# The Influence of Mimicry on a Jury Members' Evaluation of Business Pitches

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**Author's Note**

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A special thanks to Merel Jung and the second reader, who guided me through the process of writing this thesis.

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**Preface**

Dear reader,

You are about to read my exploratory paper on the influence of mimicry in an entrepreneurial setting. I would like to thank my supervisor Merel Jung for the counselling during this thesis period. Also I would like to thank all my fellow students who have been very supporting towards me and each other during this period. I hope that you as a reader will enjoy this thesis.

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*In business, lots of decisions have to be made and in order to make the right ones, information is needed. In human-to-human interaction, non-verbal behaviour is an excellent source of information. Moreover, mimicry has been researched quite extensively in other fields of research and has been shown to have a positive influence on human-to-human interaction. Using state-of-the-art facial behavioural analysis software, namely OpenFace, we tried to explore the influence of mimicry in facial expression on evaluation of a business pitcher by the jury members. We did this by analysing video material of pitchers, where both the pitchers and the jury members faces were recorded. A degree of mimicry was calculated and was compared to evaluation forms, which the jury members filled out. Results show that mimicry can be calculated more accurately than in the past using new data science techniques. Based on the analyses, which yields a non-significant classification and non-significant predictive effects of mimicry on positive evaluation, limited conclusion can be formed. Lastly, this paper offers a basis for further experimental research.*

## 1. Introduction

In entrepreneurial studies, it becomes unequivocally clear that decision-making is at the heart of running a successful modern business (Shepherd, 2011; Dew, Read, Sarasvathy & Wiltbank, 2009; Maxwell, Jeffrey & Lévesque, 2011). Making important decisions is a daily activity for entrepreneurs as they want to make sure they discover and exploit profitable opportunities for their own ventures (Shane & Venkataraman, 2000). Additionally, entrepreneurial ventures have a great risk of failing, so it is important to make the right decisions (Busenitz, 1999). This might seem apparent, but entrepreneurial decision-making often involves high uncertainty, time pressure and big consequences for business (Shepherd, Williams & Patzelt, 2014; Baron, 2008). In order to make these decisions, entrepreneurs need a good procedure to rely on. The concerned procedures are often based on certain heuristics and biases which speed up the decision-making process, which is useful for entrepreneurs (Sarasvathy, 2001). A heuristic can be defined as a rule of thumb (Ritter, 2003). Heuristics and biases are often shaped by past experiences, which will give entrepreneurs a general idea of how certain decisions will unfold (Lewis, 2018). However, not all decisions can be brought to a good end this way, since decision-making can actually fall prey to heuristics and biases. Quite a few entrepreneurial activities that involve decision-making, involve human-to-human interaction. Some examples of such decisions involve job interviews, whether or not to invest in opportunities that arise, mergers and acquisitions and so on. But even in human-to-human interaction, decision-making can fall prey to some kind of bias, namely stereotyping. Moreover, job applicants as well as entrepreneurs trying to get funding often use behaviour to impress those who rule over the decision. This is better known as impression management (IM) (Bourdage, Roulin & Levashina, 2017). A meta-analysis by Higgins et al. (2003) showed that, although the relation between IM and positive assessment is not always a positive relationship itself, some components of IM are related to positive assessment and other work-related outcomes. It is therefore of utmost importance for entrepreneurs to be aware of these influences. Lots of research has been devoted to the importance of hiring the right people, building the right team and investing in the right direction, so it is important these decision involving social interaction is based on information that is processed consciously and accurately (e.g., Unger, Rauch, Frese & Rosenbusch, 2011; Hoang, 2018; Brown, 2011).

Evidence shows that decision-making which includes human-to-human interactions is largely influenced by both verbal and non-verbal communication and has been widely researched in the field of cognitive and behavioural psychology (Blahova, 2015). In recent years, non-verbal communication has gotten a lot more attention, especially when linked with fields of science other than behavioural psychology, for instance in business and organisational psychology. Communication has shown to be essential in business and especially non-verbal communication is of high importance to modern business (Colta, 2010). For example, research shows that 60% to 80% of communication during a negotiation is through body language (Pease & Pease, 2008). Non-verbal communication contains information that can for instance be transferred through voice, for example intonation, tone and pitch of voice. Moreover, there are a number of ways in which non-verbal communication can take place besides vocally and be equally as important, like through facial expression, gesture, posture and physical appearance. Among these non-verbal signals, facial expressions have a major part in social interaction (Adolphs, 1999; de Gelder, 2009). Moreover, facial cues are a big source of information about human behaviour (Cohn, Zlochower, Lien & Kanade, 1999). Therefore, in this study, we will focus on facial expressions in entrepreneurial human-to-human interaction.

It has been shown in multiple studies that we relate to people and create an empathic feeling through facial expressions. People are constantly sending social signals to each other using body language (Argyle & Kendon, 1967). The process of sending signals in a social situation is called social signalling, which has been widely researched within social psychology. Early research suggests that people with a better awareness of the communicative importance of their actions, which includes non-verbal communication and thus facial expression, are more successful in human-to-human interaction (Mehrabian, 1971). For example, when humans observe a human face expressing fear, it elicits fearful response in the observer, as indexed by increases in autonomic makers of arousal and increased activity in the amygdala (Ohman & Soares, 1998; Morris et al. 1996). In other words, facial expressions tell a lot and help induce empathy and understanding between one another. Mimicking each other’s non-verbal as well as verbal cues helps people to do so. This phenomenon is called mimicry (Stel & Vonk, 2010). Mimicry helps us shape the ability to empathise and understand the mind of other people. Its origins can be found in our own neurones (Iacoboni, 2009). Certain neurones have motor properties in the premotor and parietal cortex, parts of the brain which are used in the planing and selection of actions. These neurones are called mirror neurones. These neurones fire not only during one's own actions, but also while observing someone else performing the same action. This is why mimicry is important throughout all stages of human life (Nadel, 2002). For instance, infants use mimicry to shape their understanding of their environment. But also later in life, mimicry remains important for human-to-human interaction. In a recent study by Stel and Vonk (2010), results on mimicry showed that mimickers and mimickees become more affectively attuned to each other due to bidirectional influences of mimicry. There is evidence that showed that common brain areas serve both perception and execution of actions, indicating that there is a link between observed and mimicked actions (Stel & Vonk, 2010). This translates well when studied, because both mimickers and mimickees have a stronger feeling of having bonded which each other and rate the interaction as smoother. Studies in behavioural psychology suggest this phenomenon occurs largely outside of our awareness, but is closely related with the social dynamics of the interaction (Vacaru, van Schaik & Hunnius, 2019). This shows that mimicry in facial expression is an essential part of social interaction.

Building upon the idea that facial expressions and mimicry in facial expression especially are a crucial part of social interaction, which in turn might influence decisions in entrepreneurial ventures, it is important to better understand which facial expressions can positively influence an evaluation or decision. To exactly find out the relationship of mimicry in facial expression during social interaction on the one hand and success in business on the other hand, an analysis of facial expressions during such an interaction is needed. The past has shown this to be quite a challenge, because computers themselves are ignorant of social context, while this is important for human social interaction (e.g. Bainbridge et al., (1994)). In early research they tried to code such analyses manually. However, this is a very time-consuming process. Besides the fact that the quality of the analysis will suffer, because small facial expressions called micro-expressions might be missed, while those can play a big role in revealing underlying emotions (Ko, 2018; Liebregts, Darnihamedani, Postma & Atzmuller, 2019). The solution to these problems can be found in one of the state-of-the-art techniques in data science, where social signals are recognised and analysed using machine analysis and artificial intelligence (Vinciarelli, Salamin & Pantic, 2009). This is better known as social signal processing (SSP). SSP as a mean to analyse non-verbal behaviour has already been adapted in multiple prior studies (see section "Related work"). Even though studies with similar research methodology have been conducted, to my best knowledge none of these studies have focussed on entrepreneurial interaction.

In this exploratory study we will focus on exploring the influence of mimicry on entrepreneurial success using state-of-the-art facial behaviour analysis algorithms. Literature suggests that, because of the importance of business decisions, and the influence that non-verbal communication and thus facial expressions can have on decisions, it is important that these decisions are based on accurate information which is explored thoroughly (Liebregts, Darnihamedani, Postma & Atzmuller , 2019; Blahova, 2015; Adolphs, 1999; de Gelder, 2009). In this research, features will be composed out of Action Units (henceforth AUs), according to the Facial Action Coding System (FACS) (Ekman, Friesen & Hager, 2002). FACS is widely used to describe facial movement. This system discriminates between 44 different AUs. The features that will be used in the research are facial expressions expressed by the pitcher that are socially relevant according to literature. The dataset that will be used, which will be explained in detail in the section “Experimental Setup”, contains video material of student pitchers who are pitching a business idea to a jury panel, consisting of jury members who have a background in business. That’s why we will try to answer the following question:

**RQ**: What is the influence of mimicry in facial expression on the probability to invest between a business pitcher and the jury members?

The hypothesis for this research is when jury members mimic socially relevant facial expressions in a higher frequency, they will have a better evaluation of a pitcher compared to when they mimick in a lower frequency. In terms of our evaluation methods, this means that a higher degree of mimicry will implicate a higher probability of investment from the jury members on the evaluation form used to express feeling towards the pitcher.

## 2. Related Work

Data science is a rapidly emerging trend which appears to have applications in lots of research fields (van der Aalst, 2016). Especially big data seems to be important for the survival of businesses. Nonetheless, as stated earlier, to my best knowledge advanced facial analysis techniques have yet to be applied to find an answer to our specific research question. So, that means that the influence of mimicry in business-like human-to-human interaction has yet to be researched. However, there has been research on mimicry and facial expressions using these techniques, although not for entrepreneurial research. Besides that, mimicry in other non-verbal behaviour has also been researched in entrepreneurial context. This offers the opportunity to help draw a clear picture of the influences of mimicry. In this section, multiple studies will be discussed which might be relevant to this topic, but also relevant to the methodology of the current study.

### 2.1. Mimicry in Facial Expression

A study by Sato & Yoshikawa (2007) confirms some basal remarks we have made so far. They investigated whether visible facial mimicry actually occurs when participants faces were being recorded, while they had to observe dynamic or static facial expressions. Static expressions consisted of single images of facial expressions, while dynamic expressions were represented by a computer morphing technique that morphed a neutral face into a facial expression. The latter resulted in consecutive images, much like a video. Although this study used FACS to score facial movement, a limitation of this study, given the current state of affairs with regard to technology, is that it is scored manually by two scorers, which makes this research less accurate than a study with modern facial analysis techniques. In this study mimicry occurred within 900 ms after the onset of changes in dynamic facial expression. They found that prototypical actions of happiness, like pulling the corners of the lips in an upward direction, occur more frequently in response to happy expressions compared to an angry expression. This research indicates and confirms that dynamic facial expressions elicit facial mimicry.

A field within mimicry that has been researched extensively is affiliation and increased liking (Stel & Vonk, 2010; Gueguen & Martin, 2009; Stel, Blascovich, McCall, Mastop, Baaren & Vonk, 2010). An extensive early study by Chartrand and Bargh (1999) conducted three experiments, on the basis of which the following conclusions have been drawn: people unintentionally mimic behaviour of strangers whom they work with in a task, mimicry facilitates the smoothness of interactions and increases liking within a social interaction, and, lastly, they showed that individuals who take a perspective of other views in a greater extent exhibit mimicry more then those who are less likely to consider the perspective of others.

The general conclusion that can be drawn from such studies is that mimicry increases liking and affiliation between a mimicker and mimickee, especially if the mimicry occurs bidirectional within a social interaction. Mimicry in non-verbal behaviour is hence sometimes called "social glue” (Lakin, Jefferis, Cheng & Chartrand, 2003). This goes for any normal social interaction. The main conclusion that can be drawn from this strain of research is that mimicry in facial expression is a powerful tool for influencing a social interaction.

**2.2. Mimicry’s Window**

Because mimicry is basically a reaction in behaviour, a time window is needed to see whether mimicry has taken place after the activation of a certain AU. Although research is not completely coherent about the time window in which mimicry can occur, it is not completely arbitrary either. In most studies on mimicry in facial expression, a time window of a 1000 ms is used (Moody et al, 2007; Sato & Yoshikawa, 2007; Dimberg, 1982). Besides that, people need some time to able to react to a facial expression. How fast mimicry can occur seems to depend on the AU or facial muscle. Some research state that mimicry in eyebrows can be visible after only 300-400 ms, with one study stating that it is visible after only 200 ms (Passardi et al, 2019; Dimberg, Thunberg, 1998). For the lip pulling muscle, better known as the *zygomaticus major* or the smiling muscle, mimicry can occur within 400-500 ms (Niedenthal, Mermillod, Maringer & Hess, 2010; Passardi et al, 2019).

### 2.3. Facial Expression as Features

FACS breaks down facial expressions in many different AUs. However, in practice, most of these AUs do not appear in isolation. In a former study by Tong, Liao and Ji (2007), they showed that there are relationships between these AUs. They showed for instance that, raising the cheeks, combined with pulling the corners of the lips and parting the lips (AU 06, AU 12 and AU 25) together represent happiness. Pulling the corners of the lips alone can also represent a smile, but when the intensity of the emotion increases, other action units start to add up as well. There are a number of other combinations that represent meaningful expressions. So, although AUs are useful in breaking down facial activity, sometimes combinations represent meaningful expressions instead of just AUs on their own.

In general, mimicry is inhibited when there is a negative attitude or disposition towards another person, and visa versa (Hess & Fischer, 2013). So when facial expressions are being mimicked more often, people tend to have a more positive attitude towards the people whom they mimic. One of the most important facial expressions or emotions that can be recognised in the face, is smiling (Maringer, Kramhuber, Fischer & Niedenthal, 2011). People who smile more, receive a higher rating of competence, are liked more and get more positive responses than people who do not smile (Reis et al., 1990; Mussel, Göritz & Hewig, 2013). Moreover, in a study that looked at the link between facial feedback and neural activity, it was found that feedback from facial muscles during mimicry modulates the neural activity that is involved with representing emotional states. This implies that not only the facial expressions of mimickees are adopted, but also that part of the emotion is adopted too, although conclusions about felt emotions are not conclusive.

### 2.4. Differences Between People Within Mimicry

Not every individual exhibits the same amount of mimicry. For instance, gender differences can be found with regard to mimicry. Early research has shown that women are more emotionally expressive and show more facial mimicry than man. Apart from that, women are more likely to copy someone else's emotion during an interaction than men (Eisenberg & Lennon, 1983; Dimberg & Lundquist, 1990; Korb et al. (2015). Not only do gender differences exist, but cultures also differ from each other in terms of the degree of mimicry. A study by Semnani-Azad et al. (2019) researched the differences between western culture and Asian culture by comparing behavioural mimicry amongst Chinese and Canadian business negotiations. They found that Canadians exhibit more mimicry due to the overt and direct nature of western communication; Chinese negotiators were more indirect.

### 2.5. Non-verbal Communication and Mimicry in Business

Looking at the bigger picture to which this research contributes, literature suggests that non-verbal communication as a whole, not just facial expression, is tremendously important for a positive evaluation of others (Colta, 2010). For a long time it has been established that non-verbal behavioural cues like remaining eye contact and a more forward body orientation towards another person receive a more favourable evaluation than those who do not.

Maddux, Mullen & Galinksy (2008) conducted two experiments in which the influence of mimicry on business negotiations was explored. The outcomes of the first experiment implied that negotiators who mimicked the behaviour of their opponents both secured better individual outcomes. This means that better mimicking during business negotiations lead to a more favourable outcome for themselves, but not at the expense of others. Experiment two showed that, even in a unfavourable business disposition for both, mimicking resulted in the ability to create an outcome that is beneficial for both parties. So, mimicking is not only advantageous for social interaction, but can actually result in better outcomes for business.

### 2.6. Advanced Facial Behavioural Analysis Tools

Thus far we can conclude that research on the influence of mimicry in facial expression on social interaction is not limited at all. However, the ways to conduct facial analysis have changed during the last decade (De la Torre & Cohn, 2011). Although FACS is a very well put together system, which is still used in automated facial analysis, scoring FACS manually seems to yield lesser results with regard to correct classification and validity than automating coding (Skiendziel, Rösch, Schultheiss, 2019; Cohn, 2010). Besides that, manual methods require lots of human labor and can be quite subjective at times. In a study by Cohn (2010), manual FACS was compared with automated facial analysis. Automated facial analysis was proven to be more efficient overall, showing improvements in analysis time and a high concurrent validity with manual coding.

## 3. Experimental Setup

Because the current study utilises an existing dataset, the experimental setup will be divided in two parts: the first section will give a description of the concerned data set and what particular data this study uses from said data set. The second section will cover the software and methods used to process and analyse the data.

### 3.1. Description of the Data set

In order to properly measure and analyse the degree of mimicry between people in an entrepreneurial context, video material is needed. An existing dataset of twenty-five pitches divided over four pitch sessions has been used for this purpose, which was recorded for a competition for pitchers and will be reused for scientific purposes during this research (Liebregts, Urbig & Jung (2018-2020). All pitching sessions were part of a course from the data science program, most of them from the bachelor program. The remaining part comes from the master program. After developing a business idea with a small study group, one representative had the task to pitch their business idea in from of three investors. The investors came from different backgrounds, but all had close relationships with the business world.

The dataset, which is around 575 GB in total, does not only include video footage, but also a number of forms which were used during the pitching competition and some data from CERT on facial expression (Littlewort et al., 2011). Because the footage is confidential footage, a non-disclosure agreement was signed before access was given to the data set. It is particularly useful for the current study to analyse this video footage, because during these video's twenty-five speakers pitch a business idea for a board of jury members. Each speaker had to speak in front of three jury members, presented by the investors. First a short speech was given about their business idea, followed by a Q&A which took about ten minutes. Based on this the investors gave their opinion by means of an assessment form. Both the social interaction and the evaluation form are useful for this study, because in this way we can measure mimicry in facial expression between the two and link them to the ranking made by the jury members. For these reasons, only the video footage and the judges' assessment are used from the data set during this research.

There are four relevant videos per pitch session; one video of the pitcher and one video of each jury member. Throughout the whole interaction between the pitcher and the jury members, all of their faces were recorded. All videos have the file extension, namely .MP4. To the best of my knowledge, all videos are recorded with the same camera, concluded on the basis of the quality and especially the frame rate of the video's, which is the same for each video (25 frames per second). In addition to the videos, there was an evaluation form for each member of the jury, which were filled out on paper. Here they could give their opinions about each pitcher individually. In total, there are three evaluation forms per pitcher. These evaluation forms have been converted into an Excel file, where for each pitcher the evaluation of the juries per session is stored, including a jury-individual ranking of the pitchers of the session in question.

Based on these evaluations, each jury member made a ranking. The evaluation form can be roughly divided into two parts: evaluation with regard to the business-idea and evaluation with regard to the pitching student. After all pitchers had spoken and had been evaluated, the jury members made a ranking for themselves for the current pitch session. One variable, namely probability to invest, has been selected as the evaluation measure for one of the analyses. This number summarises lots of other variables, including the judges view of the degree of risk, feasibility, probability of success and other evaluation measures that are relevant to investment in a business idea. However, as stated in the "Related Work" section, mimicking non-verbal behaviour can positively influence evaluation. In this study we used this matter to determine what influence mimicry might have on this summarising measure. The other variable that will be used is jury-individual ranking of the pitch.

### 3.2 Software

The software that was used during this study consists of OpenFace (version 2.2.0), Microsoft Excel (version 1908), RStudio (version 1.2.5042) and Python (version 3.5.3). All the software was hosted on a 3.5 GHz i7 core computer, using a 64-bit Windows 7 Ultimate operating system. Mainly OpenFace was used, because this way the video images could be analysed from the pitching competition dataset using OpenFace. Excel and R assisted in processing the data outputted by OpenFace. Finally, Python has been used to carry out the analyses used in this study. All Python code was created in Jupyter Notebook (version 5.2.2.). Within Python the following packages have been used:

- NumPy (version 1.18.1)
- Pandas (version 0.25.3)
- SciPy (version 1.4.1)
- Seaborn (version 0.9.1)
- Matplotlib (version 3.0.3)
- StatsModels (version 0.10.2)
- Scikit Learn (version 0.22.1)

NumPy, Pandas and SciPy were mainly used to process the data. Seaborn and Matplotlib were used for created the plots and figures. StatsModels and Scikit Learn were used to perform the analyses in this study.

#### 3.2.1. OpenFace

OpenFace is an open source framework which combines a number of advanced facial behaviour analysis algorithms (Baltrusaitis, Robinson, & Morency, 2016). An important feature that OpenFace has, is the automatic detection of facial AUs. These AUs will be very useful in detecting certain facial expressions. The building blocks of OpenFace originate from Constrained Local Neural Fields (CLNF), which is a facial feature landmark detector algorithm, which is based on the Constrained Local Model (CLM) used for facial detection presented by Cristinacce and Cootes (2006). The CLNF differs from the CLM in two ways. To better explain their differences, a breakdown of the CLM is useful. It consists of three main parts: a point distribution model (PDM), patch experts and fitting. The PDM models the landmark points in the face, which is the same for both the CLM and the CLNF.

However, the algorithms differ in the patch experts and the fitting approach. The CLNF utilises a local neural field (LNF) patch expert whilst the CLM uses a Support Vector Regressor. Besides offering an excellent explanation on this comparison, Baltrusaitis et al. (2016) showed that, because of spatial constraints used in LNF, LNF outperforms the SVR patch expert, which leads to a more accurate fitting. For the fitting approach, regularised landmark mean shift (RLMS) is used in CLM. When an initial estimate of the parameter has been made, the right parameter update has to be found to get closer to the optimal solution. RLMS does this, by finding the least squares solution. The problem for the algorithm is that for RLMS fitting, each patch expert weighs equally as much, while not all patch expert are equally reliable. So, an update rule is added to the regular RLMS, where the reliability of each patch expert is calculated, which leads to better accuracy. Overall, CLNF has shown to outperform CLM and many state of the art facial feature detection techniques (Baltrusaitis, Robinson, & Morency, 2013).

### 3.3. Features and Independent Variables

During the video analysis, both the actual pitch and the Q&A were part of the analysis, because both are part of the interaction, based on which the judgement by the judges is made. After analysing the video footage of the pitchers and the jury members, OpenFace outputted a .CSV file with a number of features, one for each analysed person. These features comprise some basic information like frame number and timestamps, gaze related features, head pose features and certain action units, which can be divided into two sections: action unit intensity (AU_r) and action unit presence (AU_c). Since intensity can give us more insight into the intensity of the facial expression and possibly intensity of the emotion, action unit intensity was used. The action units that were used are the features that should reveal interest, acceptance or liking in a person's face, so only a number of features were used. An example of such a feature might be raising eyebrows or smiling, as it shows a positive attitude towards another person (McIntosh, 2006). The features were measured in each timestamp. Based on related work, the features that were used are the cheek raiser (AU06_r), the lid tightener (AU07_r) and the lip corner puller (AU12_r). The first and the latter action units relate to smiling, which is a widely researched topic within the field of mimicry and facial expression in general, and can be linked to lots of positive interaction related outcomes (e.g. Maringer, Kramhuber, Fischer & Niedenthal, 2011; Reis et al., 1990; Mussel, Göritz & Hewig, 2013). Although lid tightening can be related to negative emotions, it is more often than not related to a happy emotion, compared to other facial action units (Kohler et al., 2004).

Since we want to know if judges mimic the facial expressions of the pitchers, a frame of 1000 ms was taken based on literature in which the judges can respond (Moody et al., 2007). In addition, given that people need some time to react to the mimickee's facial expression, a minimum was added to said frame. Literature suggests that mimicry can take place after 200-400 ms (Passardi et al, 2019; Dimberg, Thunberg, 1998).

Corresponding to the frame rate, which is 25 frames per second, facial expressions of the jury are considered mimicry after 8 to 25 frames, which in milliseconds is a timeframe of 320 ms to 1000 ms after a facial expression from the pitcher.

This was done for every single facial expression of the pitcher, so for each frame of the pitcher, a mean for the facial expression of the jury was taken for the 8 to 25 frames, or 320 ms to 1000 ms, after said frame of the pitcher. We use the mean because we can get an idea of the average response of a jury member after an expression of the pitcher. This process was repeated for all three action units. Such a technique is better known as a sliding window technique in data mining (Chang & Lee, 2005). The technique described above was performed by using a loop in R that iterates over the frames of the jury member. This created a new column for that specific AU for each jury member for that specific pitch. We used this column to compare it to the column of that AU of the pitcher by using a correlation. By calculating the correlation between the column of a certain AU of the pitcher and the column of the jury member that is created using the loop that is described above, we basically calculated a cross-correlation, because the newly created column has already taken the lag of 8 to 25 frames into account. Cross-correlation measures the similarity between $x$ and $y$, where $y$ is lagged, in which lag is $k$. The lag $k$ value returned by cross correlation of $(x, y)$ estimates the correlation between $x[t+k]$ and $y[t]$. Because we accounted for the lag in the loop, Pearson's correlation between our $x$ and $y$ calculated a cross correlation. The $x$ and $y$ in our study are represented by the column of an AU of a pitcher and the newly created column of said AU of the jury member respectively. Consequently, for all three action units, a correlation between the column of the pitcher and the newly created column of the jury members was calculated. This results in a single number, namely the correlation between the two columns, which in turn represents the average degree of mimicry for that AU between the pitcher and the jury member over the entire pitch.

### 3.4. Evaluation Analyses

The evaluation analysis consists of two parts: first we explore relationships between probability to invest as a continuous number and the degree of mimicry. The ranking jury members gave to the pitchers was into account to some extent. In the second part, the probability to invest is transformed to categories which makes classification using machine learning possible.

#### 3.4.1. Regression Analysis and Spearman Rank Correlation

After calculating the degree of mimicry over the chosen AUs between the pitcher and jury members, this measure could be used to look at its implications. The evaluation form contains a continuous variable, "Probability to invest", which contains a number from 0 to 100 that reflects the feelings of the jury member's towards a business idea in terms of the probability that they would invest in that business. Naturally, lots of variables and factors play a part in this number. However, we wanted to explore what influence mimicry in facial expressions might have on that probability. Therefore, a multiple linear regression was used to explore the influence of such facial expressions.

In total there were four groups of pitchers. These all contained five to seven pitchers. Altogether, 25 people pitched their idea in front of a panel of judges. In addition, there were three independent jury members in each group, so in total twelve judges participated. Ideally, these groups would be analysed separately. However, given the small number of observations, the dataset does not allow this. In order to be able to carry out an analysis in which implications can be somewhat explored, it is necessary to add the observations together in one dataset. This resulted in 25 observations. As a result, intra-individual differences of the jury members cannot be considered in this exploratory study. Subsequently, each pitcher was added three times as an observation to the dataset used to perform the analysis, namely in combination with each of the judges. This results in 75 observations with 3 independent variables, namely the degree of mimicry of each of the three AUs between the jury member and the pitcher. Structuring the dataset this way makes sure there are enough observations to start discovering the relationship between the degree of mimicry and the probability of investment.

Given the exploratory nature of this study, we also looked at ranking as a dependent variable. This variable was used to rank the pitchers amongst each other, which was done by each jury member individually. The same AUs used in the regression model will be used in combination with ranking as a dependent variable. Using Spearman's rank correlation, we wanted to asses whether mimicry in individual AUs was associated with the ranking.

### 3.4.2. Decision Tree, K-Nearest Neighbour and Support Vector Machine

#### 3.4.2.1. Variable Transformation for Classification and Class Imbalance

To further explore the relationship between the probability to invest and the degree of mimicry, machine learning classifiers were used to try to predict classification of the probability to invest based on the degree of mimicry on the three AUs. Since this thesis is exploratory and classifiers have not been applied to similar data to the best of my knowledge, three different classifiers, which were picked based on relevance to the data, were used and compared to each other. However, in order to train these classifiers, the variable "Probability to invest" had to be transformed to classes, because this variable was measured as a continuous number, from 0 to 100.

Given the limited amount of data points available in this dataset, namely 75, we chose to created two classes to maximise the amount of training data for each class. The classes represent the following: class 1 represent the pitches that received a probability to invest of 0 to 29 by a jury member. Class 2 represents the pitches that received a probability to invest of 30 to 100 by a jury member. A cut-off value of 30 was chosen to make sure both classes were balanced. An ideal cut-off value might naturally be closer to 50, but given the limited amount of data, options to fight class imbalance are limited (e.g. downsampling). By using 30 as a cutoff value, class imbalance is minimised as much as possible, which results in 35 observations in class 1 and 40 observations in class 2.

### 3.4.2.2. Decision Tree Algorithm and Hyperparameters

The first classifier that will be used for the current study is the decision tree classifier. A decision tree classifier, according to Swain and Hauska (1977), is defined as the following:

*"The decision tree classifier is characterised by the fact that an unknown sample is classified into a class using one or several decision functions in a successive manner."*

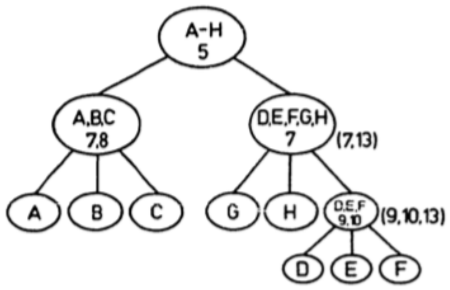


*Figure 1.* A simple decision tree to visualise the working of the decision tree algorithm.

This can be visualised best using Figure 1, which the paper from Swain and Hauska uses to illustrate their definition. The tree starts at the top, better known as the root node, and works its way down to the bottom. The sample splits at the root node and gets divided into more internal nodes, which are used after the root node to split the data even further. Finally, data arrives at the leaf nodes, in which classification is made. The splits of data which are made in the root and internal nodes are based on a decision that has to be made, for instance: "is the number higher than 5?" This can cause the data to go in two directions; either above or under that threshold and thus the data gets divided into two parts.

This algorithm is widely used within the field of machine learning and data science in general, because of the simplicity of the algorithm and the transparency that decision trees can offer. Because of the simplicity of the model, it is a very rapid and computationally efficient algorithm (Aitkenhead, 2008). Because this algorithm is well known within machine learning and is still widely used within the field, it offers an excellent benchmark when comparing multiple classifiers.

The values of the hyperparameters of the decision tree in this study were picked using a grid search. This way hyperparameters are tuned in the most optimal way for the data. The hyperparameters that are tuned for the decision tree are the following (Pedregosa et al., 2011):

- *Min_sample_split*: this number represents the minimum number of samples required to split an internal node.
- *Max_depth*: this number represents the maximum number of splits until the tree stops splitting.
- *Criterion*: this hyperparameter picks the criterion that measures the quality of the split. There are two options that Scikit Learn offers, namely “gini” and “entropy”. Respectively they represent gini impurity and a measure of information gain.
- *Splitter*: this represents the strategy used to choose the data at each node.

### 3.4.2.3. K-Nearest Neighbour Algorithm and Hyperparameters

The second classifier that will be used in this study is k-Nearest Neighbour classifier (henceforth, KNN). The algorithms working is quite straight forward, namely that every object is classified by means of a plurality vote of its neighbours. It takes into account only the closest neighbours and the amount of neighbours it takes into account is set by the hyper parameter *k*, hence k-Nearest Neighbours (Altman, 1992). The way that the distance to the closest neighbour is calculated can differ, which can also be tuned as a hyperparameter.

Since we only have a small number of input variables, namely the degree of mimicry on the three specified AUs, using KNN as a classifier is a good fit, since it works best with low-dimensional data (Schuh, Wylie & Angryk, 2014). Furthermore, KNN works better with a small dataset since its efficiency declines as the dataset grows, as it starts working from the start; it needs little training.

The values of the hyperparameters of KNN in this study were picked using a grid search, just like the former classifier. The hyperparameters that are tuned for the KNN are the following (Pedregosa et al., 2011):

- N*_neighbours*: this number represents the amount of neighbours the classifier takes into account.
- *Weights*: weight function that the classifier uses in prediction. For instance, uniform weights will take all neighbours into account with equal weight, while the distance weights will weigh differently depending on their distance.
- *Metric*: this parameter defines the metric that the classifier uses (e.g. Euclidean, Manhattan).

### 3.4.2.4. Support Vector Machine Algorithm and Hyperparameters

The final classifier that will be used in this study is the Support Vector Machine (henceforth, SVM). A SVM tries to find a hyperplane in an N-dimensional space that classifies data points correctly. SVM tries to fit the hyperplane using a margin, which is padded around the hyperplane, as shown in Figure 2.

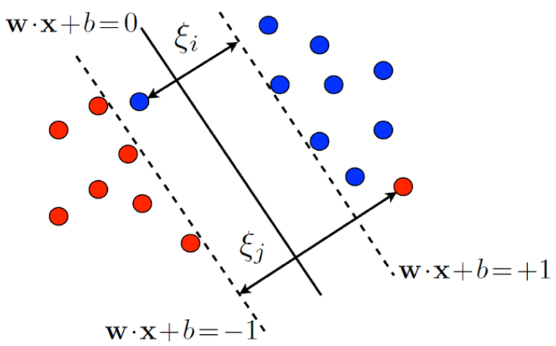


*Figure 2*. A simple representation of the working of a Support Vector Machine.

These hyperplanes are boundaries that decide which classification is right for each data point. By using the margin around this decision boundary, we can try to maximise the margin to make sure future data points will be classified correctly (Noble, 2006).

Although the topic of the current research has not been studied broadly, another study by Chuang and Shih (2006) uses SVM as a classifier for recognising facial action units. Apart from that, SVMs are very efficient at finding the optimal hyperplane for the data. SVMs are computationally not very efficient, but given that we use little data, this is not a big problem for this study.

The values of the hyperparameters of SVM in this study were picked using a grid search, just like the other two classifiers that were used in this study. The hyperparameters that are tuned for the Support Vector Machine are the following (Pedregosa et al., 2011):

- *C*: this is a regularisation parameter. This parameter decides how strongly you want to avoid misclassification and how strong mistakes should be penalised.
- *Kernel*: this parameter decides what kind of kernel the SVM uses.
- *Gamma*: gamma in SVM defines how much influence a single example has on the model. This hyperparameter decides between “auto” or “scale”, where in both cases gamma is calculated differently.

### 3.5. Features and Evaluation for the Classifiers

As input for all classifiers, the degrees of mimicry on the three specified AUs are used, similar to the regression analysis. All three classifiers try to classify the probability to invest as categories, as described in paragraph “Variable transformation for classification and class imbalance". The evaluation metric used is mean accuracy. All classifiers are tuned using a grid search. Consequently they are ran on 100 different splits, where for each split a measure of accuracy, which represent the total percentage of correct predictions, on the test set is calculated. This is necessary, given that we trained the algorithms on very little data. Using the mean accuracy over 100 splits, we can get a more stable view of the results. Furthermore, considering that the classes are ever so slightly imbalanced, the baseline for the classifiers will be set by the majority class, which had 40 cases of the 75 cases. This results in a baseline of 53.33% accuracy.

## 4. Results

### 4.1. Occurrence of Mimicry

In order to explore the relationships between mimicry and entrepreneurial success, a score of mimicry was calculated by calculating a cross-correlation between each frame of the specified action units. In Table 1, the degree of mimicry for each action unit between all pitchers and jury members from the first pitching group are shown. The tables corresponding to the other three groups of pitchers are added in Appendix A.

Table 1.
*The degree of mimicry from jury member to the pitcher in year 2018-2019, measured as Pearson's cross-correlation.*

| Groepsnaam | AU06 Jury 1 | AU06 Jury 2 | AU06 Jury 3 | AU07 Jury 1 | AU07 Jury2 | AU07 Jury 3 | AU12 Jury 1 | AU12 Jury 2 | AU12 Jury 3 |
|---|---|---|---|---|---|---|---|---|---|
| Little Sister | 0.34 | 0.16 | 0.22 | 0.21 | 0.11 | 0.13 | 0.30 | 0.28 | 0.29 |
| FLIPR | 0.21 | -0.04 | 0.11 | 0.05 | -0.04 | 0.03 | 0.14 | 0.12 | 0.51 |
| BubblePop | 0.10 | 0.14 | 0.02 | -0.07 | -0.10 | 0.23 | 0.10 | 0.02 | 0.01 |
| RecognEyes | 0.07 | -0.07 | 0.06 | -0.02 | 0.03 | 0.06 | 0.18 | -0.05 | 0.06 |
| HOTIDY | 0.10 | 0.12 | 0.07 | 0.02 | 0.00 | 0.04 | 0.13 | 0.02 | 0.19 |
| FitPoint | 0.05 | -0.01 | 0.21 | -0.01 | 0.06 | 0.08 | 0.06 | 0.09 | 0.31 |
| SOLON | 0.37 | 0.14 | 0.22 | 0.11 | 0.03 | 0.08 | 0.35 | 0.24 | 0.31 |

Although this tables summarises the extent in which each jury member mimicked certain action units of the pitcher, a more clear visualisation of this process can be portrayed through figures. In Figure 3, two correlograms are displayed in which lag per frame displayed on the x-axis shows the correlation for that particular moment, on the y-axis. The left graph show a gradual increase from frame 0 to where the correlation peaks, where the lag equals 15. This means that, after 15 frames, or 600 ms, the correlation between that pitcher and jury member is highest, namely $r(22064) = 0.30$, $p < 0.01$. In this case, mimicry was clearly visible. In the right graph, no clear sign of mimicry could be detected as the correlation stays around $r(20707) = 0.02$, $p < .001$. The left graph portrays a higher degree of mimicry than the right graph.

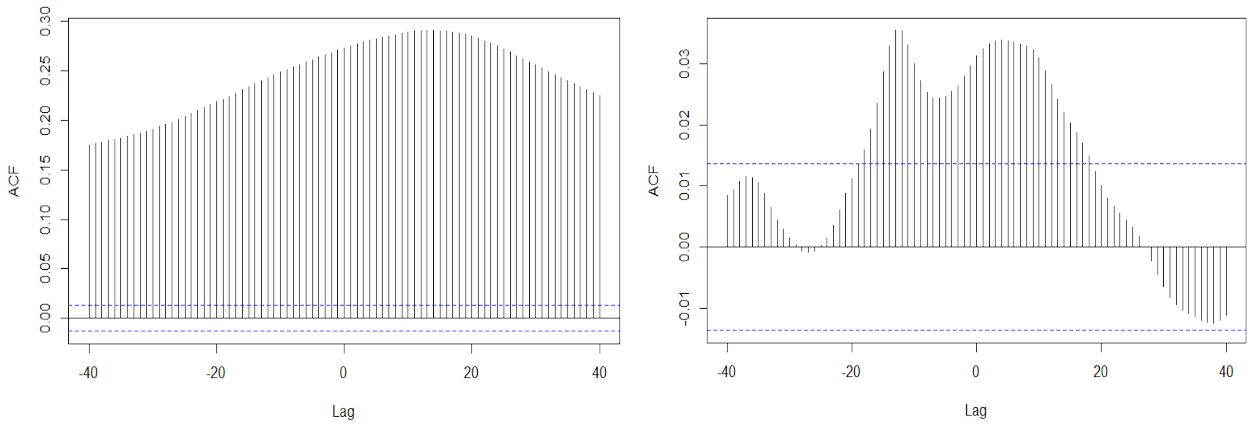


*Figure 3.* Two correlograms that depict the degree of mimicry over time.

### 4.2. Multiple Linear Regression

In order to explore the relationship between the degree of mimicry and the evaluation measure, probability to invest, a multiple linear regression was ran. The independent variables were the three different action units, AU 06, AU 07 and AU 12. The dependent variable was probability to invest. To be able to use the results of this analysis, some key assumptions that multiple linear regression made had to be checked.

#### 4.2.1. Assumptions

Both the dependent and independent variables used in this research are continuous variables. First outliers were checked using Cook's distance, showing no values above 1, which implicates that no outliers can de be found in the data. To test if the data meets the assumption of collinearity, VIF scores were considered. The VIF-values did not implicate any sign of multicollinearity for the variables AU 06, AU 07 and AU 12 ($VIF = 1.87$, $VIF = 1.16$ and $VIF = 1.91$ respectively). Consequently, the data met the assumption of independent errors with a Durbin-Watson value of 2.00. In order to check the assumption that the values of the residuals are normally distributed, the graphs in Figure 4 were used. That graphs shows that the data points are not all completely on the line, but follow the line closely. Although the distribution seems to be normal, this assumptions might be violated, possibly due to limited data. The results of the analysis therefore have to be interpreted with care.

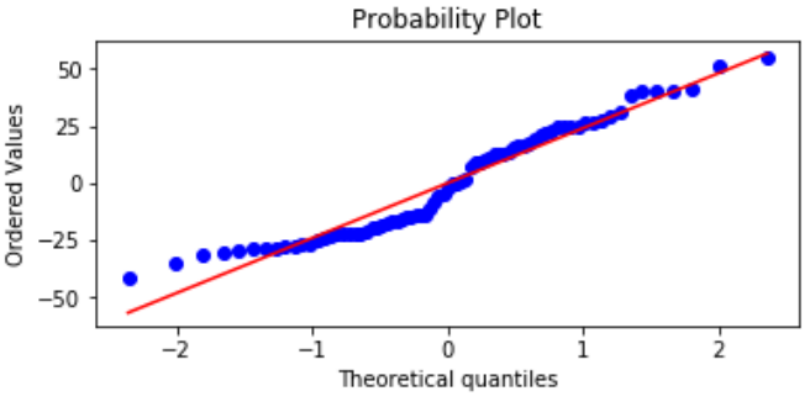


*Figure 4.* Probability plot to check the normality of the distribution of the residuals.

Finally, the assumption of homoscedasticity was assessed using Figure 5. In this scatterplot, the values that the model predicts are plotted against the residuals. The data in this figure shows no clear sign of funnelling or non-linearity. This means that the assumptions of homoscedasticity has been met as well. Based on the assumption tests, the multiple linear regression could be ran.

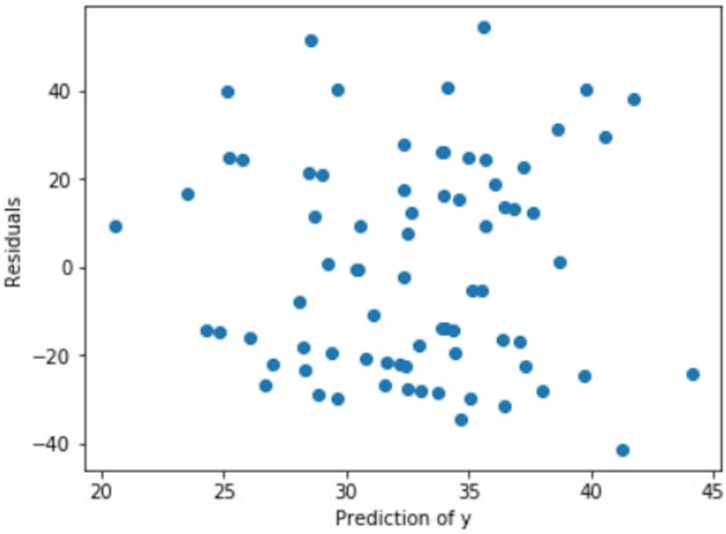


*Figure 5.* Scatterplot in which the residuals are plotted against the expected values.

#### 4.2.2. Multi Linear Regression Analysis

After checking the assumptions, the multiple regression was conducted to see whether the degree's of mimicry from three different action units influenced the probability to invest. The analysis showed that the degree of mimicry in AU 06, AU 07 and AU 12 did not explain a significant amount in probability to invest, ($F$(3, 71) = 0.89, $p$ = .45, $R^2$ = 0.04. Neither of the AUs mentioned predicted probability to invest significantly, $B$ = -35.25, $p$ = .24, $B$ = -27.93, $p$ = .35, and $B$ = 25.05, $p$ = .39 respectively. These results implicate that based on this data, mimicry in the specified AUs does not have a direct predictive relationship on the probability to invest.

### 4.3. Spearman's Rank Correlation Analysis

For AU 06, no significant association was found with ranking, $r_s$ = .08, $p$ = .49. For AU 07, no significant association was found with ranking either, $r_s$ = .09, $p$ = .42. Lastly, AU 12 had no significant association with ranking as well, $r_s$ = -0.10, $p$ = .42.

### 4.4. Decision Tree, k-Nearest Neighbours and Support Vector Machine Classification

#### 4.4.1. Hyperparameter Optimisation

*Decision Tree Hyperparameters*

For the Decision Tree classifier, a grid search for hyperparameter optimisation resulted in the following values for the hyperparameters:

- *Min_sample_split*: 4
- *Max_depth*: 7
- *Criterion*: Entropy
- *Splitter*: Random

*k-Nearest Neighbours Hyperparameters*

For the k-Nearest Neighbours classifier, a grid search for hyperparameter optimisation resulted in the following values for the hyperparameters:

- N*_neighbours*: 9
- *Weights*: Uniform
- *Metric*: Euclidean
-

*Support Vector Machine Hyperparameters*

For the Support Vector Machine classifier, a grid search for hyperparameter optimisation resulted in the following values for the hyperparameters:

- *C*: 5
- *Kernel*: Sigmoid
- *Gamma*: Scale

#### 4.4.2. Mean Accuracy

As specified earlier, the baseline was set by the majority class, which resulted in a baseline accuracy of 53.33%. In Table 2, mean accuracies for all classifiers are shown. While using AU 06, AU 07 and AU 12 as input for the classifiers, none of the classifiers classify the probability to invest better than the majority class baseline.

Table 2.
*The mean accuracy of all classifiers compared to baseline.*

| | Mean Accuracy |
|---|---|
| Baseline | 53.33% |
| Decision Tree Classifier | 49.80% |
| k-Nearest Neighbours Classifier | 50.66% |
| Support Vector Machine Classifier | 51.40% |

## 5. Discussion

The aim of the current exploratory study was to investigate what kind of influence mimicry in facial expression can have on the evaluation of judges during a business pitch. The degree of mimicry on socially relevant action units, namely lip corner pulling, cheek raising and lid tightening, was determined by means of a cross-correlation between the pitcher and the jury members. Consequently, variables deriving from the evaluation forms of the judges were used as dependent variables to determine the influence of mimicry and explore this novel relationship.

Results from the regression analysis show that, in our data set, no significant portion of the probability to invest was explained by the degree of mimicry in any of the action units. This mean that, in this study, no evidence was found that implicates that the degree mimicry influences the probability to invest. Besides that, during the analysis using Spearman's rank correlation, the degree of mimicry in none of the action units had a significant association with the ranking that they got from the jury members. These results imply that none of the AUs individually can predict ranking. Lastly, the machine learning classifiers could not classify the probability to invest (as categories) better than the baseline. These results are not in line with the expectations with respects to the research question, namely that jury members who mimic socially relevant facial expression in a high frequency would give better evaluations to the pitcher in comparison to when they mimic in a lower frequency.

Although the current study is at the forefront in terms of the technology used to determine mimicry in facial expressions, especially in relation to entrepreneurial studies, no conclusions can yet be drawn with respect to the research question and the purpose of this study. Overall, the results seem to imply that mimicry during business pitches do not significantly influence the probability to invest and the ranking of the pitches. Even though these results seem to be evident, these results should be interpreted with care for a number of reasons.

First of all, some critical notes should be made with respects to the design of this study. As proposed by Liebregts, Darnihamedani, Postma and Atzmueller (2019), the processing of social signals is an emerging domain and can provide a breakthrough in analysing behavioural cues, including facial expressions and mimicry in those facial expressions. In addition, the positive influence of mimicry on social interaction and even in an entrepreneurial setting has been widely studied and discussed extensively during this study. Even though this study was not able to substantiate claims regarding a positive influence of mimicry with respect to entrepreneurial success based on this data, it is dangerous to conclude that such influences are non-existent. The data used to explore this relationship derives from a pitching competition as discussed in the description of the data set in the “Experimental Setup” section. The video material is excellent material to be able to demonstrate that mimicry during such pitches can be present, which was done using state-of-the-art facial analysis software during this study. Nonetheless, the data set used has some limitations with respect to the extent in which the data can be used for research. Firstly, it is hard to examine the influence of mimicry without having ran a controlled experiment. In an experimental setting, group differences could be compared by means of a t-test or an ANOVA. Using a similar setup, mimicry can be compared between subjects as controlled as possible.

Besides the fact that the current study is not a controlled experiment, many other factors that might have been present in this study could have influenced the results as well. Despite the excellent camera setup, which made facial analysis easy, this competition was not designed to be an experimental setup, which results in lots of variables that can hardly be accounted for. First off, there are four different pitching groups, each with different jury members. These groups can contain differences and are to be compared with care. Secondly, intra-individual differences amongst the jury members could not be accounted for in this study, given that insight in these differences had to be sacrificed in order to get more observations. Taking into consideration that the amount of pitchers in the dataset is little with respects to the number of observations needed to run a regression analysis and train a machine learning classifier, this sacrifice was necessary to run the evaluation analyses of which the results can be detected with power (Green, 1991). Consequently, each jury member is influenced differently when determining the probability to invest, considering each jury member has different expertises and experiences with investing. Naturally, the degree in which they mimic pitchers differs and their reasons to do so might differ as well. Taking into account that many factors are detrimental when investing, it might be hard to find predictive value in mimicry. However, this does not mean that a decision cannot be influenced by mimicry or that mimicking a pitcher has no implications for the evaluation. In future research, an experimental design combined with clear factors to evaluate on might reveal interesting effects, as studies by Colta (2010) and Maddux, Mullen & Galinksy (2008) have proven.

Another limitation to this study is the fact that none of the people that participated in the pitching competition, including jury members, were aware of the fact that analyses would be ran over the video's, which is logical bearing in mind that the purpose of this competition was not scientific. Nevertheless, this resulted in many sections of the video in which jury members look sideways, put their hands in front of their faces or other ways of hindrance in which the video material is made partly unfit for a confident facial analysis.

Lastly, two final remarks should be made about the data after processing the video material. Firstly, a closer look regarding the assumption of normality of the residuals is in place. As can be seen in Figure 4 in the "Results" section, the values are close to the line, but do not completely follow that line. This might indicate that the distribution of the residuals is not normal. Taking into consideration that there are very few observations in this dataset, it is hard to conclude whether the residuals actually differ from a Gaussian distribution, since the differences are not drastic. However, the results of the regression analysis must still be interpreted with care. Not only might the limited amount of observations be of influence concerning the normality of the residuals, but for the regression analysis in general, in future research it would be desirable to have a higher amount of observations.

The current study shows that mimicry in an entrepreneurial setting could be analysed better than in the past using the state-of-the-art facial behavioural analysis software. However, this study did show the influence of mimicry on the probability to invest. While this influence might still exist, the findings suggest that so far, entrepreneurs should be careful to solely rely on mimicry as an indication for business success. However, this thesis provides an interesting agenda for researching mimicry in an entrepreneurial setting.

## 6. Conclusion

The goal of this exploratory thesis was to discover what kind of influence mimicry in facial expression can have on the evaluation of judges during a business pitch. In order to examine this relationship, video material from a dataset derived from a pitching competition was used in order to calculate the degree of mimicry, which was done using OpenFace, which is composed out of advanced facial behaviour analysis algorithms. Consequently, jury members evaluations, more specifically their estimate of the probability to invest in a business that was being pitched, were used to explore the influence of mimicry in entrepreneurial success and answer the following research question:

**RQ**: What is the influence of mimicry in facial expression on the probability to invest between a business pitcher and the jury members?

Based on our dataset, influences of mimicry on the probability to invest have yet to be found. However, the new state-of-the-art technology regarding facial analyses software shows great promise for research regarding mimicry as a field of research, but more specifically for mimicry in entrepreneurial setting. Although similar data might not be the best fit, the exploration of mimicry in entrepreneurial shows great promise when conducted in an experimental setting.

The main implication of this thesis is that mimicry in entrepreneurial setting is present and can be explored using on a precise level using state-of-the-art facial analysis software. Literature suggests that non-verbal behaviour and mimicry are of influence in an entrepreneurial setting and this thesis explored the relationships between them. Even though no effects were found, this thesis sheds light on an interesting agenda for data science regarding mimicry in entrepreneurial setting.

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## Appendix A: Mimicry Tables Between Pitchers and Jury Members

Table 3.

*The degree of mimicry from jury member to the pitcher in group 2, measured as Pearson's cross-correlation.*

| Groepsnaam | AU06 Jury 1 | AU06 Jury 2 | AU06 Jury 3 | AU07 Jury 1 | AU07 Jury2 | AU07 Jury 3 | AU12 Jury 1 | AU12 Jury 2 | AU12 Jury 3 |
|---|---|---|---|---|---|---|---|---|---|
| tAIste | 0.17 | 0.28 | 0.48 | -0.02 | 0.26 | 0.08 | 0.19 | 0.37 | 0.36 |
| Choos3Wis-ely | 0.04 | -0.02 | 0.00 | 0.07 | 0.21 | 0.03 | 0.06 | -0.07 | -0.05 |
| SmArt | 0.08 | 0.23 | 0.05 | 0.01 | 0.12 | 0.04 | 0.22 | 0.33 | 0.03 |
| StudentFood | 0.06 | 0.03 | 0.00 | 0.02 | 0.06 | -0.06 | 0.13 | 0.24 | -0.06 |
| wAIste | 0.16 | 0.21 | -0.10 | 0.00 | 0.03 | 0.02 | 0.29 | 0.34 | -0.09 |
| Chattern | 0.14 | 0.15 | 0.21 | 0.04 | 0.18 | -0.08 | 0.19 | 0.37 | 0.22 |
| FindIT | 0.02 | 0.23 | 0.34 | 0.04 | 0.06 | 0.08 | 0.05 | 0.24 | 0.34 |

Table 4.

*The degree of mimicry from jury member to the pitcher in group 3, measured as Pearson's cross-correlation.*

| Groepsnaam | AU06 Jury 1 | AU06 Jury 2 | AU06 Jury 3 | AU07 Jury 1 | AU07 Jury2 | AU07 Jury 3 | AU12 Jury 1 | AU12 Jury 2 | AU12 Jury 3 |
|---|---|---|---|---|---|---|---|---|---|
| Ar_T_ficial | 0.19 | 0.15 | 0.08 | 0.14 | 0.08 | -0.05 | 0.27 | 0.28 | 0.12 |
| Recipe_Me | 0.41 | 0.20 | 0.03 | 0.20 | 0.19 | 0.05 | 0.47 | 0.20 | 0.05 |
| Salix | 0.25 | -0.05 | -0.01 | -0.01 | -0.07 | -0.04 | 0.25 | -0.06 | 0.03 |
| Peech | 0.22 | -0.01 | 0.09 | 0.17 | 0.02 | -0.04 | 0.25 | -0.04 | 0.07 |
| HoodFood | -0.07 | 0.02 | -0.04 | -0.08 | -0.01 | 0.01 | 0.02 | -0.04 | -0.01 |
| LockUp | 0.18 | 0.03 | -0.05 | 0.07 | -0.01 | -0.02 | 0.15 | 0.02 | -0.07 |

Table 5.

*The degree of mimicry from jury member to the pitcher in group 4, measured as Pearson's cross-correlation.*

| Groepsnaam | AU06 Jury 1 | AU06 Jury 2 | AU06 Jury 3 | AU07 Jury 1 | AU07 Jury2 | AU07 Jury 3 | AU12 Jury 1 | AU12 Jury 2 | AU12 Jury 3 |
|---|---|---|---|---|---|---|---|---|---|
| Ziggurat | 0.37 | 0.19 | 0.39 | 0.08 | -0.04 | 0.12 | 0.17 | 0.00 | 0.38 |
| PREA | 0.15 | -0.06 | 0.16 | 0.08 | -0.03 | 0.3 | 0.16 | 0.07 | 0.25 |
| YoungBoos-ters | 0.22 | 0.16 | 0.28 | 0.32 | 0.35 | 0.35 | 0.17 | 0.14 | 0.47 |
| Whitebox | 0.17 | -0.03 | 0.16 | 0.12 | 0.16 | 0.10 | 0.30 | 0.09 | 0.48 |
| SoccerAca-demy | 0.29 | 0.12 | 0.25 | 0.40 | 0.16 | 0.22 | 0.24 | 0.05 | 0.37 |

**Appendix B: Github Repository Link**

The code that has been used for the analysis, as well as the code that has been used for calculating mimicry and the analysis data have been stored in the following Github repository: https://github.com/TimEikelenboom/ThesisProject