	21345	0.03	0.13	0.00	0.00	1.50	5.26	33.21	0.00
AU14	21345	0.29	0.55	0.00	0.00	3.73	2.18	4.23	0.00
Judge 3									
AU06	21345	0.33	0.32	0.26	0.00	2.21	0.98	0.74	0.00
AU07	21345	0.86	0.63	0.90	0.00	3.22	0.10	-1.02	0.00
AU12	21345	0.31	0.31	0.25	0.00	2.21	0.92	0.48	0.00
AU14	21345	1.06	0.68	1.14	0.00	2.89	-0.07	-1.08	0.00

Table A11

Information on the data from pitch FitPoint

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	22989	0.09	0.24	0.00	0.00	2.60	4.21	22.40	0.00
AU07	22989	0.30	0.34	0.18	0.00	3.15	1.40	2.76	0.00
AU12	22989	0.26	0.43	0.07	0.00	3.05	2.77	9.40	0.00
AU14	22989	0.64	0.54	0.59	0.00	3.81	0.79	0.47	0.00
Judge 1									
AU06	22989	0.68	0.38	0.66	0.00	2.59	0.64	1.19	0.00
AU07	22989	0.32	0.42	0.14	0.00	2.91	1.62	2.65	0.00
AU12	22989	0.68	0.41	0.64	0.00	2.72	0.67	0.92	0.00
AU14	22989	0.52	0.53	0.38	0.00	2.65	0.72	-0.61	0.00
Judge 2									
AU06	22989	0.37	0.28	0.35	0.00	2.03	0.66	0.45	0.00
AU07	22989	0.15	0.28	0.00	0.00	3.28	3.01	12.13	0.00
AU12	22989	0.04	0.13	0.00	0.00	2.13	4.84	31.48	0.00
AU14	22989	0.35	0.53	0.04	0.00	4.07	1.59	1.96	0.00
Judge 3									
AU06	22989	0.44	0.36	0.41	0.00	2.49	1.18	2.74	0.00
AU07	22989	0.75	0.58	0.78	0.00	2.80	0.25	-0.86	0.00
AU12	22989	0.37	0.33	0.32	0.00	2.54	1.01	1.64	0.00
AU14	22989	0.99	0.69	0.99	0.00	3.84	0.09	-1.02	0.00

Table A12

Information on the data from pitch SOLON

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	21832	0.07	0.33	0.00	0.00	3.86	6.18	44.63	0.00
AU07	21832	0.44	0.46	0.33	0.00	4.78	2.22	9.02	0.00
AU12	21832	0.08	0.35	0.00	0.00	2.90	5.36	29.53	0.00
AU14	21832	0.07	0.31	0.00	0.00	3.37	5.51	32.31	0.00
Judge 1									
AU06	21832	0.88	0.36	0.86	0.00	2.97	0.83	3.06	0.00
AU07	21832	0.30	0.37	0.16	0.00	2.91	1.83	4.66	0.00
AU12	21832	0.85	0.40	0.77	0.00	3.05	0.94	2.17	0.00
AU14	21832	0.72	0.48	0.71	0.00	2.68	0.39	-0.22	0.00
Judge 2									
AU06	21832	0.50	0.31	0.52	0.00	2.86	1.04	5.07	0.00
AU07	21832	0.26	0.37	0.10	0.00	3.03	2.43	8.08	0.00
AU12	21832	0.08	0.27	0.00	0.00	3.34	5.27	37.59	0.00
AU14	21832	0.27	0.56	0.00	0.00	4.22	2.29	4.83	0.00
Judge 3									
AU06	21832	0.40	0.36	0.34	0.00	3.57	1.76	6.49	0.00
AU07	21832	0.59	0.61	0.45	0.00	4.00	0.91	0.25	0.00
AU12	21832	0.25	0.34	0.10	0.00	3.40	2.71	13.48	0.00
AU14	21832	0.79	0.62	0.73	0.00	2.70	0.36	-0.98	0.00

Table A13

Information on the data from pitch tAIste

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	17907	0.13	0.29	0.00	0.00	2.52	3.51	14.90	0.00
AU07	17907	0.53	0.45	0.46	0.00	3.89	1.33	2.81	0.00
AU12	17907	0.06	0.25	0.00	0.00	2.38	5.47	32.37	0.00
AU14	17907	0.15	0.37	0.00	0.00	3.93	4.06	21.42	0.00
Judge 1									
AU06	17907	0.76	0.45	0.72	0.00	3.64	1.04	2.53	0.00
AU07	17907	1.62	0.56	1.64	0.00	4.54	-0.23	0.65	0.00
AU12	17907	0.43	0.56	0.20	0.00	3.09	1.49	1.60	0.00
AU14	17907	0.92	0.59	0.95	0.00	3.71	0.19	-0.16	0.00
Judge 2									
AU06	17907	0.36	0.52	0.07	0.00	3.25	1.70	3.00	0.00
AU07	17907	0.51	0.59	0.26	0.00	3.10	1.11	0.47	0.00
AU12	17907	0.44	0.52	0.28	0.00	3.06	1.62	3.07	0.00
AU14	17907	0.60	0.55	0.44	0.00	3.12	0.90	0.23	0.00
Judge 3									
AU06	17907	0.18	0.47	0.00	0.00	3.04	3.38	11.85	0.00
AU07	17907	0.07	0.81	0.95	0.00	3.90	0.52	-0.42	0.01
AU12	17907	0.22	0.53	0.00	0.00	3.41	3.33	12.04	0.00
AU14	17907	0.51	0.46	0.40	0.00	3.18	0.90	0.34	0.00

Table A14

Information on the data from pitch Choos3Wisely

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	15374	0.03	0.12	0.00	0.00	1.37	5.91	39.43	0.00
AU07	15374	0.31	0.41	0.12	0.00	3.47	1.72	3.19	0.00
AU12	15374	0.01	0.10	0.00	0.00	1.52	9.05	94.62	0.00
AU14	15374	0.05	0.22	0.00	0.00	3.87	7.60	79.52	0.00
Judge 1									
AU06	15374	0.77	0.50	0.77	0.00	3.45	0.37	0.20	0.00
AU07	15374	1.40	0.80	1.38	0.00	4.26	0.16	-0.50	0.01
AU12	15374	0.33	0.49	0.07	0.00	3.23	1.87	3.44	0.00
AU14	15374	0.66	0.54	0.60	0.00	3.36	0.79	0.74	0.00
Judge 2									
AU06	15374	0.39	0.58	0.06	0.00	3.97	1.83	3.29	0.00
AU07	15374	0.40	0.54	0.15	0.00	3.13	1.80	3.46	0.00
AU12	15374	0.51	0.54	0.32	0.00	3.77	0.98	0.45	0.00
AU14	15374	0.60	0.75	0.30	0.00	3.90	1.53	1.75	0.01
Judge 3									
AU06	15374	0.06	0.26	0.00	0.00	2.79	6.33	47.31	0.00
AU07	15374	0.55	0.69	0.25	0.00	3.94	1.42	1.59	0.01
AU12	15374	0.14	0.32	0.00	0.00	3.75	4.54	32.11	0.00
AU14	15374	0.39	0.49	0.04	0.00	2.45	0.92	-0.32	0.00

Table A15

Information on the data from pitch SmArt

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	15211	0.09	0.32	0.00	0.00	3.03	5.02	28.99	0.00
AU07	15211	0.25	0.35	0.08	0.00	2.46	1.92	4.07	0.00
AU12	15211	0.14	0.45	0.00	0.00	3.76	4.69	25.13	0.00
AU14	15211	0.09	0.32	0.00	0.00	2.46	4.23	18.57	0.00
Judge 1									
AU06	15211	0.83	0.52	0.88	0.00	4.44	0.39	0.99	0.00
AU07	15211	1.79	0.78	1.82	0.00	5.00	-0.09	-0.09	0.01
AU12	15211	0.23	0.36	0.06	0.00	3.06	2.68	9.86	0.00
AU14	15211	0.55	0.47	0.49	0.00	3.95	0.94	1.69	0.00
Judge 2									
AU06	15211	0.43	0.68	0.07	0.00	3.42	1.87	2.91	0.01
AU07	15211	0.35	0.47	0.13	0.00	3.63	1.60	2.29	0.00
AU12	15211	0.42	0.61	0.07	0.00	3.35	1.65	2.38	0.00
AU14	15211	0.49	0.53	0.33	0.00	3.53	1.32	1.40	0.00
Judge 3									
AU06	18254	0.07	0.29	0.00	0.00	2.88	5.44	33.04	0.00
AU07	18254	1.31	0.83	1.38	0.00	3.77	-0.05	-0.72	0.01
AU12	18254	0.28	0.37	0.18	0.00	2.99	3.07	13.54	0.00
AU14	18254	0.88	0.56	0.95	0.00	3.06	-0.17	-0.89	0.00

Table A16

Information on the data from pitch StudentFood

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	15365	0.04	0.17	0.00	0.00	2.57	7.41	67.69	0.00
AU07	15365	0.19	0.34	0.00	0.00	2.71	2.62	8.48	0.00
AU12	15365	0.08	0.26	0.00	0.00	2.61	4.94	31.03	0.00
AU14	15365	0.19	0.33	0.00	0.00	1.97	1.95	3.44	0.00
Judge 1									
AU06	15365	0.87	0.64	0.83	0.00	3.18	0.44	-0.33	0.01
AU07	15365	1.58	0.88	1.64	0.00	4.76	0.11	-0.32	0.01
AU12	15365	0.33	0.49	0.12	0.00	3.51	2.26	6.27	0.00
AU14	15365	0.65	0.56	0.61	0.00	4.14	0.85	0.71	0.00
Judge 2									
AU06	15365	0.35	0.48	0.13	0.00	2.70	1.56	1.71	0.00
AU07	15365	0.33	0.45	0.14	0.00	2.96	1.97	4.70	0.00
AU12	15365	0.46	0.45	0.36	0.00	2.52	1.31	1.77	0.00
AU14	15365	0.70	0.52	0.69	0.00	3.46	0.52	0.03	0.00
Judge 3									
AU06	15365	0.11	0.32	0.00	0.00	3.50	4.64	26.04	0.00
AU07	15365	1.12	0.68	1.09	0.00	3.98	0.31	-0.31	0.01
AU12	15365	0.35	0.50	0.17	0.00	3.59	2.56	8.39	0.00
AU14	15365	0.84	0.56	0.80	0.00	3.13	0.61	0.23	0.00

Table A17

Information on the data from pitch wAIste

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	16906	1.04	0.60	0.96	0.00	3.34	0.49	-0.23	0.00
AU07	16906	0.08	0.21	0.00	0.00	2.90	4.38	25.66	0.00
AU12	16906	1.84	0.62	1.83	0.00	3.54	0.08	-0.67	0.00
AU14	16906	0.99	0.55	0.99	0.00	3.00	0.16	-0.44	0.00
Judge 1									
AU06	16906	1.13	0.55	1.14	0.00	3.41	0.16	0.62	0.00
AU07	16906	1.67	0.73	1.65	0.00	5.00	0.28	0.47	0.01
AU12	16906	0.32	0.46	0.13	0.00	2.44	1.81	2.67	0.00
AU14	16906	0.82	0.61	0.81	0.00	3.82	0.75	1.22	0.00
Judge 2									
AU06	16906	0.36	0.52	0.12	0.00	3.94	2.20	6.63	0.00
AU07	16906	0.37	0.47	0.14	0.00	2.70	1.41	1.56	0.00
AU12	16906	0.60	0.57	0.48	0.00	3.81	1.15	1.65	0.00
AU14	16906	0.62	0.57	0.55	0.00	4.81	0.76	0.65	0.00
Judge 3									
AU06	16906	0.20	0.47	0.00	0.00	3.21	2.93	8.50	0.00
AU07	16906	1.12	0.84	1.05	0.00	3.89	0.44	-0.64	0.01
AU12	16906	0.31	0.57	0.06	0.00	3.16	2.49	5.66	0.00
AU14	16906	0.75	0.50	0.82	0.00	3.02	0.05	-0.45	0.00

Table A18

Information on the data from pitch Chattern

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	17626	0.23	0.36	0.05	0.00	2.88	2.25	5.82	0.00
AU07	17626	0.08	0.24	0.00	0.00	3.61	5.29	38.11	0.00
AU12	17626	0.20	0.47	0.00	0.00	2.57	2.79	7.23	0.00
AU14	17626	0.20	0.40	0.00	0.00	2.63	2.34	5.18	0.00
Judge 1									
AU06	17626	0.79	0.66	0.67	0.00	3.80	0.93	0.44	0.00
AU07	17626	1.36	0.73	1.39	0.00	5.00	0.15	-0.12	0.01
AU12	17626	0.20	0.39	0.00	0.00	2.80	2.40	5.78	0.00
AU14	17626	0.49	0.58	0.24	0.00	3.53	1.15	0.99	0.00
Judge 2									
AU06	17626	0.25	0.48	0.00	0.00	3.63	2.48	6.01	0.00
AU07	17626	0.35	0.45	0.16	0.00	2.71	1.50	2.00	0.00
AU12	17626	0.55	0.55	0.41	0.00	3.41	1.03	0.79	0.00
AU14	17626	0.56	0.51	0.49	0.00	2.95	0.76	-0.03	0.00
Judge 3									
AU06	17626	0.19	0.52	0.00	0.00	3.57	3.62	13.90	0.00
AU07	17626	0.73	0.71	0.60	0.00	4.07	0.95	0.46	0.00
AU12	17626	0.22	0.56	0.00	0.00	3.43	3.05	9.10	0.00
AU14	17626	0.64	0.53	0.58	0.00	3.42	1.05	1.40	0.00

Table A19

Information on the data from pitch FindIT

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	17804	0.13	0.32	0.00	0.00	2.19	3.17	11.00	0.00
AU07	17804	0.63	0.51	0.59	0.00	3.00	0.55	-0.33	0.00
AU12	17804	0.22	0.47	0.00	0.00	2.91	2.84	8.27	0.00
AU14	17804	0.39	0.47	0.20	0.00	2.57	1.31	1.04	0.00
Judge 1									
AU06	17804	1.02	0.60	1.01	0.00	3.52	0.39	0.54	0.00
AU07	17804	1.76	0.56	1.76	0.00	4.32	-0.13	0.62	0.00
AU12	17804	0.25	0.45	0.00	0.00	3.02	2.51	7.09	0.00
AU14	17804	0.66	0.68	0.47	0.00	2.67	0.71	-0.80	0.01
Judge 2									
AU06	17804	0.28	0.44	0.08	0.00	3.78	2.80	10.78	0.00
AU07	17804	0.32	0.50	0.03	0.00	3.21	1.79	2.86	0.00
AU12	17804	0.69	0.64	0.52	0.00	3.13	0.99	0.21	0.00
AU14	17804	0.66	0.57	0.59	0.00	3.27	0.68	-0.20	0.00
Judge 3									
AU06	17804	0.20	0.43	0.01	0.00	3.48	3.78	17.45	0.00
AU07	17804	0.59	0.77	0.20	0.00	3.52	1.25	0.55	0.01
AU12	17804	0.20	0.44	0.02	0.00	3.45	3.96	17.80	0.00
AU14	17804	0.32	0.56	0.01	0.00	4.87	2.62	8.68	0.00

Table A20

Information on the data from pitch Ar-T-ficial

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	16673	0.07	0.20	0.00	0.00	2.52	5.81	43.55	0.00
AU07	16673	1.09	0.37	1.09	0.00	3.17	0.14	1.35	0.00
AU12	16673	0.20	0.28	0.08	0.00	2.43	2.39	9.15	0.00
AU14	16673	0.18	0.29	0.04	0.00	3.76	3.22	20.34	0.00
Judge 1									
AU06	16673	0.38	0.48	0.23	0.00	3.24	2.07	5.29	0.00
AU07	16673	0.35	0.57	0.04	0.00	3.25	1.93	2.94	0.00
AU12	16673	0.11	0.32	0.00	0.00	2.92	3.84	16.33	0.00
AU14	16673	0.45	0.46	0.33	0.00	2.88	1.55	2.97	0.00
Judge 2									
AU06	16623	0.54	0.62	0.37	0.00	3.77	1.65	3.07	0.00
AU07	16623	0.40	0.52	0.13	0.00	3.50	1.45	2.10	0.00
AU12	16623	0.72	0.64	0.58	0.00	3.55	1.39	1.98	0.00
AU14	16623	0.95	0.53	0.98	0.00	2.60	0.02	-0.65	0.00
Judge 3									
AU06	16123	0.81	0.54	0.83	0.00	4.15	0.36	0.21	0.00
AU07	16123	0.80	0.70	0.68	0.00	3.42	0.57	-0.69	0.01
AU12	16123	0.38	0.45	0.27	0.00	4.04	2.39	7.50	0.00
AU14	16123	1.03	0.67	1.01	0.00	4.01	0.51	0.57	0.01

Table A21

Information on the data from pitch Recipe-Me

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	22987	0.10	0.40	0.00	0.00	3.53	5.03	26.76	0.00
AU07	22987	0.27	0.43	0.08	0.00	3.81	2.47	7.81	0.00
AU12	22987	0.14	0.52	0.00	0.00	3.73	4.74	23.24	0.00
AU14	22987	0.17	0.38	0.00	0.00	3.35	2.98	9.89	0.00
Judge 1									
AU06	22987	0.68	0.78	0.34	0.00	4.99	1.53	2.53	0.01
AU07	22987	0.46	0.67	0.05	0.00	4.27	1.60	2.22	0.00
AU12	22987	0.36	0.67	0.00	0.00	3.47	1.88	2.56	0.00
AU14	22987	0.55	0.52	0.41	0.00	3.09	1.36	1.91	0.00
Judge 2									
AU06	22987	0.67	0.77	0.40	0.00	3.91	1.03	0.34	0.01
AU07	22987	0.55	0.67	0.15	0.00	3.62	1.04	0.23	0.00
AU12	22987	0.81	0.75	0.58	0.00	3.16	0.82	-0.20	0.00
AU14	22987	0.83	0.57	0.77	0.00	3.01	0.52	-0.29	0.00
Judge 3									
AU06	22987	0.90	0.58	0.88	0.00	3.45	0.48	0.29	0.00
AU07	22987	0.73	0.96	0.43	0.00	5.00	2.09	4.65	0.01
AU12	22987	0.59	0.63	0.41	0.00	3.48	1.52	2.01	0.00
AU14	22987	1.40	0.75	7.36	0.00	4.31	0.26	0.29	0.00

Table A22

Information on the data from pitch Salix

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	23399	0.02	0.12	0.00	0.00	1.88	9.92	114.07	0.00
AU07	23399	0.20	0.30	0.05	0.00	2.58	2.08	5.29	0.00
AU12	23399	0.03	0.15	0.00	0.00	2.45	10.28	125.06	0.00
AU14	23399	0.12	0.24	0.00	0.00	3.48	2.86	9.16	0.00
Judge 1									
AU06	23399	0.32	0.36	0.20	0.00	2.61	1.70	4.37	0.00
AU07	23399	0.26	0.43	0.07	0.00	2.90	2.64	7.87	0.00
AU12	23399	0.10	0.29	0.00	0.00	2.73	4.27	22.81	0.00
AU14	23399	0.41	0.43	0.28	0.00	2.19	0.91	0.13	0.00
Judge 2									
AU06	23399	0.40	0.55	0.14	0.00	3.71	1.75	3.54	0.00
AU07	23399	0.40	0.52	0.15	0.00	4.02	1.78	4.48	0.00
AU12	23399	0.53	0.57	0.35	0.00	3.25	1.31	1.42	0.00
AU14	23399	0.63	0.41	0.62	0.00	3.20	0.40	0.19	0.00
Judge 3									
AU06	23399	0.93	0.73	0.89	0.00	4.26	0.50	-0.38	0.00
AU07	23399	0.73	0.73	0.55	0.00	4.13	1.13	1.02	0.00
AU12	23399	0.66	0.70	0.44	0.00	4.28	1.45	1.78	0.00
AU14	23399	1.37	0.78	1.42	0.00	3.75	-0.02	-0.58	0.01

Table A23

Information on the data from pitch Peech

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	17852	0.42	0.63	0.17	0.00	4.51	2.59	8.36	0.00
AU07	17852	1.13	0.67	1.13	0.00	4.15	0.47	0.31	0.01
AU12	17852	0.32	0.59	0.03	0.00	3.62	2.89	9.33	0.00
AU14	17852	0.12	0.32	0.00	0.00	2.70	3.49	13.44	0.00
Judge 1									
AU06	17852	0.95	0.99	0.56	0.00	4.21	1.00	-0.01	0.01
AU07	17852	0.85	0.93	0.48	0.00	4.50	0.88	-0.38	0.01
AU12	17852	0.65	0.88	0.11	0.00	3.55	1.21	0.25	0.01
AU14	17852	0.77	0.71	0.67	0.00	3.78	0.88	0.40	0.01
Judge 2									
AU06	17840	1.33	1.03	1.07	0.00	4.42	0.80	-0.04	0.01
AU07	17840	0.75	0.86	0.43	0.00	3.85	1.00	0.09	0.01
AU12	17840	1.24	0.83	1.12	0.00	3.88	0.86	0.12	0.01
AU14	17840	1.08	0.73	1.16	0.00	3.34	0.05	-0.71	0.01
Judge 3									
AU06	17852	1.15	0.84	1.06	0.00	4.66	0.64	-0.14	0.01
AU07	17852	0.95	0.90	0.83	0.00	3.73	0.74	-0.36	0.01
AU12	17852	0.90	0.67	0.79	0.00	3.36	1.04	0.81	0.01
AU14	17852	0.79	0.69	0.70	0.00	4.01	0.73	0.07	0.01

Table A24

Information on the data from pitch HoodFood

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	15837	0.25	0.38	0.02	0.00	2.35	1.80	3.37	0.00
AU07	15837	0.44	0.45	0.31	0.00	3.32	1.10	0.96	0.00
AU12	15837	0.43	0.53	0.19	0.00	2.35	1.22	0.56	0.00
AU14	15837	0.15	0.29	0.00	0.00	2.73	2.37	6.36	0.00
Judge 1									
AU06	15837	0.71	0.68	0.53	0.00	3.61	0.90	-0.09	0.01
AU07	15837	0.93	0.75	0.81	0.00	4.39	0.72	0.08	0.01
AU12	15837	0.47	0.66	0.06	0.00	3.28	1.29	0.56	0.01
AU14	15837	0.80	0.71	0.72	0.00	3.35	0.51	-0.86	0.01
Judge 2									
AU06	15837	0.82	0.82	0.69	0.00	3.75	1.27	1.35	0.01
AU07	15837	0.61	0.69	0.48	0.00	3.80	1.41	2.45	0.01
AU12	15837	1.04	0.68	0.98	0.00	3.22	0.62	-0.01	0.01
AU14	15837	0.81	0.60	0.85	0.00	3.15	0.21	-0.75	0.00
Judge 3									
AU06	15837	0.57	0.59	0.43	0.00	3.28	1.19	1.47	0.00
AU07	15837	0.55	0.57	0.41	0.00	3.73	1.27	2.46	0.00
AU12	15837	0.74	0.61	0.71	0.00	3.07	0.99	1.19	0.00
AU14	15837	0.79	0.81	0.55	0.00	3.56	0.88	-0.26	0.01

Table A25

Information on the data from pitch LockUp

Pitch	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
AU06	19499	0.70	0.50	0.60	0.00	2.81	1.05	0.86	0.00
AU07	19499	1.26	0.59	1.21	0.00	4.57	0.60	1.00	0.00
AU12	19499	0.82	0.53	0.69	0.00	2.66	0.90	0.25	0.00
AU14	19499	0.60	0.59	0.44	0.00	3.20	0.79	-0.26	0.00
Judge 1									
AU06	19499	0.79	0.72	1.14	0.00	3.61	0.76	-0.18	0.01
AU07	19499	0.93	0.76	1.65	0.00	3.14	0.44	-0.91	0.01
AU12	19499	0.51	0.67	0.13	0.00	3.10	1.28	0.73	0.00
AU14	19499	0.95	0.77	0.81	0.00	3.67	0.75	-0.03	0.01
Judge 2									
AU06	19499	1.11	0.94	1.00	0.00	3.92	0.49	-0.71	0.01
AU07	19499	0.83	0.82	0.69	0.00	3.81	0.86	0.01	0.01
AU12	19499	1.07	0.63	0.99	0.00	3.27	0.78	0.70	0.00
AU14	19499	1.10	0.52	1.17	0.00	4.12	-0.28	-0.16	0.00
Judge 3									
AU06	19499	0.92	0.68	0.93	0.00	3.48	0.49	-0.03	0.00
AU07	19499	0.81	0.72	0.74	0.00	3.62	0.63	-0.37	0.01
AU12	19499	0.67	0.54	0.60	0.00	3.37	0.99	1.24	0.00
AU14	19499	0.98	0.69	0.94	0.00	3.99	0.36	-0.55	0.00

Appendix B

Table B1

Example of the new file created after looping over the files per pitch to detect mimicry (All done in Microsoft Access).

Th1.pitch	Frame	Timestamp	Th2.pitch	AU06_r	Max_AU06	AU12_r	Max_AU12	AU14_r	Max_AU14
Ar-T-ficial_pitch	1	0.00	Ar-T-ficial_judge1	0.27	0.54	0.50	0.50	0.56	0.23
Ar-T-ficial_pitch	2	0.04	Ar-T-ficial_judge1	0.39	0.55	0.21	0.41	0.23	0.23
Ar-T-ficial_pitch	1	0.00	Ar-T-ficial_judge2	0.20	0.32	0.31	0.23	0.58	0.89
Ar-T-ficial_pitch	2	0.04	Ar-T-ficial_judge2	0.30	0.32	0.29	0.56	0.45	0.99
Ar-T-ficial_pitch	1	0.00	Ar-T-ficial_judge3	0.21	0.40	0.56	0.89	0.65	0.56

Appendix C

Link for Github Repository with code:

https://github.com/Annanaus/Thesis_mimicy_in_entrepreneurial_pitches

Table C1

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Ziggurat	AU06	AU07	AU12	AU14	Ranking
Judge1	0.36***	0.19***	0.40***	0.22***	2
Judge2	0.13***	-0.03***	0.18***	-0.18***	4
Judge3	0.19***	-0.01	0.40***	0.25***	3

*p < .05. **p < .01.***p < .001

Table C2

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

PREA	AU06	AU07	AU12	AU14	Ranking
Judge1	0.15***	-0.06***	0.19***	0.18***	3
Judge2	0.12***	-0.03***	0.31***	0.03***	1
Judge3	0.16***	0.06***	0.26***	0.21***	1

*p < .05. **p < .01.***p < .001

Table C3

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

YoungBoosters	AU06	AU07	AU12	AU14	Ranking
Judge1	0.23***	0.17***	0.30***	0.14***	5
Judge2	0.36***	0.33***	0.38***	0.01	5
Judge3	0.19***	0.13***	0.46***	0.03***	5

*p < .05. **p < .01.***p < .001

Table C4

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Whitebox	AU06	AU07	AU12	AU14	Ranking
Judge1	0.19***	-0.01	0.18***	0.01	1
Judge2	0.01***	0.09***	0.12***	-0.03***	3
Judge3	0.28***	0.09***	0.46***	0.02**	2

*p < .05. **p < .01.***p < .001

Table C5

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

SoccerAcademy	AU06	AU07	AU12	AU14	Ranking
Judge1	0.29***	0.11***	0.27***	0.15***	4
Judge2	0.41***	0.13***	0.24***	0.02***	2
Judge3	0.23***	0.04***	0.32***	0.07***	4

*p < .05. **p < .01.***p < .001

Table C6

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

LittleSister	AU06	AU07	AU12	AU14	Ranking
Judge1	0.28***	0.13***	0.31***	0.02***	2
Judge2	0.08***	0.08***	0.16***	0.10***	4
Judge3	0.22***	0.09***	0.28***	-0.07***	1

*p < .05. **p < .01.***p < .001

Table C7

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

FLIPR	AU06	AU07	AU12	AU14	Ranking
Judge1	0.22***	-0.01	0.19***	0.22***	4
Judge2	-0.01	-0.06***	0.10***	0.10***	1
Judge3	0.06***	0.07***	0.37***	0.04***	4

*p < .05. **p < .01.***p < .001

Table C8

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

BubblePop	AU06	AU07	AU12	AU14	Ranking
Judge1	0.11***	-0.07***	0.14***	0.04***	7
Judge2	0.15***	-0.12***	0.16***	-0.04***	7
Judge3	0.01	0.20***	0.02*	0.02*	6

*p < .05. **p < .01.***p < .001

Table C9

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

RecognEyes	AU06	AU07	AU12	AU14	Ranking
Judge1	0.08***	-0.02*	0.17***	-0.01	1
Judge2	-0.08***	-0.01	-0.05***	0.13***	3
Judge3	0.03***	0.07***	0.03***	-0.04***	3

*p < .05. **p < .01.***p < .001

Table C10

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

HOTIDY	AU06	AU07	AU12	AU14	Ranking
Judge1	0.08***	0.02*	0.12***	-0.01	5
Judge2	0.08***	0.05***	0.02*	0.17***	2
Judge3	0.06***	0.04***	0.16***	-0.13***	2

*p < .05. **p < .01.***p < .001

Table C11

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

FitPoint	AU06	AU07	AU12	AU14	Ranking
Judge1	0.06***	-0.03***	0.08***	0.02***	3
Judge2	0.02**	0.04***	0.07***	0.01	6
Judge3	0.20***	0.10***	0.29***	-0.05***	7

*p < .05. **p < .01.***p < .001

Table C12

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

SOLON	AU06	AU07	AU12	AU14	Ranking
Judge1	0.34***	0.10***	0.33***	0.16***	6
Judge2	0.17***	0.02*	0.25***	0.08***	5
Judge3	0.28***	0.34***	0.34***	0.04***	5

*p < .05. **p < .01.***p < .001

Table C13

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

tAIste	AU06	AU07	AU12	AU14	Ranking
Judge1	0.20***	-0.02**	0.22***	0.21***	6
Judge2	0.28***	0.22***	0.34***	0.27***	7
Judge3	0.47***	0.01	0.35***	0.12***	8

*p < .05. **p < .01.***p < .001

Table C14

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Choos3Wisely	AU06	AU07	AU12	AU14	Ranking
Judge1	0.05***	0.06***	0.07***	0.06***	8
Judge2	0.13***	0.13***	0.17***	0.15***	6
Judge3	0.31***	0.09***	0.14***	0.15***	6

*p < .05. **p < .01.***p < .001

Table C15

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

SmArt	AU06	AU07	AU12	AU14	Ranking
Judge1	0.17***	0.04***	0.31***	0.21***	3
Judge2	0.26***	0.10***	0.36***	0.25***	1
Judge3	0.60***	0.03***	0.47***	0.11***	4

*p < .05. **p < .01.***p < .001

Table C16

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

StudentFood	AU06	AU07	AU12	AU14	Ranking
Judge1	0.09***	0.03***	0.15***	0.04***	4
Judge2	0.04***	0.08***	0.24***	0.03***	2
Judge3	0.33***	0.09***	0.31***	0.15***	7

*p < .05. **p < .01.***p < .001

Table C17

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

wAIste	AU06	AU07	AU12	AU14	Ranking
Judge1	0.16***	0.00	0.26***	0.03***	5
Judge2	0.23***	0.05***	0.33***	0.16***	5
Judge3	0.43***	0.08***	0.40***	-0.01	5

*p < .05. **p < .01.***p < .001

Table C18

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Chattern	AU06	AU07	AU12	AU14	Ranking
Judge1	0.16***	0.05***	0.22***	0.21***	1
Judge2	0.19***	0.17***	0.37***	0.13***	3
Judge3	0.45***	0.00	0.52***	0.05***	1

*p < .05. **p < .01.***p < .001

Table C19

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

FindIT	AU06	AU07	AU12	AU14	Ranking
Judge1	0.03***	0.06***	0.07***	0.09***	2
Judge2	0.20***	0.06***	0.24***	0.10***	8
Judge3	0.34***	0.06***	0.37***	0.18***	2

*p < .05. **p < .01.***p < .001

Table C20

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Ar-T-ficial	AU06	AU07	AU12	AU14	Ranking
Judge1	0.22***	0.12***	0.27***	0.04***	4
Judge2	0.20***	0.06***	0.30***	0.12***	3
Judge3	0.12***	-0.05***	0.14***	0.07***	3

*p < .05. **p < .01.***p < .001

Table C21

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Recipe-Me	AU06	AU07	AU12	AU14	Ranking
Judge1	0.40***	0.17***	0.44***	0.22***	5
Judge2	0.33***	0.13***	0.36***	0.07***	5
Judge3	0.03***	0.25***	0.08***	0.05***	5

*p < .05. **p < .01.***p < .001

Table C22

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Salix	AU06	AU07	AU12	AU14	Ranking
Judge1	0.23***	-0.02*	0.23***	0.18***	1
Judge2	0.20***	-0.04***	0.25***	0.14***	1
Judge3	0.12***	0.06***	0.13***	-0.00***	1

*p < .05. **p < .01.***p < .001

Table C23

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

Peech	AU06	AU07	AU12	AU14	Ranking
Judge1	0.24***	0.16***	0.25***	0.11***	2
Judge2	0.26***	0.18***	0.33***	0.09***	4
Judge3	0.27***	0.23***	0.29***	0.07***	4

*p < .05. **p < .01.***p < .001

Table C24

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

HoodFood	AU06	AU07	AU12	AU14	Ranking
Judge1	-0.06***	-0.10***	0.06***	-0.05***	6
Judge2	0.19***	0.08***	0.11***	-0.04***	6
Judge3	0.15***	0.00	-0.01	-0.14***	6

*p < .05. **p < .01.***p < .001

Table C25

Pearson r correlation between the pitch AU values and maximum values of the corresponding AUs in a range of 0.48 up to 1.00 timestamps further in the judge files.

LockUp	AU06	AU07	AU12	AU14	Ranking
Judge1	0.18***	0.08***	0.18***	0.01	7
Judge2	0.30***	0.13***	0.21***	-0.08***	7
Judge3	0.04***	0.03***	-0.03***	0.10***	7

*p < .05. **p < .01.***p < .001

Table C26

Table showing the pitches and the average degree of mimicry per pitch. Also, the ranking of the pitches is displayed. All pitches that belong to the DEiA session are mentioned in this table.

Pitch	Average degree of mimicry	Ranking
Ziggurat_1	0.29	2
Ziggurat_2	0.03	4
Ziggurat_3	0.21	3
PREA_1	0.12	3
PREA_2	0.11	1
PREA_3	0.17	1
YoungBoosters_1	0.21	5
YoungBoosters_2	0.27	5
YoungBoosters_3	0.20	5
Whitebox_1	0.09	1
Whitebox_2	0.05	3
Whitebox_3	0.21	2
SoccerAcademy_1	0.21	4
SoccerAcademy_2	0.20	2
SoccerAcademy_3	0.17	4

Table C27

Table showing the pitches and the average degree of mimicry per pitch. Also, the ranking of the pitches is displayed. All pitches that belong to the 2018-2019 session are mentioned in this table.

Pitch	Average degree of mimicry	Ranking
LittleSister_1	0.19	2
LittleSister_2	0.11	4
LittleSister_3	0.13	1
FLIPR_1	0.16	4
FLIPR_2	0.03	1
FLIPR_3	0.14	4
BubblePop_1	0.06	7
BubblePop_2	0.04	7
BubblePop_3	0.06	6
RecognEyes_1	0.06	1
RecognEyes_2	0.00	3
RecognEyes_3	0.02	3
HOTIDY_1	0.05	5
HOTIDY_2	0.08	2
HOTIDY_3	0.03	2
FitPoint_1	0.03	3
Fitpoint_2	0.04	6
FitPoint_3	0.14	7
SOLON_1	0.23	6
SOLON_2	0.13	5
SOLON_3	0.25	5

Table C28

Table showing the pitches and the average degree of mimicry per pitch. Also, the ranking of the pitches is displayed. All pitches that belong to the first session of 2019-2020 are mentioned in this table.

Pitch	Average degree of mimicry	Ranking
tAIste_1	0.15	6
tAIste_2	0.28	7
tAIste_3	0.24	8
Choos3Wisely_1	0.06	8
Choos3Wisely_2	0.15	6
Choos3Wisely_3	0.17	6
SmArt_1	0.18	3
SmArt_2	0.24	1
SmArt_3	0.30	4
StudentFood_1	0.08	4
StudentFood_2	0.10	2
StudentFood_3	0.22	7
wAIste_1	0.11	5
wAIste_2	0.19	5
wAIste_3	0.23	5
Chattern_1	0.16	1
Chattern_2	0.22	3
Chattern_3	0.26	1
FindIT_1	0.06	2
FindIT_2	0.15	8
FindIT_3	0.24	2

Table C29

Table showing the pitches and the average degree of mimicry per pitch. Also, the ranking of the pitches is displayed. All pitches that belong to the second session of 2019-2020 are mentioned in this table.

Pitch	Average degree of mimicry	Ranking
Ar-T-ficial_1	0.16	4
Ar-T-ficial_2	0.17	3
Ar-T-ficial_3	0.07	3
Recipe-Me_1	0.31	5
Recipe-Me_2	0.22	5
Recipe-Me_3	0.10	5
Salix_1	0.16	1
Salix_2	0.14	1
Salix_3	0.08	1
Peech_1	0.19	2
Peech_2	0.22	4
Peech_3	0.22	4
HoodFood_1	-0.04	6
HoodFood_2	0.09	6
HoodFood_3	0.01	6
LockUp_1	0.11	7
LockUp_2	0.14	7
LockUp_3	0.04	7
Ar-T-ficial_1	0.16	4
Ar-T-ficial_2	0.17	3
Ar-T-ficial_3	0.07	3

Appendix D

Table D1

Spearman rho correlations of the degree of mimicry from each AU per pitch and the average degree of mimicry, with the ranking of the pitches

Sessions	AU06	AU07	AU12	AU14	Average
DEiA	0.19	0.39	0.21	-0.11	0.28
Startups 2018-2019	0.21	0.06	0.10	0.00	0.21
Startups 2019-2020 1	0.12	0.08	-0.27	-0.04	-0.11
Startups 2019-2020 2	-0.13	0.12	-0.38	-0.54	-0.31
All pitches	0.06	0.16	-0.11	-0.11	-0.01

*p < .05. **p < .01.***p < .001

Table D2

Kendall's tau correlations of the degree of mimicry from each AU per pitch and the average degree of mimicry, with the ranking of the pitches

Sessions	AU06	AU07	AU12	AU14	Average
DEiA	0.14	0.32	0.16	-0.10	0.21
Startups 2018-2019	0.16	0.08	0.07	-0.02	0.13
Startups 2019-2020 1	0.09	0.04	-0.18	-0.06	-0.08
Startups 2019-2020 2	-0.05	0.08	-0.19	-0.43*	-0.16
All pitches	0.05	0.12	-0.07	-0.09	-0.01

*p < .05. **p < .01.***p < .001